

# jurnal3

by dodi mulyadi

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## General metrics

**16,422**

characters

**2,417**

words

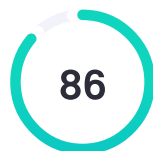
**170**

sentences

**9 min 40 sec**reading  
time**18 min 35 sec**speaking  
time

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## Score



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## Writing Issues

**84**

Issues left

**41**

Critical

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## Writing Issues

<b>10</b>	<b>Engagement</b>	
10	Word choice	<div><div></div></div>
<b>53</b>	<b>Correctness</b>	
24	Misspelled words	<div><div></div></div>
1	Unknown words	<div><div></div></div>
3	Incorrect noun number	<div><div></div></div>
3	Comma misuse within clauses	<div><div></div></div>
5	Improper formatting	<div><div></div></div>
1	Closing punctuation	<div><div></div></div>
10	Punctuation in compound/complex sentences	<div><div></div></div>
3	Determiner use (a/an/the/this, etc.)	<div><div></div></div>
1	Redundant words	<div><div></div></div>
2	Confused words	<div><div></div></div>
<b>21</b>	<b>Clarity</b>	
16	Passive voice misuse	<div><div></div></div>
5	Wordy sentences	<div><div></div></div>

## Unique Words

Measures vocabulary diversity by calculating the percentage of words used only once in your document

**16%**

unique words

## Rare Words

**35%**

Measures depth of vocabulary by identifying words that are not among the 5,000 most common English words.

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rare words

## Word Length

**3.4**

Measures average word length

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characters per word

## Sentence Length

**14.2**

Measures average sentence length

words per sentence

# jurnal3

## OPTIMAL KNOT SELECTION IN SPLINE REGRESSION USING UNBIASED RISK (UBR) AND GENERALIZED CROSS VALIDATION (GCV) METHODS

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Abstract. Spline regression is a nonparametric regression method that estimates data patterns that do not form certain patterns with the help of knots. The best model is obtained from the optimal knot. There are several methods that can be used to select optimal knots, including Generalized Cross Validation (GCV) and Unbiased Risk (UBR). The best model selection criteria used are based on the Mean Squared Error (MSE) and R-Square values. This study discusses the comparison of spline regression models using the UBR and GCV methods as a method for selecting optimal knots in data generation simulations. This research resulted in the best nonparametric spline regression model from the UBR method obtained by using three knots which produced an MSE value of 738.67 and R -Square of 85.65%. Whereas, the best nonparametric spline regression model of the GCV method was obtained using

three knots which<sup>12</sup> produced an MSE value of 121.43 and R-Square of 97.64%. So, it can be concluded<sup>13</sup> that in this study the<sup>14</sup> more appropriate method used for the selection of optimal knot is the GCV method because it produces a smaller MSE value and a larger R-Square compared to the UBR method.

## Introduction

Spline regression is able to<sup>15</sup> overcome data patterns that show sharp up / down with the help of knots so that the resulting curve is relatively smooth [6]. Knots are joint fusion points that indicate changes in behavior patterns of a data<sup>16</sup> [1]. With these knots, the spline is able to<sup>17</sup> follow and adjust the data. In forming<sup>18</sup> the spline regression model, important<sup>19</sup> things to consider include<sup>20</sup> determining the orde<sup>21</sup> of the model, the number of knots and<sup>22</sup> the location of the knots [7]. Orde for the model can be known<sup>23</sup> from the patterns formed in the data, while the number of knot points and knot point locations are determined based on changes in data patterns that occur at certain sub-intervals[10]. The accuracy<sup>24</sup> of the spline regression model that is formed<sup>25</sup> is influenced by the selection of optimal knot points<sup>26</sup>. There are several methods that can be used<sup>27</sup> in the selection<sup>28</sup> of optimal knot points in spline regression, including Cross Validation<sup>29</sup> (CV) [3], Unlimited Risk (UBR) [11], Generalized Cross Validation<sup>30</sup> (GCV) ) [8], and Generalized Maximum Likelihood (GML) [5].

