

A sequential piecewise linear regression model for data analysis developed with Visual C# .NET

Mô hình hồi quy tuyến tính từng phần sử dụng cho phân tích dữ liệu được phát triển với ngôn ngữ C# .NET

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(Ngày nhận bài: 09/9/2020, ngày phản biện xong: 24/9/2020, ngày chấp nhận đăng: 30/9/2020)

Abstract

This study develops a software program used for nonlinear data analysis based on the Sequential Piecewise Linear Regression (SPLR) [1]. The SPLR is a regression analysis method relying on the concept of hinge function to identify locally linear relationship in datasets. Thus, this method can effectively used to capture nonlinear functional mapping. In this study, the SPRL software program has been developed with Visual C# .NET framework 4.6.1. The usefulness of the newly developed program is verified via several data modeling tasks.

Keywords: Piecewise Linear; Regression Analysis; Visual C# .NET; Machine Learning; Mathematical Modeling.

Tóm tắt

Nghiên cứu này phát triển một chương trình phần mềm được sử dụng để phân tích dữ liệu phi tuyến dựa trên thuật toán Hồi quy tuyến tính từng phần tuần tự (SPLR) [1]. SPLR là một phương pháp phân tích hồi quy dựa trên khái niệm hàm bản lề để xác định mối quan hệ tuyến tính cục bộ trong tập dữ liệu. Do đó, phương pháp này có thể được sử dụng hiệu quả để mô phỏng các mối liên hệ phi tuyến giữa các biến số. Trong nghiên cứu này, một chương trình phần mềm SPRL đã được phát triển với ngôn ngữ Visual C # nền tảng .NET 4.6.1. Chương trình phần mềm mới phát triển được kiểm chứng thông qua một số vấn đề mô hình hóa dữ liệu.

Từ khóa: Tuyến tính từng phần; Phân tích hồi quy; Ngôn ngữ C # .NET; Học máy; Mô hình toán học.

1. Introduction

In civil engineering field, regression analysis is a common method used for analyzing functional mapping between a dependent

variable of interest and a set of predicting variables [2-4]. Mathematical models, expressed in the form of mathematical equations, can be utilized to aid civil engineers

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in various tasks, e.g. structural design [5, 6], project management [7, 8], concrete mix component design [9-11], etc.

Traditional regression analysis approach basically relied on multiple linear regression models for constructing various mathematical models based on collected datasets [12]. This conventional method has the desired properties of simplicity and transparency. However, the critical assumption of linearity significantly hinders the capability of this method in modeling complex and nonlinear problems. To avoid such hinderance, scholars have resorted to sophisticated models for regression analysis such as artificial neural network, support vector regression, and least squares support vector regression. The advanced methods are highly powerful in data fitting [13-17]. Nevertheless, those sophisticated models have a black-box structure which creates certain difficulties for civil engineers to comprehend and interpret those models' structure.

Another direction to improve the predictive accuracy of the conventional multiple linear regression models is to employ piecewise linear regression models [18-20]. These models assume that the functional mapping of interest can be satisfactorily approximated via locally linear models [21]. By employing the concept of hinge function, piecewise linear regression models can be construct to accurately estimate complex and nonlinear mathematic relationships.

A piecewise linear regression model trained with a sequential algorithm, named as Sequential Piecewise Linear Regression Model (SPLRM), has been put forward in [1] and programmed in MATLAB environment [22]. This study further enhances the applicability of this model via a software program developed with Visual C# .NET framework 4.6.1. The rest of the paper is organized as follows: the second

section briefly mentions the formulation of SPMR; two application cases of the newly developed program are demonstrated in the third section; concluding remarks of this paper are stated in the final section.

2. The Used Method for Constructing Piecewise Linear Regression Model

The SPLRM utilizes various linear models to fit subsets of the input data X . Herein, the overall space of X is divided into disjoint regions within which a linear model can be used to describe the relationship between X and a dependent variable Y . The disjoint regions are separated via identification of various knots or break points [23]. Values of knots are sequentially identified and included in a SPLRM structure.

