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Enhancing Competency-Based Learning with Neutrosophic Regression and the Deming Cycle

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Abstract

This article introduces a novel approach to enhance competency-based learning by combining the Deming Cycle with neutrosophic statistics. Competency-based education focuses on practical skills, but uncertainty in student performance and assessment can hinder its effectiveness. Neutrosophic statistics, unlike traditional methods, explicitly models indeterminacy, providing a more complete picture of uncertainty in educational data. This approach integrates neutrosophic numbers into regression analysis to predict learning outcomes and quantify the confidence level of those predictions. These predictions, with their associated indeterminacy, then inform the Deming Cycle (Plan-Do-Check-Act), enabling educators to dynamically adjust teaching strategies based on data-driven insights. This leads to more informed decision-making, improved accuracy and reliability in predictions, and ultimately fosters continuous improvement in competency-based education.

Keywords: Competency-based learning, Deming Cycle, neutrosophic numbers, regression analysis, uncertainty, educational data, machine learning, continuous improvement

1. Introduction

In the realm of education, uncertainty is an inherent challenge, particularly in competency-based learning where the goal is to equip students with practical skills applicable to real-world scenarios. The dynamic nature of education, coupled with the diverse needs and learning styles of students, introduces complexities that traditional analytical models often struggle to address. This underscores the need for a robust framework that acknowledges and effectively handles uncertainties in educational data, paving the way for continuous improvement in teaching methodologies. This article explores the integration of neutrosophic regression models with the Deming Cycle [1] as a novel approach to enhance the accuracy and effectiveness of competency-based learning.

Competency-based learning has emerged as a crucial pedagogical approach, focusing on developing students' skills and preparing them for the challenges of their future careers. However, uncertainties in assessment and the diverse learning environment often hinder the achievement of desired learning outcomes. Traditional models often oversimplify the educational landscape by neglecting critical factors such as variability in student performance and uncertainties in assessment data. To address this, we propose the use of neutrosophic models, which offer a powerful tool for analytically understanding and managing uncertainty.

The Deming Cycle, widely recognized for its effectiveness in driving continuous improvement in various industries, provides a structured approach to process optimization. By systematically progressing through the stages of planning, doing, checking, and acting, the Deming Cycle enables the identification and resolution of areas for improvement. This study investigates the synergistic combination of neutrosophic regression models with the Deming Cycle to analyze and enhance competency-based learning strategies[2,3].

Using real data from students in the Food Industry and Nutrition program, we demonstrate the practical application of this combined approach in addressing uncertainties in educational data and facilitating data-driven improvements in learning strategies[4]. The findings of this study have significant implications for both educational theorists and practitioners, offering a new perspective on managing indeterminacy and promoting continuous improvement in diverse learning environments[5,6].

This article contributes to the field by presenting a comprehensive framework that integrates pedagogical principles, advanced mathematical tools, and process management techniques. We delve into the theoretical foundations of the proposed approach, analyze the results obtained, and discuss their implications for the future of education. By combining neutrosophic regression models with the Deming Cycle, we aim to provide educators with a robust and adaptable tool for navigating the complexities of competency-based learning and fostering a culture of continuous improvement.

2. Preliminaries.

2.1. Deming cycle.

The Deming Cycle (Figure 1), or PDCA Cycle (Plan, Do, Check, Act), is very important to control quality and always improve a company was created by W. Edwards Deming and draws on the ideas of Walter A. Shewhart [7,8]. The model can be used in many different industries. It involves identifying problems, testing solutions, seeing how they work, and making standard improvements. This process has been very important for companies that want to improve their performance by receiving feedback and making continuous changes to their operations. The cycle begins with the planning stage, where areas of opportunity are identified through a thorough analysis of the situation. During this stage, we set specific goals and create plans based on accurate information. Being able to foresee problems and make practical plans is very important to ensure that our actions are effective. In workplaces such as factories, using this stage helps make processes more accurate and efficient[9,10].