The Unbias Risk (UBR) method is the optimal knots point<sup>31</sup> selection method that requires the estimated value of the variance of known errors [11]. According to [11], the UBR method will produce good scores on non-Gaussian or data not<sup>32</sup> patterned normal distribution. Generalized Cross Validation<sup>33</sup> (GCV) method will be better used<sup>34</sup> in Gaussian or normal<sup>35</sup> distribution data. The advantage of GCV is that it is efficient and simple<sup>36</sup> in its calculations and does not require variants. GCV is asymptotic so<sup>37</sup> if the sample used is small<sup>38</sup> the results will not be maximal [16].

Research using the UBR and GCV methods has been researched several times. [13] conducted a study entitled Modeling Factors Affecting Morbidity Rates in East Java Using Spline Nonparametric Regression. In this study using the GCV method in the selection of optimal knot points from three knot points with R-Square of 89.72%. [9] conducted a study entitled Comparison of Multivariable Spline Nonparametric Regression Models Using Generalized Cross Validation (GCV) and Unbias Risk (UBR) Methods in Optimal Knot Point Selection (Case Study of Maternal Mortality Rate Data in East Java). In this study the GCV method is better used for the selection of optimal knot points with R-Square of 94.3%. [4] conducted a study entitled Unbias Risk (UBR) and Cross Validation (CV) Methods for the Selection of Optimal Knot Points in Multivariable Spline Truncated Nonparametric Regression. Based on the description above, this study focuses on the comparison of the UBR method and the GCV method in the selection of optimal knot points in spline nonparametric regression

### UBR and GCV Methods

#### Unbias Risk (UBR) Methods

The Unbias Risk (UBR) method is a method that can be used to select optimal knots. This method can be used when  $\sigma^2$  is known. In this method the most important thing is the estimated value  $\sigma^2$ . If the estimated value of  $\sigma^2$  is good, the UBR method will be appropriate. The optimal knot point uses the smallest UBR value. According to [4], the following is the formulation of the UBR method: Loss function is  $K = \frac{1}{n} \sum_{i=1}^n (f(K_i) - f_i)^2$ .

$f(K_i)$  is the  $i$  element of the vector  $f$  of size  $n \times 1$ . Next is to define the risk function. The risk function is the expected value of the loss function.

The following is a description of the risk function:

$$RK = ELK = E \left[ \frac{1}{n} \sum_{i=1}^n (f(K_i) - f_i)^2 \right]$$

$$RK = \frac{1}{n} E \left[ \sum_{i=1}^n (f(K_i) - f_i)^2 \right]$$

$$\begin{aligned}
 &= 1nE(Akf + A(k)\varepsilon) - f^2 \\
 &= 1nE(I - Ak)f + A(k)\varepsilon^2 \\
 &= 1n(I - Ak)f^2 + 0 + 1nE(\varepsilon'A'kAk\varepsilon) \\
 &= 1n(I - Ak)f^2 + \sigma^2 \text{tr}(A'kAk)
 \end{aligned}$$

The result of  $RK = E(RK)$ , where  $RK$  is the criterion of Unlock Risk (UBR). The  $RK$  is as follows:

$$\begin{aligned}
 RK &= 1n(I - Ak)y^2 - \sigma^2 \text{tr}(I - A'k)(I - Ak) + \sigma^2 \text{tr}(A'k)Ak \\
 &= 1n(I - Ak)y^2 - \sigma^2 \text{tr}I - A(k)^2 + \sigma^2 \text{tr}A^2k
 \end{aligned}$$

With,  $Ak = XX'X - 1X'$

$$\sigma^2 = I - Aky^2 \text{tr}I - A(k)$$

The selection of optimal knot points using the UBR method <sup>54</sup> is obtained by finding the optimization value as below :

$$\begin{aligned}
 \text{Min } Rk_1, k_2, k_3, \dots, k_j &= \text{Min } 1n(I - Ak)y^2 - \sigma^2 \text{tr}I - Ak^2 + \sigma^2 \text{tr}A^2k \\
 &= \text{Min } 1n(I - Ak)y^2 - I - Aky^2 \text{tr}I - Ak^2 + \text{tr}A^2k - I - Aky^2 \text{tr}I - A(k)
 \end{aligned}$$