The model structure with one knot is shown as follows [24]:

$$Y(X_i) = \begin{cases} \sum_{d=1}^{D+1} \beta_d X_{i,d} & \text{if } X_{i,d} \leq b \\ \sum_{d=1}^{D+1} \beta_d X_{i,d} & \text{if } X_{i,d} > b \end{cases} \quad (1)$$

where X_i denotes the vector of the i^{th} explanatory variable consisting of D elements. b denotes the breaking point value. Y denotes the response variable.

It is noted that the least square method is employed to compute the parameter β of the linear regression model shown in Eq. (1) as follows:

$$\beta^* = (X^T X)^{-1} X^T Y \quad (2)$$

The model with multiple variables and knots can be generally expressed as follows:

$$Y = \sum_{d=1}^D \sum_{v=1}^{V_d} LF_{d,v}(X_d) \quad (3)$$

where D and V_d denotes the number of predicting variables and the number of hinge function of the d^{th} predicting variable.

In addition to accept or reject a knot candidate, the root mean squared error (RMSE) index is used as follows:

$$RMSE = \sqrt{\sum_{i=1}^N \frac{(Y_{A,i} - Y_{P,i})^2}{N}} \quad (4)$$

where $Y_{A,i}$ and $Y_{P,i}$ are the actual and predicted values of Y . N denotes the total number of data samples.

3. Program Applications

To verify the developed SPLRM program, a simple regression analysis problem (Dataset 1), which has 1 break point, is used. The functions used to generate the first dataset are described as follows:

$$Y = -1.5X + 17 + r/10 \text{ if } X \leq 1.5 \quad (5)$$

$$Y = 1.5X + 12 + r/10 \text{ if } X > 1.5 \quad (6)$$

Herein, X is of $[0, 3]$ and generated with an interval of 0.1. The symbol r denotes a Gaussian random variable with mean = 0 and standard deviation = 1.

The second problem (Dataset 2) involves a simple regression analysis problem with two break points as follows:

$$Y = -1.5X + 14 + r/10 \text{ if } X \leq 1 \quad (7)$$

$$Y = 1.5X + 11 + r/10 \text{ if } X > 1.5 \text{ and } X < 2 \quad (8)$$

$$Y = -1.5X + 17 + r/10 \text{ if } X \geq 2 \quad (9)$$

Table 1. Prediction Performance

Phase	Indices	Dataset 1	Dataset 2	Interface yield stress	Plastic viscosity
Training Phase	RMSE	0.09	0.11	6.42	66.60
	MAPE	0.43	0.69	12.05	8.72
	MAE	0.07	0.09	4.43	41.25
	R ²	0.98	0.94	0.89	0.90
Testing Phase	RMSE	0.13	0.16	9.74	89.81
	MAPE	0.69	0.98	14.66	13.64
	MAE	0.11	0.13	7.02	64.20
	R ²	0.97	0.90	0.90	0.78

Besides the aforementioned simulation cases, real-world datasets regarding the prediction of the interface yield stress and plastic viscosity of fresh concrete [25, 26] are used. The SPLRM is employed to capture the mapping relationships between the interface yield stress and plastic viscosity and their influencing factors. The content of cement, water, sand, small coarse gravel, medium coarse gravel, superplasticizer, and time after

mixing are used as influencing variables. This dataset includes including 142 experimental tests. To evaluate the model performances, the indices of RMSE, mean absolute percentage error (MAPE), mean absolute error (MAE), and coefficient of determination (R²) are employed. The model prediction outcomes are reported in Table 1 as well as Fig. 1. The exemplary SPLRM program used for predicting the variable of plastic viscosit is provided in Fig. 2.

