Predicting Energy Efficiency

using Multinomial Logistic Regression

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Related Git Repository: https://github.com/aJiiin/2017-2-ML-Term-Project.git

***Abstract*—Food, clothing, and shelter form the requisites of our life. So, energy efficient prediction plays an important role in designing and constructing residential buildings. I perform a statistical machine learning framework to predict the category of two output variables, namely heating load (HL) and cooling load (CL) from eight input variables (relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area, glazing area distribution), of residential buildings. Research progress starts with analyzing data set, and modify types of output variables for my training model. Next, train the model by using 80% of whole data and test with 20% of those. Extensive simulations on 768 diverse residential buildings show that we can predict HL and CL with low mean absolute error deviations from the ground truth which is established using Ecotect (0.51 and 1.42, respectively).**

Keywords—Machine learning; Deep learning; Neural network; Multi-layer; Classification; Logistic regression; Energy efficiency prediction; Heating load; Cooling load

I. INTRODUCTION

There has been a considerable body of research on the topic of energy performance of buildings (EPB) recently due to growing concerns about energy waste and its perennial adverse impact on the environment [1], [2]. Moreover, buildings in European countries are legally bound to conform to appropriate minimum requirements regarding energy efficiency following the European Directive 2002/91/EC [1]. Reports suggest that building energy consumption has steadily increased over the past decades worldwide [3], [4], and heating, ventilation and air conditioning (HVAC), which have a catalytic role in regulating the indoor climate [5], account for most of the energy use in the buildings [6]. Therefore, one way to alleviate the ever increasing demand for additional energy supply is to have more energy-efficient builds designs with improved energy conservation properties.

When it comes to efficient building design, the computation of the heating load (HL) and the cooling load (CL) is required to determine the specifications of the heating and cooling equipment needed to maintain comfortable indoor air conditions. In order to estimate the required cooling and heating capacities, architects and building designers need information about the characteristics of the building and of the conditioned space (for example occupancy and activity level), the climate, and the intended use (residential buildings have generally different requirements compared to industrial buildings).

II. BACKGROUND KNOWLEDGE

Statistical classification is a problem studied in machine learning. It is a type of supervised learning, a method of machine learning where categories are predefined, and is used to categorize new probabilistic observations into said categories. When there are only two categories the problem is known as binary classification, and three categories or more the problem is known as multi-class classification or multinomial classification.

A. Binary Classification

Binary or binomial classification is the task of classifying the elements of a given set into two groups (predicting which group each one belongs to) on the basis of a classification rule. In binary classification problems, logistic regression is used by using sigmoid function. Sigmoid function has a value between 0 and 1 (1), so if hypothesis value is over 0.5, it belongs to one category and is under 0.5, it belongs to the other category.

$$\mathbf{f(x)} = \frac{\mathbf{1}}{\mathbf{1}+e^{-\boldsymbol{\beta x}}} \qquad (1)$$

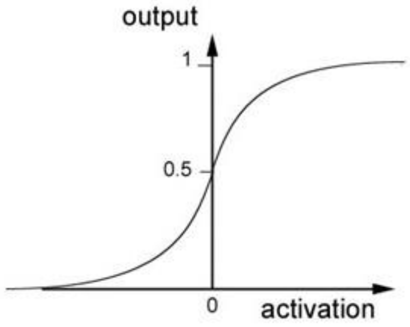

Figure 1 Graph of Sigmoid Function

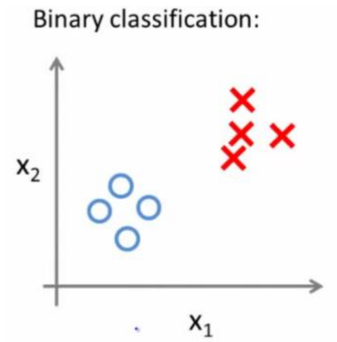

Figure 2 Binary Classification

B. *Multinomial Classification*

In machine learning, multiclass or multinomial classification is the problem of classifying instances into one of three or more classes. First of all, classes are divided into two groups, one and the rest. After that, training a single classifier per class, with the samples of that class as positive samples and all other samples as negatives. These training process is repeated for each class of entire classes.

Multilayer perceptrons provide a natural extension to the multi-class problem. Instead of just having one neuron in the output layer, with binary output, one could have N binary neurons leading to multi-class classification. In practice, the last layer of a neural network usually uses softmax function which transform each value to probability value.