Generalized Cross Validation <sup>55</sup> (GCV) Methods

The Generalized Cross Validation <sup>56</sup> (GCV) method is one of the methods often used in the selection of optimal knot points. This GCV method is the result of a modification of the CV method. According to [14], the optimal knot point <sup>57</sup> is obtained from the smallest GCV value. Following are the functions of GCV [15]:

$$CV_k = n - 1i = 1ny_i - f(x_i)^2 / (1 - n - 1\text{trace}A(k)^2)$$

$GCV_k$  is a vector that contains the GCV values from the knot points obtained from the division between the results of the sum of squared residuals from  $f_x$  with  $n\{1 - n - 1\text{trace}A(k)^2\}$ .

According to [12], the general equation of GCV is as follows

$$\begin{aligned} GCV_k &= \text{MSE}(k) \frac{n-1}{\text{tr}(A(k))} \\ &= \frac{n-1}{n} \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\text{tr}(A(k))} \\ &= \frac{n-1}{n} \frac{y' (I - A(k))' (I - A(k)) y}{\text{tr}(A(k))} \end{aligned}$$

with:

$$\hat{y} = A(k)y = XX'X^{-1}X'y$$

$$A(k) = XX'X^{-1}X'$$

Research method

The analysis steps in this research are as follows :

Generating data for response variables and predictor variables using simulation methods

Make data modeling with spline nonparametric regression using three point knots with the UBR method. Select the optimal knot point using the UBR method

Make data modeling with spline nonparametric regression using the optimal knots point from the UBR method.

Make data modeling with spline nonparametric regression using three point knots with the GCV method. Select the optimal knot point using the GCV method

Make data modeling with spline nonparametric regression using the optimal knots point from the GCV method.

Make a comparison of the spline nonparametric regression model with the optimal knot points obtained from the UBR method and the GCV method.

Choose the best model with criteria based on R-Square and MSE

Results and discussion

Modeling Spline Nonparametric Regression Using the UBR Method



The first spline nonparametric regression modeling is modeling simulation data using the UBR method for the selection of optimal knot points.

#### Optimal Knot Point Selection with Three Knot Points

The equation of the spline nonparametric regression model using three knots with five predictor variables in general<sup>63</sup> is as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_1 - k_1 + \beta_3 x_1 - k_2 + \beta_4 x_1 - k_3 + \beta_5 x_2 + \beta_6 x_2 - k_4 + \beta_7 x_2 - k_5 + \beta_8 x_2 - k_6 + \beta_9 x_3 + \beta_{10} x_3 - k_7 + \beta_{11} x_3 - k_8 + \beta_{12} x_3 - k_9 + \beta_{13} x_4 + \beta_{14} x_4 - k_{10} + \beta_{15} x_4 - k_{11} + \beta_{16} x_4 - k_{12} + \beta_{17} x_5 + \beta_{18} x_5 - k_{13} + \beta_{19} x_5 - k_{14} + \beta_{20} x_5 - k_{15} +$$

The following are the results of the 5<sup>64</sup> smallest UBR values in the simulation data using three knots:

Table 4. 1 UBR Values Using 3 Knot Points

Knot

UBR

X1

X2

X3

X4

X5

Knot 1

64,32

4,52

393,39

10,88

0,72

$1,96 \times 10^{-22}$

Knot 2

82,15

7,34

1567,24

48,97

3,25

Knot 3

99,98

10,17

2741,10

87,07

5,77

Knot 1

92,34

8,96

2238,02

70,74

4,69

$2,14 \times 10^{-22}$

Knot 2

96,58

9,63

2517,51

79,81

5,29

Knot 3

98,28

9,90

2629,31

83,44

5,53

Knot 1

76,20

6,40

1175,96

36,28

2,40

$2,25 \times 10^{-22}$

Knot 2

92,34

8,96

2238,02

70,74

4,69

Knot 3

96,58

9,63

2517,51

79,81

5,29

Knot 1

75,35

6,27

1120,06

34,46

2,28

3,07 x 10<sup>-22</sup>

Knot 2

93,19

9,09

2293,92

72,56

4,81

Knot 3

98,28

9,90

2629,31

83,44

5,53

Knot 1

77,05

6,53

1231,86

38,09

2,52

$3,07 \times 10^{-22}$

Knot 2

92,34

8,96

2238,02

70,74

4,69

Knot 3

95,73

9,49

2461,61

78,00

5,17

In Table 4.1 shows that the smallest UBR value of  $1,96 \times 10^{-22}$ .<sup>65</sup> The optimal knot points of each variable are as follows:

Table 4.2. The optimal knot points of each variable

Knot

X1

X2

X3

X4

X5

Knot 1

64,32

4,52

393,39

10,88

0,72

Knot 2

82,15

7,34

1567,24

48,97

3,25

Knot 3

99,98

10,17

2741,10

87,07

5,77

Spline Nonparametric Regression Modeling with Optimal Knot Point UBR

Method

The best spline nonparametric regression model is obtained from the optimal knot point using three knots. Based on the results of the parameter estimation,

the spline nonparametric regression model with the optimal knot point using the UBR method formed is as follows:

$$y = 1,22 + 4,16x_1 + 11,09x_1 - 64,32 - 33,47x_1 - 82,15 - 8,38x_1 - 99,98 + \\ - 8,98x_2 - 35,61x_2 - 4,52 + 18,13x_2 - 7,34 + 2,25x_2 - 10,17 + \\ 0,03x_3 - 0,04x_3 - 393,39 + 0,07x_3 - 1567,24 + 0,003x_3 - 2741,10 + \\ + 2,81x_4 - 2,71x_4 - 10,88 + 0,20x_4 - 48,97 - 51,30x_4 - 87,07 + \\ 17,96x_5 - 18,18x_5 - 0,72 + 11,90x_5 - 3,25 - 448,22x_5 - 5,77 +$$

## 4.2 Modeling Spline Nonparametric Regression Using the GCV Method

The second spline nonparametric regression modeling is modeling simulation data with the GCV method for optimal knot point selection.

### 4.2.1. Optimal Knot Point Selection with Three Knot Points

The next step is to determine the smallest GCV value from the three knot points. The following are the results of the 5 smallest GCV values in the simulation data using three knots:

Table 4. 3 GCV Values Using 3 Knot Points

Knot

GCV

X1

X2

X3

X4

X5

Knot 1

67,71

5,05

616,98

18,14

1,20

514,70

Knot 2

74,51

6,13

1064,16

32,65

2,16

Knot 3

93,19

9,09

2293,92

72,56

4,81

Knot 1

60,92

3,98

169,80

3,63

0,24

520,01

Knot 2

75,35



6,27

1120,06

34,46

2,28

Knot 3

91,49

8,82

2182,12

68,93

4,57

Knot 1

67,71

5,05

616,98

18,14

1,20

521,52

Knot 2

74,51

6,13

1064,16

32,65

2,16

Knot 3

92,34

8,96

2238,02

70,74

4,69

Knot 1

66,86

4,92

561,08

16,32

1,08

528,47

Knot 2

75,35

6,27

1120,06

34,46

2,28

Knot 3

92,34

8,96

2238,02

70,74

4,69

Knot 1

60,92

3,98

169,80

3,63

0,24

529,64

Knot 2

74,51

6,13

1064,16

32,65

2,16

Knot 3

91,49

8,82

2182,12

68,93

4,57

In Table 4.3 shows that the smallest GCV value of 514,70<sup>66</sup> . The optimal knot points of each variable are as follows:

Table 4. 4. The optimal knot points of each variable

Knot

X1

X2

X3

X4

X5

Knot 1

67,71

5,05

616,98

18,14

1,20

Knot 2

74,51

6,13

1064,16

32,65

2,16

Knot 3

93,19

9,09

2293,92

72,56

4,81

#### 4.2.2. Spline Nonparametric Regression Modeling with Optimal Knot Point GCV Method

The best spline nonparametric regression model is obtained from the optimal knot point using three knots. Based on the results of the parameter estimation, the spline nonparametric regression model with optimal knots using the GCV method formed is as follows:

$$y = -3,10 - 7,23x_1 + 165,84x_1 - 67,71 - 215,03x_1 - 74,51 + 56,91x_1 - 93,19 + 101,02x_2 - 17,21x_2 - 5,05 - 120,60x_2 - 6,13 + 5,34x_2 - 9,09 + 0,02x_3 + 2,10x_3 - 616,98 - 5,70x_3 - 1064,16 + 10,62x_3 - 2293,92 + 1,56x_4 - 5,49x_4 - 18,84 + 6,99x_4 - 32,65 + 13,56x_4 - 72,56 + 45,19x_5 - 100,12x_5 - 1,20 + 58,05x_5 - 2,16 +$$

