

## Developing A Software Package to Detect and Address the Autocorrelation Problem

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### Abstract

Autocorrelation is a common challenge in regression analysis. It can lead to biased and inefficient parameter estimates, ultimately affecting the accuracy of the results. Many statistical software packages, such as SPSS and Minitab, include features for identifying Autocorrelation, such as the graphical method and the Durbin-Watson test. However, these methods have drawbacks. The graphical method relies on subjective interpretation, and SPSS lacks the necessary information to interpret the significance of the Durbin-Watson test results. Java-based software has been developed to address these limitations and tackle the problem of Autocorrelation in regression analysis. The software utilizes the Durbin-Watson method, providing a more precise alternative to graphical methods. It presents analysts with an intuitive interface. The software has been tested using accurate data, and the results validate its ability to detect and address positive Autocorrelation, consistent with previous findings on the Dataset.

This software enhances the dependability and precision of regression analysis in different domains. The software can be further enhanced by expanding its scope to include more complex regression models, adding other methods to address Autocorrelation, and improving the user interface for greater ease of use.

**Keywords:** Simple Liner regression, Autocorrelation, Durbin-Watson, Object-oriented programming.

## تطوير حزمة برمجية لاكتشاف ومعالجة مشكلة الارتباط الذاتي

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### الملخص

تُعد مشكلة الارتباط الذاتي تحديًا شائعًا في تحليل الانحدار، حيث يمكن أن تؤدي إلى تقديرات متحيزة وغير فعالة للمعاملات مما يؤثر على دقة النتائج. توفر حزم البرامج الإحصائية الحالية مثل SPSS و Minitab طرقًا لاكتشاف الارتباط الذاتي، مثل النهج الرسومي Graphical Approach واختبار دارين واتسون. Durbin-Watson ومع ذلك، فإن هذه الأدوات محدودة في دقتها فالنهج الرسومي يعتمد على التفسير الشخصي، بينما لا يقدم SPSS معلومات كافية لفهم نتائج اختبار دارين واتسون.

تم تطوير حزمة برمجية جديدة باستخدام لغة جافا (Java) لمعالجة مشكلة الارتباط الذاتي في تحليل الانحدار. تم استخدام طريقة دارين واتسون وهي طريقة أكثر دقة من الطرق الرسومية. توفر البرمجية واجهة سهلة الاستخدام للمحللين. تم اختبار الحزمة باستخدام بيانات حقيقية، حيث أظهرت النتائج قدرة الحزمة على اكتشاف ومعالجة مشكلة الارتباط الذاتي الإيجابي، وهو ما يتوافق مع النتائج السابقة على نفس مجموعة البيانات.

يهدف هذا النظام إلى تحسين موثوقية ودقة تحليل الانحدار في مختلف المجالات. يمكن تحسين البرمجية في المستقبل من خلال توسيع النطاق ليشمل نماذج انحدار أكثر تعقيدًا، وإضافة طرق أخرى لمعالجة الارتباط الذاتي، وتحسين واجهة المستخدم لزيادة سهولة الاستخدام.

**الكلمات المفتاحية:** الانحدار الخطي البسيط، الارتباط الذاتي، دورين-واتسون، البرمجة الكائنية.

### I. Introduction

The statistical theory of regression analysis has been well developed and has found application in various fields, such as engineering, public health, management, and chemical and biological sciences. It seeks to demonstrate the link between two or more variables, examining the relationship between dependent and independent variables to determine the most significant change in the independent variable(s) when the dependent variable(s) changes.

When employing this method with real-world data for practical regression applications, it is crucial to comprehend both the theoretical and practical aspects. Estimating the unknown parameters utilizing Ordinary Least Squares (OLS) is a critical goal in

regression modelling. Still, various issues can result in incorrect regression results, even if the numerical outputs appear correct.

One such issue is the Autocorrelation between the residuals, which can lead to negative impacts such as Autocorrelation, Multicollinearity, Heteroscedasticity of residuals, and violations of the Variance and Normality assumptions. It is essential to recognize this problem and propose effective remedies to maintain the model's assumptions' coherence and ensure the results.

Numerous techniques are available for detecting Autocorrelation, such as the Graphical Method, the Durbin-Watson Test, and the Run Test. The graphical techniques can detect the presence of the autocorrelation problem based on the shape of the residuals graph, but this approach is subjective. Many statistical software packages, such as SPSS and Minitab, rely on graphical methods. At the same time, the Durbin-Watson test is a more effective and objective approach to detecting and addressing the Autocorrelation problem.