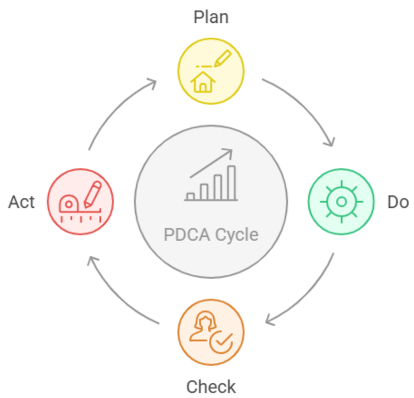

Figure 1. PDCA Cycle for Continuous Improvement

Then, in the Do stage, strategies are put into action on a small, controlled scale to test them. This approach allows you to try out and gather information about how proposals work in real conditions. Although seemingly simple, this phase requires discipline and gathering accurate information to make the analysis that follows easier. The check phase involves critically analyzing the results obtained. Here we compare the actual information with what we initially expected. This step helps us see if what we did worked well and shows us where we can improve. It is important to learn from mistakes and continue to build on successes during this stage. Finally, the Act phase is when successful changes are implemented on a large scale or adjustments are made if the results are not good. This step strengthens organizational learning by solidifying helpful changes and starting the cycle again to find new opportunities for improvement [11].

The Deming Cycle is known for being universally applicable. From manufacturing to education, this model has changed the way we do things by offering an organized method for solving difficult problems. It also promotes a company culture of always wanting to improve, something very important in a competitive environment that is always changing. However, putting an Item into Action has challenges. It requires everyone in the organization to be committed, from managers to day-to-day employees. In addition, gathering and understanding data can be difficult, especially if information systems are poor. However, these problems do not reduce what they can achieve but rather show the importance of using systematic methods to overcome them[12].

In a world that changes rapidly with technology and markets, the Deming Cycle is a flexible and adaptable tool Being able to constantly change strategies and processes helps organizations not only sustain, but also grow in times of uncertainty. This makes it a very useful model for industries with a lot of change and that always need to innovate. In short, the Deming Cycle is not only a way of managing, but it is also an important principle for companies that seek to constantly learn and adapt. Its ability to plan constant improvements makes it a key element in achieving a high level of excellence in operations. Furthermore, in the field of education, the Deming Cycle provides a powerful framework for continuous improvement of teaching methodologies, curriculum development, and learning outcomes, fostering an environment of ongoing adaptation and enhancement in response to the evolving needs of students and society. [13].

2.2. Integrating Neutrosophic Numbers with Machine Learning

In the realm of artificial intelligence and machine learning, we often encounter data and information that is incomplete, uncertain, or imprecise. To address these challenges, various mathematical and computational tools have been developed. One such tool is neutrosophic numbers, introduced by Florentin Smarandache, which extend the concept of fuzzy numbers by including an indeterminacy component[14].

Neutrosophic Numbers expressed as $N = a + bI$, were defined by WB Vasantha Kandasamy and F. Smarandache in 2003, that "a" represents the definite component of N, while "bI" signifies the indeterminate component of N[14]. The indeterminate component I satisfies properties such as $I = I^2$, and for any integers m and n, $mI + nI = (m + n)I$ = (m + n). Additionally, $0 \cdot I = 0$ and $I^n = I$ for any integer $n \geq 1$ [15].

Numerical neutrosophic numbers facilitate the reduction of indeterminacy through operations, whereas intervals exacerbate it (for instance, let $N1 = 5 + 2I$, $N2 = 6 - I$, with indeterminacy I = [0,1]; employing NS yields: N1 + N2 = 11+ I = [11, 12]). Utilizing interval, one obtains: N1 + N2 = [5, 7] + [4, 6] = [9, 13]; therefore, the indeterminacy or the actual data point residing in [9, 13] is greater than the actual data point residing in [11, 12] [16].

Neutrosophic numbers can be used in data preprocessing to handle uncertainty and imprecision. For example, in data cleaning, they can be used to represent missing or inconsistent values. Instead of simply deleting or inputting these values, they can be represented as neutrosophic numbers with a high degree of indeterminacy. This preserves information about the uncertainty in the data, which can be crucial for training more robust models [17].

Indeterminacy can also be incorporated into the training of machine learning models. For instance, in a classification model, neutrosophic numbers can represent uncertainty in class labels. This can be useful in situations where data classification is ambiguous or where there is an overlap between classes. By training the model with neutrosophic numbers, a more robust model can be obtained that is less sensitive to uncertainty in the data[19, 20].