#### 4.3 Comparison of UBR and GCV Methods in Spline Nonparametric Regression Modeling

The following is a comparison between UBR and GCV methods in spline nonparametric regression modeling on simulation data:

Table 4.5. Comparison between UBR and GCV methods

MSE

R<sup>2</sup>

UBR

738,67

85,65

GCV

121,43

97,64

Table 4.5 shows that the GCV method produces a smaller MSE value of 121.43 and a greater<sup>67</sup> R-Square value of 97.64% compared to the UBR method. Based on this, the GCV method is a better method used for the selection of optimal

knot points compared to the UBR method in spline nonparametric regression modeling on simulation data applications.

## Conclusion<sup>68</sup>

Based on the results of the analysis and discussion that was conducted<sup>69</sup>, it is possible to draw conclusions<sup>70</sup> as follows:

The results of spline nonparametric regression modeling for optimal knot point selection using the UBR method produced the smallest UBR value of  $1,96 \times 10^{-22}$ .

The results of spline nonparametric regression modeling for optimal knot point selection using the GCV method produced the smallest GCV value of 514,70.

The best model with the UBR method produces an MSE value of 738.67 with R-Square<sup>71</sup> of 85.65%, while the best model with the GCV method produces an MSE value of 121.43 with R-Square of 97.64%. So it can be concluded that in this study<sup>72</sup> the GCV method produces<sup>73</sup> a better model compared to the UBR method because it produces<sup>74</sup> a smaller MSE value and a larger<sup>75</sup> R-Square value.

## References

- Budiantara, I.N. (2009). Spline dalam Regresi Nonparametrik dan Semiparametrik: Sebuah Pemodelan Statistika Masa Kini dan Masa Mendatang. In Pidato Pengukuhan untuk Jabatan Guru Besar dalam Bidang Ilmu Matematika Statistika dan Probabilitas. nstitut Teknologi Sepuluh Nopember: Departemen Statistika.
- Budiantara, I Nyoman. (2000). Metode UBR, GLM, CV, dan GCV dalam Regresi Nonparametrik Spline. Majalah Ilmiah Himpunan Matematika Indonesia (MIHMI), 41–45.
- Craven, P., & Wahba, G. (1979a). Smoothing Noisy Data with Spline Function - Estimating the Correct Degree of Smoothing by the Method of Generalized

Cross Validation<sup>76</sup>. Numerische Mathematik, 31, 377–403.

<https://doi.org/10.1007/BF01404567>

Devi, A. R. (2018). Metode Unbiased Risk (UBR) dan Cross Validation<sup>77</sup> (CV) Untuk Pemilihan Titik Knot Optimal dalam<sup>78</sup> Regresi Nonparametrik Multivariabel<sup>79</sup> Spline Truncated ( Studi Kasus : Data Tingkat Pengangguran Terbuka di Provinsi Jawa Tengah Tahun 2015 ). Institut Teknologi Sepuluh Nopember.

Eubank, Randall L. (1990). Nonparametric Regression and Spline Smoothing (Second Edi; D.B.Owen, Ed.). New York: Marcel Dekker.

Liu, A., Tong, T., & Wang, Y. (2014). Smoothing Spline Estimation of Variance Functions. Journal of Computational and Graphical Statistics, 16(2), 312–329.

<https://doi.org/10.1198/106186007X204528>

Montoya, E. L., Ulloa, N., & Miller, V. (2014). A Simulation Study Comparing Knot Selection Methods With Equally Spaced Knots in a Penalized Regression Spline. International Journal of Statistics and Probability, 3(3), 96–110.