This paper introduces a novel solution to the limitations of existing software tools. We present the development of a dedicated software package, built using an object-oriented programming language (Java), that aims explicitly to detect and address the autocorrelation problem in regression analysis using the Durbin-Watson test. This software package is a significant advancement in the field, providing a more objective and quantitative approach than the graphical methods.

## II. Related Work

Autocorrelation is a well-known issue in regression analysis that can lead to biased and inefficient parameter estimates. Existing statistical software packages like SPSS and Minitab provide methods to detect Autocorrelation, such as the graphical approach and the Durbin-Watson test. However, these tools have some limitations.

While easy to implement, the graphical approach to detecting Autocorrelation is subjective and can be interpreted differently by different users [9]. Furthermore, even though SPSS computes the Durbin-Watson statistic, it does not provide guidance on the significance of the test results [10]. Research has also shown that SPSS and Minitab software are ineffective in interpreting regression models. They produce a significant amount of mostly irrelevant output data, which makes it difficult for users to identify and address autocorrelation issues.[11]

Some researchers have proposed alternative approaches to address these limitations. For example, Verbeek [13] developed an object-oriented framework in Java for econometric modeling, which included methods for detecting and correcting Autocorrelation. However, this framework was not explicitly designed as a standalone software package for addressing Autocorrelation.

In this paper, we present the development of a dedicated software package, built using an object-oriented programming language (Java), that explicitly detects and addresses the autocorrelation problem in regression analysis. Our package utilizes the Durbin-Watson

test, a more objective and quantitative approach than the graphical methods. Importantly, our software package is designed with the user in mind, providing a user-friendly and efficient tool for addressing Autocorrelation, thereby enhancing the reliability and accuracy of regression analysis in various fields of study.

### III.HIGH-LEVEL SYSTEM DESIGN

To achieve the goal of this paper, our proposed system has been developed based on the Regression Model—Building Process [1], as shown in Fig.1. Our software package aims to facilitate this process. It starts by utilizing the existing data to define a starting regression model. Next, this model is assessed. The model is refined if deemed insufficient, and the parameters are re-estimated until a satisfactory model is achieved.

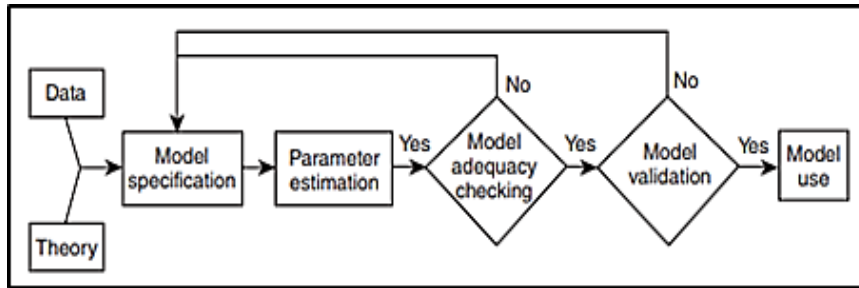


Figure 1. Regression Model – Building Process

This process has led to creating a comprehensive framework consisting of three main modules: a Desktop Application, a Database, and a User module. These modules work together seamlessly to achieve the intended outcome. The application's block diagram effectively communicates each module's unique features and capabilities (Fig.2), demonstrating the thoroughness of our approach.

#### A. Desktop Application

The desktop application includes all the tools needed to calculate Autocorrelation. It provides a user interface that communicates with users (analysts) and allows them to enter sample data and perform calculations. The sample data and calculations can then be saved to the file application for later retrieval. The analyst can automatically detect and address Autocorrelation problems and print a detailed report using this application.

#### B. Database and Users

A database is defined as a structured collection of data. The data gathered and produced by the software is stored in the database and structured in text and Excel files. This provides easy access to the data for viewing, updating, and printing. In addition to providing more features to users, the framework can print database reports. Furthermore, data can be retrieved in case of data loss or update.