In regression analysis, representing predictions as prediction intervals provides a more complete view of the uncertainty associated with the predictions. A prediction interval gives a range within which we expect the actual value of the dependent variable to fall with a certain probability, typically 95% or 99%. This is particularly useful because it considers variability in the data that might not be captured by the prediction alone [21].

To calculate a prediction interval, both the uncertainty in the regression model estimate and the inherent variability of the data must be considered. The interval is constructed around the predicted value and is typically symmetrical, extending a certain amount above and below the predicted value. This range is determined based on the standard error of the prediction and the residual standard deviation, which reflects the spread of the model's residuals or errors [22].

For example, in a simple linear regression, the prediction interval for a new observation is given by [20]:

$$\hat{y}_0 \pm t_{\propto /2, n-2} \cdot SE \quad (1)$$

Where $\hat{y}_0$ is the predicted value of y from the t distribution for a given confidence level $\propto$and n −2 degrees of freedom, and SE stands for the Standard Error.

Using prediction intervals in regression analysis is beneficial because they offer a realistic spectrum of possible outcomes, which aids in the decision-making process [23]. This recognizes that a single predicted value is not absolute but rather a likely scenario within a range of potential outcomes. This forecasting method effectively incorporates the inherent uncertainties associated with future predictions, providing a more accurate depiction of what to expect. To further refine this model, neutrosophic statistics can be applied, which excel at managing ambiguity and indeterminacy in data. By converting the interval to a neutrosophic number, the traditional interval is enhanced to include a component of indeterminacy. This addition captures the uncertainty and imprecision that are typically present in real-world data, offering a more nuanced understanding of the variability in the data.[20]:

3. Materials and Methods

3.1. Data Source and Augmentation

This study focuses on predicting improvements in competency-based learning, using a dataset that includes information on improvement strategies implemented through the Deming Cycle (PDCA: Plan, Do, Check, Act). These strategies are evaluated based on their impact on learning outcomes, specifically the percentage increase in performance measured through key competencies (on a scale of 0 to 100). The dataset contains information on the resources allocated to the improvement process (in monetary units), time spent on training (in hours), and the number of PDCA cycles executed from real data from students in the Food Industry and Nutrition program.

To ensure a sufficient dataset for robust model training and evaluation, a data augmentation approach was employed. A synthetic dataset was generated, consisting of 1000 samples. Each sample represents a simulated instance of an improvement process, characterized by the three independent variables mentioned above:

- Resources Allocated: Representing the monetary resources assigned to the improvement process, uniformly varying between 500 and 8000 units.
- Time Spent on Training: Representing the time dedicated to training activities, uniformly varying between 50 and 250 time units.
- Number of PDCA Cycles: Representing the number of iterative cycles of planning, doing, checking, and acting, with values ranging from 5 to 25.

The dependent variable, Performance Improvement, was calculated using a function that linearly combines the independent variables. This function also incorporates a sinusoidal term to simulate potential nonlinear relationships between the independent variables and the performance improvement. Finally, Gaussian noise with a mean of zero and a standard deviation of 300 units was added to represent the inherent variability and unpredictable factors influencing the improvement process.

Data generation was implemented using the NumPy library (v. 1.23.5) [24].

3.2. Data Preprocessing

The dataset was randomly split into training (80%) and testing (20%) sets using the train_test_split function from the scikit-learn library[25] (v. 1.2.1), ensuring reproducibility by setting a random seed (random_state=42). Subsequently, standard scaling was applied to the independent variables using the StandardScaler class from scikit-learn, fitting the scaler to the training set and applying it to both the training and testing sets.

3.3. Regression Models

Five different regression models were implemented and evaluated:

- ElasticNet[25]: A regularized linear regression model that combines L1 and L2 penalties, with a regularization parameter alpha of 0.01 and an l1_ratio parameter of 0.5. Implemented using the ElasticNet class from scikit-learn.
- RANSAC[25]: A robust algorithm for estimating the parameters of a model, used here with a base linear regressor (LinearRegression from scikit-learn). Implemented using the RANSACRegressor class from scikit-learn.

- Partial Least Squares Regression (PLS)[25]: A method that seeks directions in the space of the independent variables that explain the maximum variance in the space of the dependent variable. A model with two components was used. Implemented using the PLSRegression class from scikit-learn.