<https://doi.org/10.5539/ijsp.v3n3p96>

Puspitasari, E., & Sutanto, H. T. (2013). Model Regresi Spline Knot Optimal Untuk Mengetahui Faktor – Faktor yang Mempengaruhi Jumlah Kematian Di Jawa Timur. Jurusan Matematika, Fakultas Mipa, Universitas Negeri Surabaya, 1–7. Retrieved from <https://media.neliti.com/media/publications/16096-ID-pemodelan-jumlah-kematian-bayi-di-provinsi-jawa-timur-tahun-2011-dengan-pendekat.pdf>

Sari, S. U. R. (2016). Perbandingan Model Regresi Nonparametrik Spline Multivariabel<sup>80</sup> dengan<sup>81</sup> Menggunakan Metode Generalized Cross Validation<sup>82</sup> (GCV) dan Unbiased Risk (UBR) dalam<sup>83</sup> Pemilihan Titik Knot Optimal (Studi Kasus Data Angka Kematian Maternal di Jawa Timur). Institut Teknologi Sepuluh Nopember.

Tibshirani, R., & Wasserman, L. (2015). Nonparametric Regression Statistical Machine Learning<sup>84</sup>, Spring 2019. <https://doi.org/10.3109/9781439822463.147>

Wang, Y. (2011). Smoothing Splines Methods and Applications.  
<https://doi.org/10.1002/0470009675.ch6>

Wu, H., & Zhang, J.-T. (2006). Nonparametric Regression Methods for Longitudinal Data Analysis. New Jersey: John Wiley & Sons.

Wulandari, K., Budiantara, I. N., & Ratna, M. (2017). Pemodelan Faktor-Faktor yang Mempengaruhi Angka Morbiditas di Jawa Timur Menggunakan Regresi Nonparametrik Spline. Jurnal Sains Dan Seni ITS, 6(1).  
<https://doi.org/10.12962/j23373520.v6i1.22477>

Utami, T.W, Prahutama, A. (2017). Regresi Semiparametrik Spline Truncated dengan Software R. EDUSAINSTEK 2017.

Utami, T.W. (2018). PEMODELAN ANGKA KEMATIAN BAYI DENGAN PENDEKATAN REGRESI NONPARAMETRIK SPLINE TRUNCATED. EDUSAINSTEK 2018.

Utami, T. W (2018). Pendekatan Regresi Semiparametrik Spline Truncated untuk Pemodelan Tingkat Pengangguran di Jawa Tengah. Journal Statistika UNIMUS Vol 6, No 2,



1.	<del>certain</del> → specific	Word Choice	Engagement
2.	<del>patterns</del> → designs	Word Choice	Engagement
3.	<i>is obtained</i>	Passive Voice Misuse	Clarity
4.	Several methods can	Wordy Sentences	Clarity
5.	<i>be used</i>	Passive Voice Misuse	Clarity
6.	Cross-Validation	Misspelled Words	Correctness
7.	<i>are based</i>	Passive Voice Misuse	Clarity
8.	, which	Punctuation in Compound/Complex Sentences	Correctness
9.	best nonparametric	Improper Formatting	Correctness
10.	nonparametric spline	Improper Formatting	Correctness
11.	<i>was obtained</i>	Passive Voice Misuse	Clarity
12.	, which	Punctuation in Compound/Complex Sentences	Correctness
13.	<i>be concluded</i>	Passive Voice Misuse	Clarity
14.	, the	Punctuation in Compound/Complex Sentences	Correctness
15.	<del>is able to</del> → can	Wordy Sentences	Clarity
16.	<del>a</del> data	Determiner Use (a/an/the/this, etc.)	Correctness
17.	<del>is able to</del> → can	Wordy Sentences	Clarity
18.	<del>In forming</del> → Informing	Confused Words	Correctness