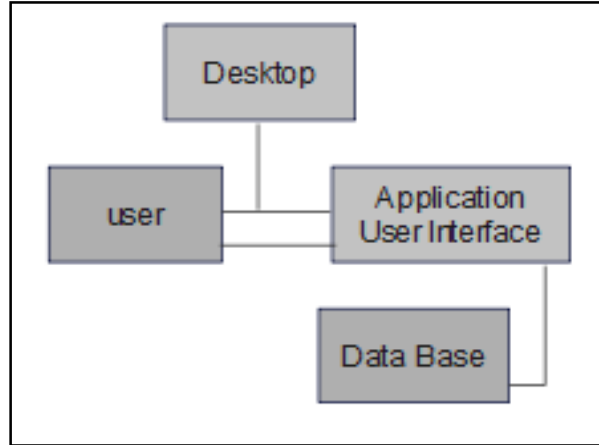


Figure 2. Application block diagram

#### IV. Technical Implementation

The application execution was completed based on the framework diagram shown above:

##### A. Desktop Application

The NetBeans bundle creates the application as its Integrated Development Environment (IDE). It utilizes internal files as its database.

##### B. File Database

The file database is directly connected to the desktop Autocorrelation application's database. The Durbin-Watson table calculates the Durbin-Watson Test's critical values for a specified sample size (n), independent variables (k), and alpha level. The collected data is saved in the database. The database of the desktop application is precisely linked to files. The files are comprised of two types. The first type stores the sample data, the calculations' details, and the detection and address results. The second type consists of the Durbin-Watson tables, which compute the critical values for the Durbin-Watson Test for a given sample size (n), number of independent variables (k), and alpha level.

##### C. Graphical User Interface (GUI)

An analyst uses a user-interface application to enter sample data and determine the method for detecting and addressing autocorrelation problems. Fig. 3 depicts the graphical user interface road map.

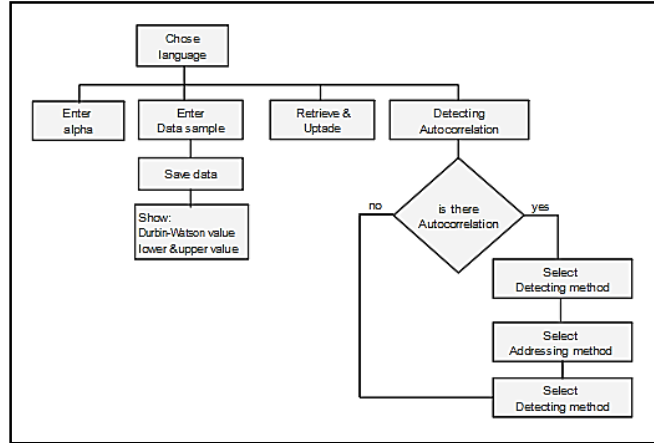


Figure 3. Road map of the graphical user interface

To provide a clearer understanding of the software's usability, the following detailed description of the user interface (U.I.) is presented in Fig.4

#### • Main Interface

The primary interface functions as the software's central point, enabling users to easily access various features such as entering data, performing analysis, and .creating reports