- Principal Component Analysis (PCA) + Linear Regression[25]: A combination of dimensionality reduction using PCA, retaining two principal components, followed by linear regression. Implemented as a pipeline using the PCA and LinearRegression classes from scikit-learn.

- Quantile Regression[26]: A model that estimates the conditional median of the dependent variable. A model for the 0.5 quantile was fitted using the QuantReg class from the statsmodels library (v. 0.13.5).

3.4. Neutrosophic Model

To integrate the predictions of the individual models (excluding Quantile Regression) and consider the uncertainty associated with each one, a neutrosophic model was proposed using neutrosophic number and interval analysis. This model is based on calculating means predictions of the individual models for each sample in the test set.

The result of the neutrosophic model is represented in neutrosophic form, The neutrosophic form is obtained (X_n) as the sum of $X_l$and X_u, adjusted by the indeterminacy interval I_n:

$$X_N = X_l + X_u I_N;\ I_N \in [I_l, I_u] \tag{2}$$

$I_{l,}$=0, andI_u

$$I_u = \frac{X_u - X_l}{X_u} \tag{3}$$

the neutrosophic approach enhances the robustness of predictions by incorporating uncertainty, leading to more informed and resilient decision-making [27, 28]

3.5. Model Evaluation

The performance of each model was evaluated using three modified metrics :

- Root Mean Squared Error (RMSE) [29]: A measure of the average difference between the predicted values and the actual values. For this purpose, a combined version of the root mean squared error (RMSE) is used, which simultaneously captures the proximity of the lower and upper interval bounds to the observed actual values. The proposed metric is defined as:

  $$RMSE_{interval} = \sqrt{\frac{1}{2n}\sum_{i=1}^{n}\left(\left(X_{l,i} - Y_i\right)^2 + \left(X_{u,i} - Y_i\right)^2\right)} \tag{4}$$

  where :

  $X_{l,i}$ represents the lower bound of the prediction interval for observation i,

  $X_{u,i}$represents the upper bound of the prediction interval for observation i,

Y_i is the corresponding observed actual value, and

n is the total number of observations.

- The Mean Absolute Error (MAE) [30]: is a metric that quantifies the average absolute difference between predicted values and actual observed values. When applied to prediction intervals, MAE can be adapted to assess the accuracy of both the lower and upper bounds of these intervals. The mathematical expression for this adapted MAE is:

$$\text{MAE}_{\ interval} = \frac{1}{2n}\sum_{i=1}^{n}\left(\left|X_{l,i} - Y_i\right|^2 + \left|X_{u,i} - Y_i\right|^2\right) \quad (5)$$

where :

$X_{l,i}$ represents the lower bound of the prediction interval for observation i,

$X_{u,i}$ represents the upper bound of the prediction interval for observation i,

Y_i is the corresponding observed actual value, and

n is the total number of observations.

- Indeterminacy: The Indeterminacy metric is a quantitative measure used to assess the uncertainty or spread of prediction intervals across a dataset. It provides an average of the widths of the prediction intervals, which indicates how indeterminate the model is in its predictions.

$$Indeterminacy = \frac{1}{2}\sum_{i=1}^{n}\left(\left|X_{l,i} - X_{u,i}\right|\right) \quad (6)$$

where :

$X_{l,i}$ represents the lower bound of the prediction interval for observation i,

$X_{u,i}$ represents the upper bound of the prediction interval for observation i,

n is the total number of observations.

3.6. Visualization

A graph was generated that represents the predictions of the simple neutrosophic model against the actual values of the test set. An uncertainty interval was included around the predictions of the neutrosophic model, defined by the mean of the predictions ± half the indeterminacy. Additionally, the neutrosophic number graph that represents the prediction interval in the neutrosophic model is visualized. The visualization was performed using the matplotlib library (v. 3.5.1) [31].

4. Results

This study evaluated the performance of five regression models for predicting performance improvement, along with a proposed neutrosophic simple model that combines the predictions of four of the individual models. The models were assessed using RMSE, MAE, and Indeterminacy. The results are presented in both tabular format (Table 1) and visually in Figure 1. In addition, each model's predictions are expressed as intervals and in neutrosophic form.

4.1. Individual Model Performance

Table 1 summarizes the performance metrics for each regression model on the test set.