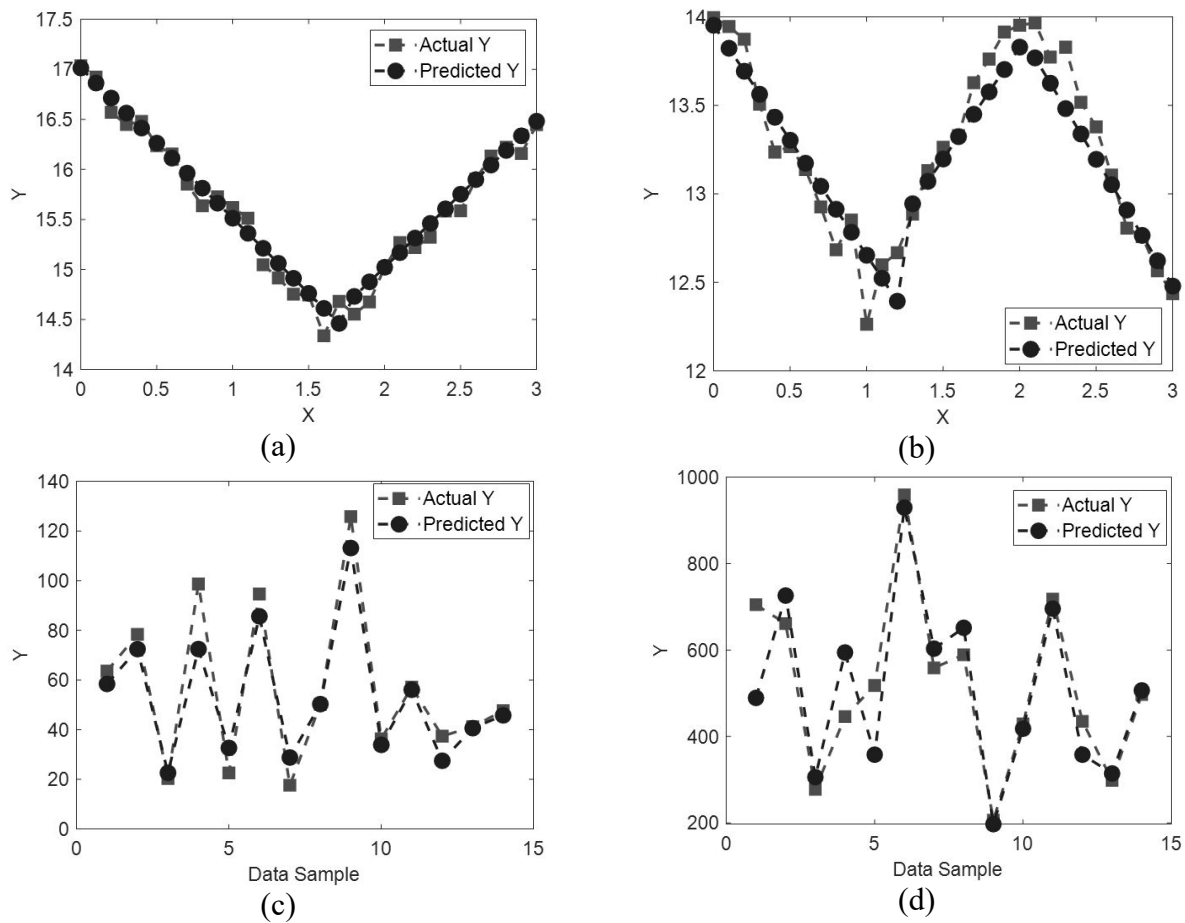


Fig. 1. Demonstrations of testing performances: (a) Dataset 1, (b) Dataset 2, (c) Interface yield stress, and (d) Plastic viscosity

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E:\[0] MyVStudio\ConsoleApp\MyStudy\bin\Debug\MyStudy.exe
Enter Data Location (e.g. E:/csvFiles/PlasticViscosity.csv):
E:/csvFiles/PlasticViscosity.csv
Enter Data Name (e.g. PlasticViscosity):
PlasticViscosity
Enter Testing Data Ratio (e.g. 0.1):
0.1
Enter Iteration Number (e.g. 2):
2
Enter Interval Number (e.g. 20):
10
    
```

Fig. 2. The compiled program SPLRM developed with Visual C# .NET

4. Conclusion

In civil engineering, data fitting via regression analysis is an important task. This study develops a computer program based on the established SPRLM used for approximating nonlinear data relationships. The software program has been developed in Visual C# .NET and its performances have been demonstrated via 4 applications. Good predictive

performances show that the newly developed tool can be helpful to assist civil engineers in various data modeling tasks.

Supplementary materials

The compiled SPLRM program and the experimental datasets can be accessed via: https://github.com/NDHoangDTU/SPLRM-Program_VC

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