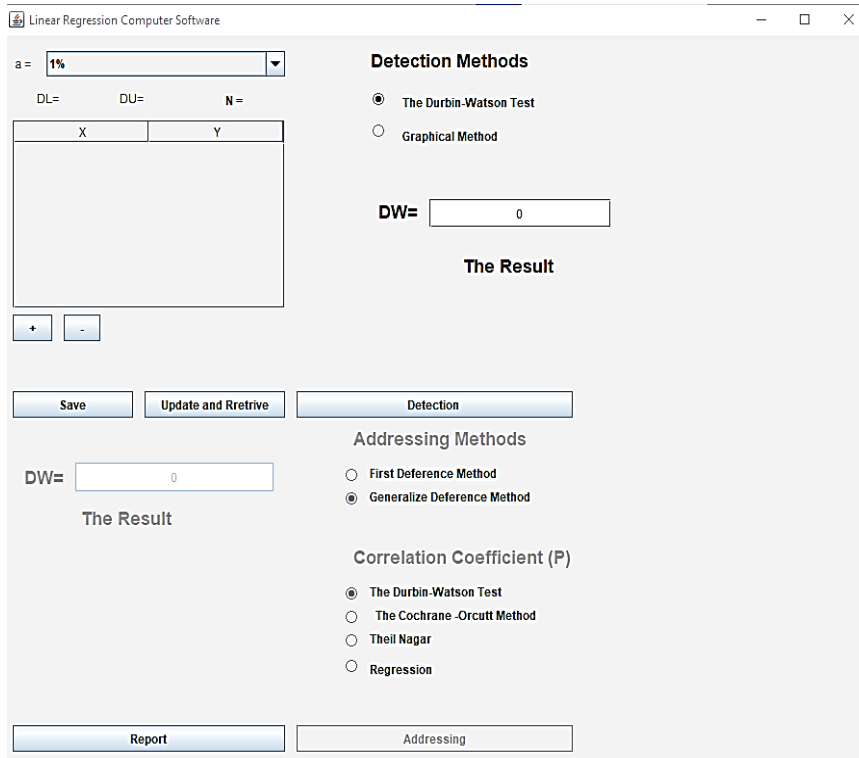


Figure 4. Main GUI for Application

- **Entering Data**

This part is made so that users can efficiently enter their sample data. The form is organized with labeled fields for each variable, ensuring clarity and user-friendliness. Data can be entered in a tabular format, which minimizes errors during input. The form includes validation features to ensure that the entered data is in the correct format, providing real-time feedback to users.

- **Analysis Results Display**

This section clearly and concisely presents the results. It includes graphical representations designed to enhance users' understanding of the presence or absence of Autocorrelation. Furthermore, it offers a graphical illustration of the process for addressing Autocorrelation when detected.

- **Graphical Outputs**

The software generates visual representations of the residuals and autocorrelation functions. These graphs assist users in visually identifying patterns that may indicate Autocorrelation.

- **Report Generation Feature**

Users can create comprehensive reports summarizing their analyses, including input data, results, and graphical outputs. Reports can be exported in various formats, such as PDF or Word. The report generation interface allows users to customize the content and format of their reports, ensuring that they meet specific requirements.

## V. System architecture

The entire system process is described in the pseudocode, as shown in Fig. 5.

```
1 read data sample
2 Estimate parameters of the model
3 Initial regression model
4 Evaluate model
5 If model inadequate then
6     Estimate new parameters
7     build the model
8 Else model is adequate
9
```

Figure 5 System architecture Pseudocode

### A. Software Algorithms

The core algorithm implemented in our software is the Durbin-Watson test, a statistical method used to measure the presence of Autocorrelation in regression residuals. This process consists of four main steps:

1. **Estimating the Model:** Ordinary least squares (OLS) estimate parameters and establish connections between variables.

At the start, the software uses Ordinary Least Squares (OLS) to calculate the parameters of the regression model. OLS is crucial as it minimizes the squared variances between observed values and those predicted by the model, thus identifying the most suitable line. This stage also involves checks to ensure that the assumptions of linear regression, such as linearity, homoscedasticity, and normality of residuals, are satisfied. The accuracy of the estimated parameters might be affected by the presence of multicollinearity or non-linearity in the data, which could create difficulties. The software is designed to detect these issues and offer guidance on the necessary corrective actions.

2. **Residual Calculation:** The process involves computing the differences between observed and predicted values.

Once the model has been estimated, the software calculates residuals, defined as the variances between the observed and predicted values. This step is essential for evaluating the model's performance; ideally, the residuals should exhibit characteristics similar to white noise, indicating that the model has effectively captured all systematic patterns in the data.

3. **Durbin-Watson Calculation:**

Finally, the software assesses Autocorrelation by calculating the Durbin-Watson statistic, which ranges from 0 to 4. The software provides clear interpretations of these values, including critical thresholds based on the sample size and number of predictors, to help users draw meaningful conclusions from the results. This detailed feedback is essential for users to understand the implications of Autocorrelation on their regression analysis and take corrective actions if necessary.

4. **Addressing Autocorrelation:**

To further enhance the reliability of the regression model, the software applies the generalized deference Method to adjust for Autocorrelation. This powerful technique transforms the data to account for the correlation among residuals, ensuring that the model's assumptions are met and improving the efficiency of parameter estimates. By implementing this method, the software not only corrects for the effects of Autocorrelation but also provides users with a more robust model for inference and prediction, thereby enhancing the overall accuracy of the analysis.

**B. Comparison to Existing Methods**

Graphical techniques, although simple to use, depend on visual analysis, which may differ significantly among users, resulting in inconsistent conclusions. Likewise, software such as SPSS and Minitab calculates the Durbin-Watson statistic but gives little assistance in interpreting these findings, which raises the potential for misinterpretation. In contrast, our



software enhances the understanding of Autocorrelation by delivering more apparent output and actionable insights that focus directly on the Durbin-Watson test.