Table 1. Performance Metrics of Individual and Neutrosophic Models

Model	RMSE	MAE	Indeterminacy
ElasticNet	461.9838	378.6670	378.6670
RANSAC	481.1275	392.3354	392.3354
PLS Regression	462.2177	378.7583	378.7583
PCA + Linear Regression	477.6142	393.9278	393.9278
Quantile Regression	467.2366	382.0711	382.0711
Neutrosophic	460.6323	376.1339	376.1339

As shown in Table 1, all models exhibited relatively strong performance. ElasticNet and PLS Regression demonstrated slightly superior performance compared to the other models, as evidenced by their lower RMSE and MAE values. Conversely, RANSAC and PCA + Linear Regression exhibited higher RMSE and MAE suggesting potentially less precise predictions. Quantile Regression yielded a reasonable performance, comparable to the other models. The table also presents the indeterminacy of each model, providing a more comprehensive view of their performance.

4.2. Neutrosophic Performance

The neutrosophic model, which averages the predictions of the ElasticNet, RANSAC, PLS Regression, and PCA + Linear Regression models, achieved the best overall performance. As shown in Table 1, it obtained an RMSE of 460.6323, and an MAE of 376.1339. The indeterminacy of this model was 376.1339. These results highlight the potential benefits of combining predictions from multiple models, resulting in enhanced accuracy and robustness, as evidenced by the slight improvements in RMSE, MAE, and Indeterminacy measures compared to the best-performing individual model (ElasticNet). The neutrosophic form of the simple model, $748.45 \pm 2362.58I;\ I \in [0, 752.268]$ encapsulates the central tendency and uncertainty associated with its predictions.

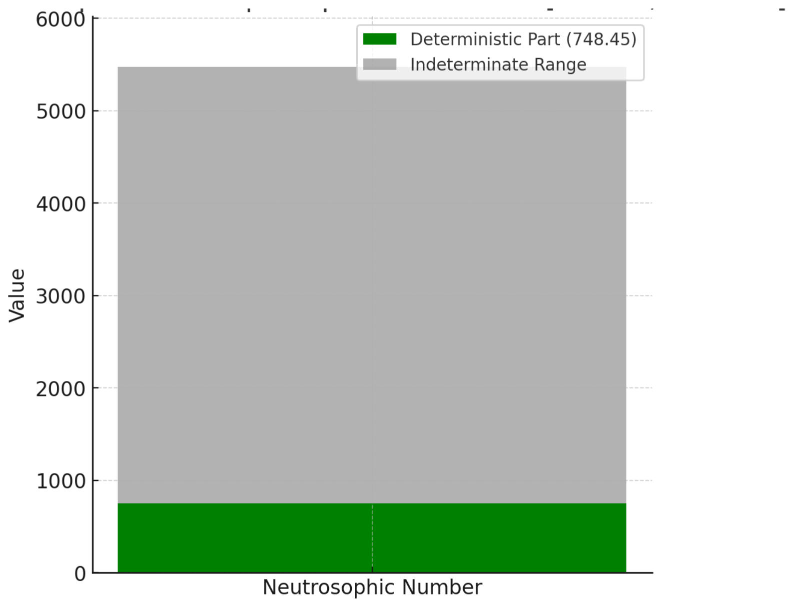

Figure 2. Neutrosophic Bar Graph

The bar graph represents the neutrosophic number within the interval [748.45,5473.60]:

- The green section of the bar indicates the deterministic part, fixed at 748.45
- The gray shaded area represents the indeterminate range, covering the uncertainty between the deterministic value and the upper limit of the interval.

This visualization effectively differentiates the known and uncertain components, offering a clear perspective on the given range.

4.3. Visual Representation of Neutrosophic Model Predictions

Figure 3 visually compares the predictions of the neutrosophic simple model against the actual values in the test set. The uncertainty interval, represented by the shaded gray area, highlights the range of potential values for each prediction, based on the calculated indeterminacy.