19.	<del>important</del> → essential	Word Choice	Engagement
20.	<i>consider include</i>	Redundant Words	Correctness
21.	<del>orde</del> → order	Confused Words	Correctness
22.	, and	Punctuation in Compound/Complex Sentences	Correctness
23.	<i>be known</i>	Passive Voice Misuse	Clarity
24.	<i>is formed</i>	Passive Voice Misuse	Clarity
25.	The selection of optimal knot points influences the accuracy of the spline regression model that is formed	Passive Voice Misuse	Clarity
26.	Several methods can	Wordy Sentences	Clarity
27.	<i>be used</i>	Passive Voice Misuse	Clarity
28.	<del>selection</del> → range, collection, variety	Word Choice	Engagement
29.	Cross-Validation	Misspelled Words	Correctness
30.	Cross-Validation	Misspelled Words	Correctness
31.	the point of the optimal knot	Incorrect Noun Number	Correctness
32.	, not	Punctuation in Compound/Complex Sentences	Correctness
33.	Cross-Validation	Misspelled Words	Correctness
34.	<i>be better used</i>	Passive Voice Misuse	Clarity
35.	<del>normal</del> → standard, average	Word Choice	Engagement
36.	<del>simple</del> → straightforward	Word Choice	Engagement

37.	, so	Punctuation in Compound/Complex Sentences	Correctness
38.	small,	Punctuation in Compound/Complex Sentences	Correctness
39.	<del>the</del> UBR	Determiner Use (a/an/the/this, etc.)	Correctness
40.	been researched	Passive Voice Misuse	Clarity
41.	, using	Punctuation in Compound/Complex Sentences	Correctness
42.	<del>three knot</del> → three-knot	Misspelled Words	Correctness
43.	Cross-Validation	Misspelled Words	Correctness
44.	study,	Comma Misuse within Clauses	Correctness
45.	Cross-Validation	Misspelled Words	Correctness
46.	be used	Passive Voice Misuse	Clarity
47.	be used	Passive Voice Misuse	Clarity
48.	method,	Comma Misuse within Clauses	Correctness
49.	value.	Punctuation in Compound/Complex Sentences	Correctness
50.	<del>fKi</del> → fi, FK <sub>i</sub> , for	Misspelled Words	Correctness
51.	<del>fKi</del> → Kim	Misspelled Words	Correctness
52.	i → I	Misspelled Words	Correctness
53.	<del>Ak</del> → Ask	Misspelled Words	Correctness

54.	<i>is obtained</i>	Passive Voice Misuse	Clarity
55.	Cross-Validation	Misspelled Words	Correctness
56.	Cross-Validation	Misspelled Words	Correctness
57.	<i>is obtained</i>	Passive Voice Misuse	Clarity
58.	kyn	Unknown Words	Correctness
59.	<del>three point</del> → three-point	Misspelled Words	Correctness
60.	the point of the optimal knot	Incorrect Noun Number	Correctness
61.	<del>three point</del> → three-point	Misspelled Words	Correctness
62.	the point of the optimal knot	Incorrect Noun Number	Correctness
63.	, in general,	Comma Misuse within Clauses	Correctness
64.	5 → five	Improper Formatting	Correctness
65.	→ → , ...	Closing Punctuation	Correctness
66.	514,70-.	Improper Formatting	Correctness
67.	greater → higher, more excellent	Word Choice	Engagement
68.	Conclussion → Conclusion, Conclusions	Misspelled Words	Correctness
69.	<i>was conducted</i>	Passive Voice Misuse	Clarity
70.	<del>draw conclusions</del> → conclude	Wordy Sentences	Clarity
71.	an R-Square	Determiner Use (a/an/the/this, etc.)	Correctness
72.	study,	Punctuation in Compound/Complex Sentences	Correctness

73.	<del>produces</del> → provides	Word Choice	Engagement
74.	<del>produces</del> → provides, creates	Word Choice	Engagement
75.	<del>larger</del> → more considerable, more substantial, more immense, more enormous	Word Choice	Engagement
76.	Cross-Validation	Misspelled Words	Correctness
77.	Cross-Validation	Misspelled Words	Correctness
78.	<del>dalam</del> → Dalam	Misspelled Words	Correctness
79.	<del>Multivariabel</del> → Multivariable	Misspelled Words	Correctness
80.	<del>Multivariabel</del> → Multivariable	Misspelled Words	Correctness
81.	<del>dengan</del> → Dengan	Misspelled Words	Correctness
82.	Cross-Validation	Misspelled Words	Correctness
83.	<del>dalam</del> → Dalam	Misspelled Words	Correctness
84.	Learning-,	Improper Formatting	Correctness