## VI. System testing and results

The application was tested by inserting various data samples to ensure the framework's accuracy and usefulness. The application performs the Durbin-Watson test to examine Autocorrelation among residuals. The non-existence of Autocorrelation among residuals is one of the main assumptions of a regression model. If Autocorrelation does exist, the model's outcomes are unreliable. Therefore, it's essential to check the adequacy of the model.

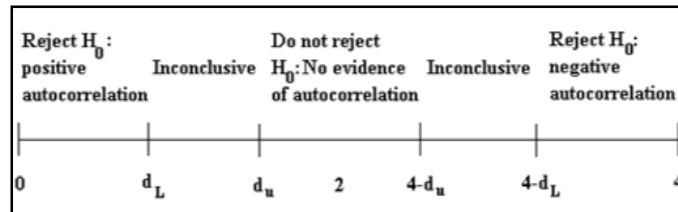


Figure 6. Acceptance and Rejection Regions for the Durbin-Watson Statistic (after Johnson et al., 1987)

The Durbin-Watson test's outcome ranges from 0 to 4. A value of D.W. equal to 2 indicates no autocorrelation. When the value is below 2, it means a positive autocorrelation and a value greater than 2 denotes a negative autocorrelation.

To test for positive Autocorrelation at a significance level  $\alpha$  (alpha), the test statistic D.W. is compared with lower and upper critical values. If D.W. is less than the Lower critical value, There is statistical evidence that the data is positively autocorrelated. If D.W. is greater than the Upper critical value, There is no statistical evidence that the data is positively correlated. The test is inconclusive if D.W. is between the lower and upper critical values.

Similarly, to test for negative Autocorrelation at a significance level  $\alpha$  (alpha), the test statistic  $4-DW$  is compared with lower and upper critical values: If D.W. is greater than the  $4-dL$  critical value, There is statistical evidence that the data is negatively autocorrelated. If D.W. is less than the  $4-dU$  critical value, There is no statistical evidence that the data is negatively correlated. The test is inconclusive if D.W. is between the  $4-du$  and  $4-dL$  critical values.

To validate our software, we tested it using historical data on U.S. imports from 1960-1979, a dataset previously analyzed for Autocorrelation. The Dataset includes Gross National Product (GNP) and imports, as shown in Table I. The Dataset was inserted into the application via the central GUI. This data was tested for Autocorrelation, with a significance level of 5%, by calculating the regression:  $M/GNP$ . The results showed that there had been a positive autocorrelation in the Dataset, consistent with previous analyses. Autocorrelation has also been addressed [13], ensuring the model's assumptions are met.

**Table I. Sample data: Gross National Product,1960-79 [14]**

year	1960	1961	1962	1963	1964
M	23.2	23.1	25.2	26.4	28.4
GNP	506.0	523.3	563.8	594.7	635.7
year	1965	1966	1967	1968	1969
M	32.0	37.7	40.6	47.7	52.9
GNP	688.1	753.0	796.3	868.5	935.5
year	1970	1971	1972	1973	1974
M	58.5	64.0	75.9	94.4	131.9
GNP	982.4	1,063.4	1,171.1	1,306.6	1,412.9
year	1975	1976	1977	1978	1979
M	126.9	155.4	185.8	217.5	260
GNP	1,528.8	1,702.2	1,899.5	2,127.6	2,368.5

The software package implements a regression analysis framework incorporating a robust approach to detecting and addressing Autocorrelation, beginning with estimating the regression model using the widely accepted Ordinary Least Squares (OLS) method. OLS seeks to find the best linear (or non-linear) connection between the independent and dependent variables by reducing the total squared variance between predicted and actual values. This is a crucial step in the autocorrelation detection and correction process. Following model estimation, the software calculates the residuals, representing the discrepancies between the observed data points and the model's predictions. These residuals are then subjected to the Durbin-Watson test, a statistical procedure designed to assess the presence and significance of Autocorrelation. Autocorrelation refers to the correlation between successive residuals, indicating a pattern of dependence in the error terms. The software utilizes the Durbin-Watson table to determine critical values ( $d_u$  and  $d_l$ ) based on the sample size and the number of independent variables. These vital values serve as thresholds for determining the significance of the calculated Durbin-Watson statistic. If the statistic falls outside these thresholds, it suggests the presence of Autocorrelation. In this instance, the software detected positive Autocorrelation, as shown in Figure 7, suggesting a positive correlation between consecutive residuals, indicating a pattern of dependence in the error terms. To address this, the software employs the generalized deference method, as demonstrated in Figure 8, to transform the data and mitigate the effects of Autocorrelation. This transformation ensures that the model's assumptions are met and the estimated parameters are more reliable. The software's efficacy was evaluated using the sample data presented in Table 1, where an initial model was constructed based on the estimated parameters, and the software's ability to detect and address Autocorrelation was rigorously assessed.