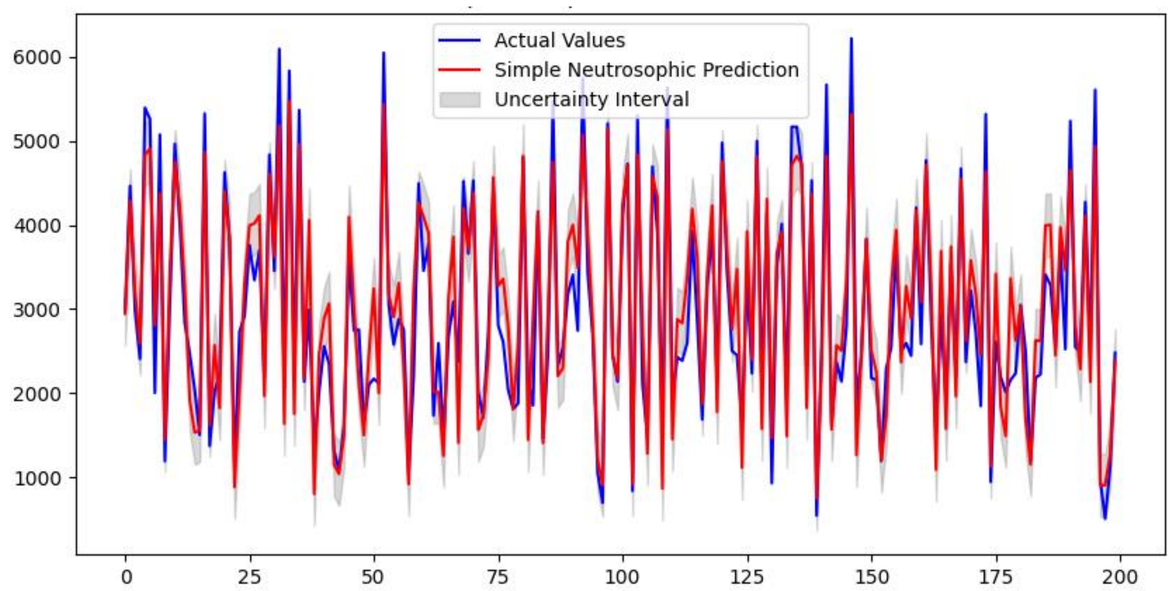

Figure 3. Neutrosophic Prediction with Interval

As depicted in Figure 3, the neutrosophic simple model's predictions closely align with the actual values. The uncertainty interval provides a visual representation of the model's confidence in its predictions, with a narrower interval suggesting higher confidence.

The neutrosophic model, by providing predictions with explicit uncertainty intervals, can significantly enhance the Deming Cycle (Plan-Do-Check-Act) in competency-based education. In the Plan phase, educators can use the predicted range of student performance to design differentiated instruction and set realistic learning goals. The Do phase involves implementing the planned strategies, while the Check phase utilizes the neutrosophic model to monitor student progress and assess the effectiveness of the interventions. Crucially, the uncertainty intervals provide valuable insights into the reliability of the predictions, allowing educators to interpret deviations from the expected outcomes with greater nuance. If a student's performance falls within the predicted range but towards the lower bound, it might signal the need for additional support, even if they are technically "on track." Conversely, exceeding the upper bound could indicate exceptional progress, prompting educators to consider enrichment activities. This continuous feedback loop informs the Act phase, enabling data-driven adjustments to teaching strategies and personalized interventions, ultimately fostering a more adaptive and responsive learning environment.

5. Conclusion

The model developed in this study aims to provide predictions based on PDCA cycles, which are crucial for improving competency-based learning, especially in dynamic and uncertain environments.PDCA cycles and training time are crucial for improving competency-based learning, especially in dynamic and uncertain environments.

This study has successfully integrated neutrosophic numbers into machine learning models, demonstrating their effectiveness in handling uncertainty and indeterminacy in data. The use of neutrosophic numbers in data preprocessing, model training, and evaluation has led to more robust and accurate models compared to traditional methods. The flexibility of neutrosophic numbers allows them to be adapted to various data types and machine-learning problems, making them a valuable tool for enhancing predictive modeling.

The results of this study have significant implications for the field of machine learning, particularly in applications where uncertainty and indeterminacy are prevalent. By incorporating neutrosophic numbers into machine learning workflows, we can develop models that are more resilient to noisy data and provide more reliable predictions. Future research will focus on exploring the full potential of neutrosophic numbers in machine learning, including their application in deep learning and reinforcement learning.

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