

How to Calculate Linear Regression on a TI-84 Calculator

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Understanding the Fundamentals of Linear Regression

In the vast field of **statistics**, **linear regression** stands as a cornerstone technique for modeling and analyzing the numerical relationship between variables. This powerful **statistical method** allows researchers and students alike to determine how a change in one variable, known as the independent or **explanatory variable**, influences another variable, termed the dependent or **response variable**. By establishing a mathematical framework for these interactions, we can derive insights that are not immediately obvious from raw data alone, transforming a scattered set of observations into a coherent narrative of cause and effect.

The primary objective of performing a **simple linear regression** is to find the "line of best fit"--a straight line that minimizes the vertical distances between the observed data points and the line itself. This line acts as a predictive model, enabling users to estimate unknown values based on historical or experimental evidence. Whether you are analyzing economic trends, biological growth, or academic performance, the ability to quantify these trends through a linear equation is an essential skill in data science and **quantitative research**.

For many students and professionals, the **TI-84 Plus** family of **graphing calculators** serves as the most accessible tool for performing these complex calculations. These devices are equipped with sophisticated internal **algorithms** designed to handle large datasets and execute statistical tests with precision. By leveraging the built-in functions of the **TI-84**, users can bypass the tedious manual calculations associated with the **least squares** method and focus instead on the **interpretation** of the results and the practical implications of their findings.

Defining the Variables: Explanatory vs. Response

Before initiating any calculation on your **TI-84**, it is imperative to correctly identify the roles of the variables in your dataset. The **explanatory variable**, usually denoted as **x**, represents the factor that we suspect causes a change or explains the variation in another quantity. In the context of an academic study, for instance, the number of hours a student spends reviewing material is the **explanatory variable** because it is the input that we believe influences the final outcome. In a graphical representation, this variable is always plotted along the horizontal axis.

Conversely, the **response variable**, denoted as **y**, is the outcome or result that we are measuring. In our exam example, the **exam score** serves as the **response variable** because its value is dependent upon the input of study hours. The goal of **linear regression** is to see how much of the variation in the **response variable** can be attributed to the **explanatory variable**. Distinguishing between these two is vital; swapping them would result in a completely different **regression analysis** that might not make logical sense in a real-world context.

A high-quality **dataset** for **linear regression** consists of paired observations, where each **x** value

is linked to a specific **y** value. These pairs are treated as coordinates on a **scatter plot**. When you observe a visual trend where the points roughly follow a straight path, **linear regression** becomes a viable tool for summarizing that relationship. Understanding this conceptual framework ensures that when you begin the technical process on your calculator, you are doing so with a clear analytical purpose.

Step 1: Inputting Data into the TI-84 Lists

The first practical step in performing **linear regression** on a **TI-84** is the meticulous entry of your data into the calculator's list editor. Accuracy at this stage is paramount, as a single typo can significantly skew the **slope** and **intercept** of your final equation. To begin, power on your device and press the **STAT** key, which is located near the center of the keypad. This will open the primary statistics menu where you can manage your data sets and select various analytical tools.

Once in the **STAT** menu, ensure that the **EDIT** tab is highlighted and press the **ENTER** key to access the list columns. Typically, **L1** is used for the **explanatory variable** (hours studied) and **L2** is used for the **response variable** (exam scores). If there is existing data in these columns, you can clear them by highlighting the list name at the top (e.g., **L1**), pressing **CLEAR**, and then pressing **ENTER**. Do not use the **DEL** key on the list name, as this will remove the column from the display entirely.

Carefully type each value for your **x** variable into **L1**, pressing **ENTER** after each entry. Once **L1** is complete, use the right arrow key to move to **L2** and input the corresponding **y** values. It is essential that the number of entries in **L1** matches the number of entries in **L2**; if the lists are of unequal length, the calculator will return a "DIM MISMATCH" error when you attempt to run the **regression**. Below is a visual representation of how your screen should appear once the data is correctly entered:

L1	L2	L3	L4	L5	1
1	76	-----	-----	-----	
2	78				
2	85				
4	88				
2	72				
1	69				
5	94				
4	94				
2	88				
4	92				
-----	-----				
L1(11)=					

Step 2: Navigating the Statistical Calculation Menu

With your data safely stored in the lists, the next phase involves navigating to the specific **regression** function. Press the **STAT** button again, but this time, use the right arrow key to highlight the **CALC** menu. This menu contains a variety of commands for **univariate** and **bivariate analysis**. For the purposes of standard **linear regression**, you have two primary options: **4: LinReg(ax+b)** and **8: LinReg(a+bx)**. While both perform the same mathematical operation, the latter is more commonly used in advanced statistics to denote the **intercept** as the starting point.