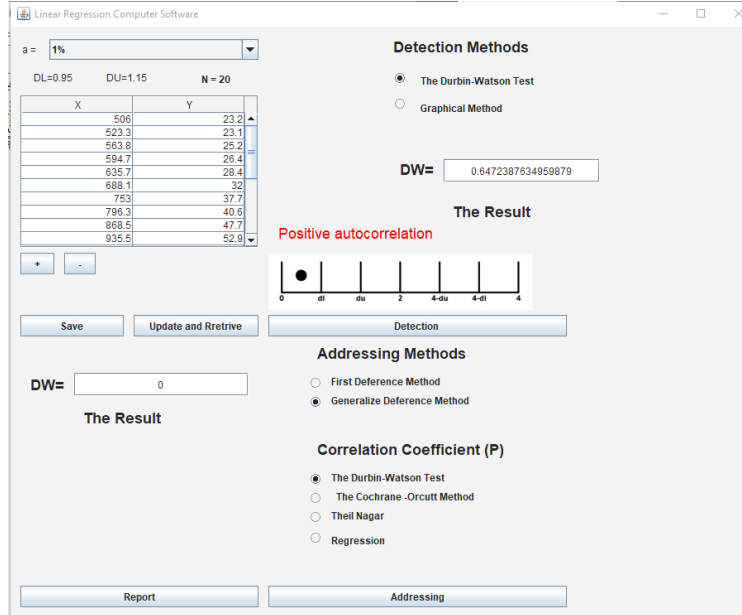


Figure 7. Screenshot of the detection result of sample data

After performing appropriate calculations, the model was resolved, as shown in Fig.8.

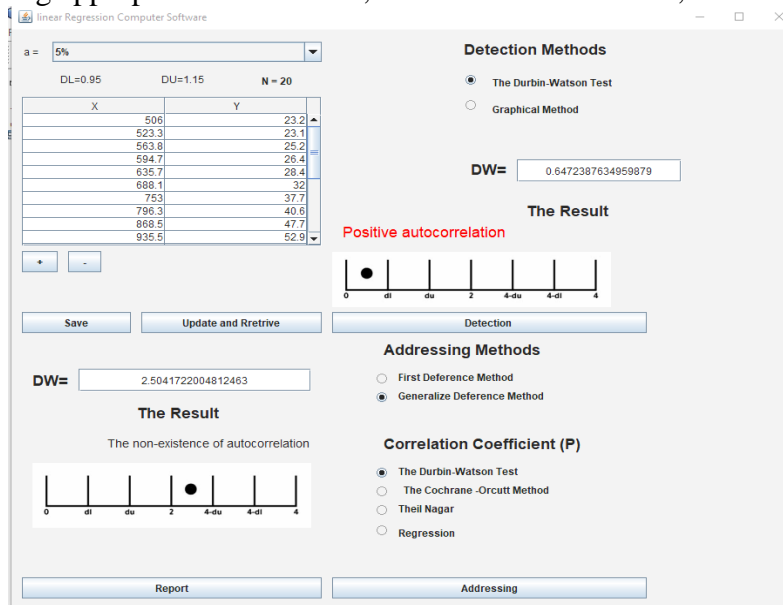


Figure 8. Screenshot of the addressing result of sample data

Fig.9 and Fig.10 showcase the functionality of printing a report containing all the data the application has gathered.



graphical techniques. Empirical testing with real-world data has demonstrated the application's effectiveness in detecting and mitigating positive Autocorrelation, which is consistent with prior analyses of the same Dataset. This software is a user-friendly and efficient tool for analysts, enhancing the reliability and accuracy of regression analysis, particularly in contexts where Autocorrelation poses a significant challenge.

Nonetheless, there remains considerable potential for further research and development to expand the software's capabilities and applicability. Future work could focus on several critical areas:

- Expand model support to include multiple linear regression and non-linear models.
- Incorporate advanced autocorrelation methods like autoregressive models (AR) and Generalized Least Squares (GLS).
- Optimize performance for managing larger datasets and executing complex calculations
- Improve user interface with visual data exploration tools, customizable dashboards, and automated reporting features.
- Integrate with other software through APIs for seamless data import and export.

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