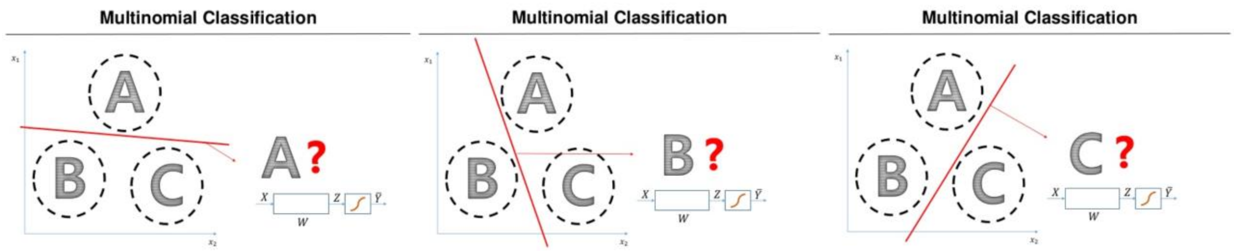

Figure 3 Binary Classification for Each Class

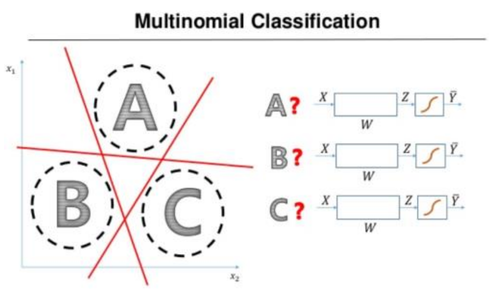

Figure 4 Multinomial Classification

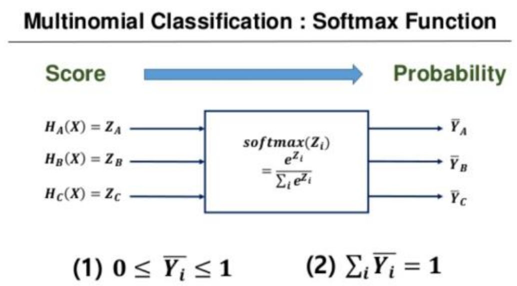

Figure 5 Transformation of Score Using Softmax Function

III. DATA SET INFORMATION

Buildings differ with respect to the glazing area, the glazing area distribution, and the orientation, amongst other parameters. The simulated buildings were generated using Ecotect. All the buildings have the same volume, which is 771.75 m3, but different surface areas and dimensions. The simulation assumes that the buildings are in Athens, Greece, residential with seven persons, and sedentary activity (70W). The internal design conditions were set as follows: clothing:0.6 clo, humidity: 60%, air speed: 0.30m/s, lighting level: 300 Lux.

There are three types of glazing areas, which are expressed as percentages of the floor area: 10%, 25%, and 40%. Furthermore, five different distribution scenarios for each glazing area were simulated. 1) uniform: with 25% glazing on each side, 2) north: 55% on the north side and 15% on each of the other sides, 3) east: 55% on the east side and 15% on each of the other sides, 4) south: 55%

on the south side and 15% on each of the other side, and 5) west: 55% on the west side and 15% on each of the other sides. In addition, it contains samples with no glazing areas.

Thus, considering twelve building forms and three glazing area variations with five glazing area distributions each, for four orientation, data set contains $12 \times 3 \times 5 \times 4 = 720$ building samples. In addition it has twelve building forms for the four orientations without glazing. Therefore, in total I used $12 \times 3 \times 5 \times 4 + 12 * 4 = 768$ buildings. Each of the 768 simulated buildings can be characterized by eight building parameters (to conform to standard mathematical notation and facilitate the analysis in this work, henceforth these building parameters will be called input variables and will be represented with X) which we are interested in exploring further. Also, for each of the 768 buildings there are recorded HL and CL (henceforth these parameters will be called output variables and will be represented with y). Table 1 summarizes the input variables and the output variables in this data set, introduces the mathematical representation for each variable, and indicates the unit for the variables used in this research.

TABLE 1

Mathematical representation of the input and output variables

Mathematical representation	**Input or output variable**	**Unit for the variables**
X1	Relative Compactness	No units
X2	Surface Area	m^2
X3	Wall Area	m^2
X4	Roof Area	m^2
X5	Overall Height	m
X6	Orientation	No units 2: North, 3: East, 4: South, 5: West
X7	Glazing Area	No units 0%, 10%, 25%, 40% (of floor area)
X8	Glazing Area Distribution	1: Uniform, 2: North, 3: East, 4: South, 5: West
Y1	Heating Load	kWh/m^2 0: 10, 1: 20, 2: 30, 3: 40
Y2	Cooling Load	kWh/m^2 0: 10, 1: 20, 2: 30, 3: 40, 4: 50

IV. TRAINING MODEL

A. Training set and Test set

Unfortunately, energy efficiency data set doesn’t have fully enough data, so I divided whole data set into 8:2 (80% for training set and 20% for test set).

B. Multi-layer perceptron

The neural network, which has 8 input parameters and 1 output value, consists of five layers. The number of hidden nodes for each layer is 50, 20, 30, 70 and Xavier initializer is used for weight value in each layer. Also, except output layer, each layer uses ReLU function instead of sigmoid function for better performance and accuracy. In contrast, output layer uses softmax function and one-hot to classify one category which each Y1 and Y2 belongs to.

C. Optimizer and Learning Rate

Comparing with ‘Gradient Descent Optimizer’, ‘Adam Optimizer’ performed better accuracy. So, I used ‘Adam Optimizer’ in this model and set learning rate for Y1 to 0.001 and for Y2 to 0.0001

V. CONCLUSION

By using training set, the model was trained to determine two output variable's category for 2000 times. After that, it was tested with test set and the result was not so bad.

A. Y1: Heating Load

The number of categories that Y1 value can belong to was four and learning rate of Adam Optimizer was 0.001. During the training from step 0 to step 2000, cost has been dramatically reduced from 60.900 to 0.343 and accuracy has increased from 28.34% to 81.43%. TABLE2 reports the comparison of change in each cost and accuracy during training.

TABLE 2

Comparison of change in each cost and accuracy for Y1

	Step 0	**Step 2000**
Cost	60.900	0.343
Accuracy	28.34%	81.43%

While testing the model with test set, I counted the number of each class instances in both test set and predicted Y1 set and showed in a graph to compare the results and calculate performance. Figure 6 shows the number of each y1 class instances in test set and Figure 7 shows those in predicted Y1 set. In addition, Figure 8 reports the number of correct prediction for each category.

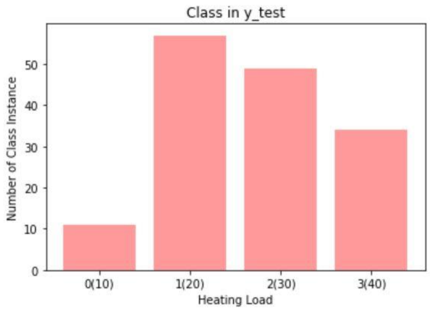

Figure 6 number of each instances in Y1 test set

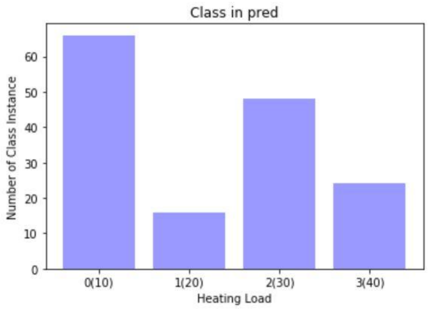

Figure 7 number of each instances in pred. set

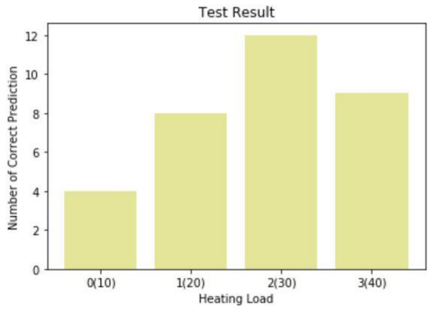

Figure 8 number of correct Y1 predictions

B. Y2: Cooling Load

The number of categories that Y2 value can belong to was five and learning rate of Adam Optimizer was 0.0001. During the training from step 0 to step 2000, cost also has been dramatically reduced from 65.116 to 0.589 and accuracy has increased from 33.39% to 72.15%. TABLE3 reports the comparison of change in each cost and accuracy during training.

TABLE 3

Comparison of change in each cost and accuracy for Y2

	Step 0	**Step 2000**
Cost	65.116	0.589
Accuracy	33.39%	72.15%

While testing the model with test set, I also counted the number of each class instances in both test set and predicted Y2 set and showed in a graph to compare the results and calculate performance. Figure 9 shows the number of each y2 class instances in test set and Figure 10 shows those in predicted Y2 set. In addition, Figure 11 reports the number of correct prediction for each category.

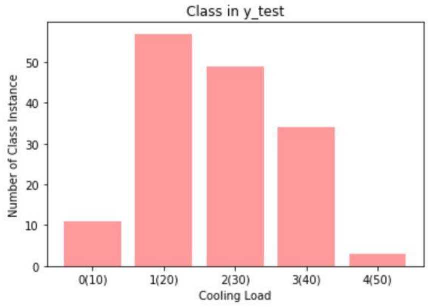

Figure 9 number of each instances in Y2 test set

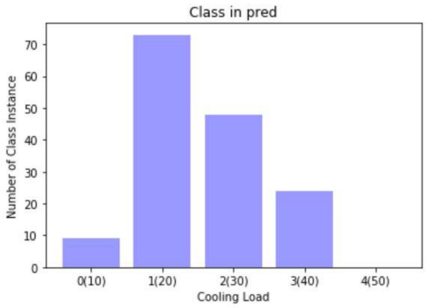

Figure 10 number of each instances in pred. set

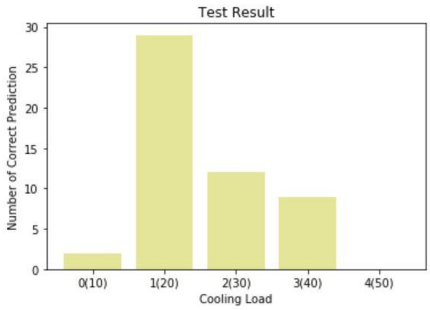

Figure 11 number of correct Y2 predictions

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