Scroll down to **8: LinReg(a+bx)** and press **ENTER**. This selection will take you to a setup screen where you must specify which lists contain your data. By default, the **TI-84** usually suggests **L1** for the **Xlist** and **L2** for the **Ylist**. If you have used different lists, you can change these by pressing **2nd** followed by the number corresponding to the desired list (e.g., **2nd + 1** for **L1**). This flexibility allows you to store multiple datasets and choose which ones to compare at any given time.

The **FreqList** field should remain blank unless you are working with **weighted data**, which is uncommon for basic introductory problems. Additionally, if you wish to see your regression line on a graph later, you can use the **Store RegEQ** option to save the resulting equation into one of the graphing variables like **Y1**. Once all fields are set correctly, scroll down to **Calculate** and press **ENTER** to execute the command. The following visual illustrates the selection process:



```
EDIT CALC TESTS
1:1-Var Stats
2:2-Var Stats
3:Med-Med
4:LinReg(ax+b)
5:QuadReg
6:CubicReg
7:QuartReg
8:LinReg(a+bx)
```

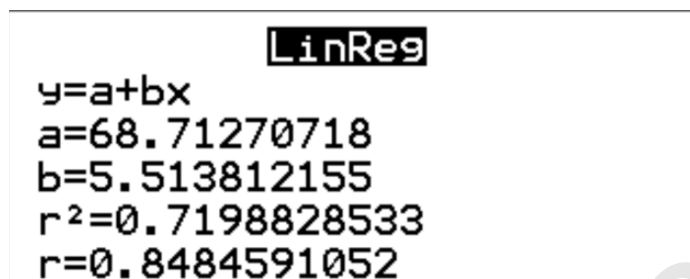
Step 3: Analyzing the Regression Output

After the calculator processes the data, a screen will appear displaying several key values that define the **linear regression** model. The first two values, **a** and **b**, represent the **intercept** and the **slope** of the line, respectively. In the equation format $y = a + bx$, **a** is the value of **y** when **x** is zero, and **b** is the rate of change--how much **y** is expected to increase or decrease for every one-unit increase in **x**. These coefficients are the heart of your mathematical model.

In addition to the coefficients, if your **DiagnosticOn** setting is enabled, the calculator will also

display r and r^2 . The value r is the **correlation coefficient**, which ranges from -1 to 1 and indicates the strength and direction of the **linear relationship**. A value close to 1 suggests a strong positive relationship, while a value close to 0 suggests no **linear relationship** exists. The r^2 value, or **coefficient of determination**, provides a measure of how well the regression line fits the data points.

Interpreting these results requires a clear understanding of the context. For instance, if the output shows a positive **slope**, it confirms that as the **explanatory variable** increases, the **call response variable** also tends to increase. If the r^2 is high, you can be more confident that your model accurately captures the underlying trend of the data. Review the output screen below to see an example of what these results look like in practice:

A screenshot of a TI-84 calculator screen displaying linear regression results. The title 'LinReg' is at the top. Below it, the equation 'y=a+bx' is shown. The statistics listed are: 'a=68.71270718', 'b=5.513812155', 'r^2=0.7198828533', and 'r=0.8484591052'.

```
LinReg
y=a+bx
a=68.71270718
b=5.513812155
r^2=0.7198828533
r=0.8484591052
```

Step 4: Formulating the Regression Equation

Once you have the values for **a** and **b** from the **TI-84** output, you can construct the specific **linear regression equation** for your dataset. Using the example of exam scores and study hours, let's assume the calculator provided an **intercept (a)** of 68.7127 and a **slope (b)** of 5.5138. The resulting equation would be written as: **exam score = 68.7127 + 5.5138 * (hours studied)**. This formula is a powerful tool for summarizing the entire relationship into a single line of **algebra**.

The **slope** of 5.5138 tells us something very specific: for every additional hour a student spends studying, their predicted exam score increases by approximately 5.5 points. This **marginal analysis** is crucial for decision-making and understanding the efficiency of a particular input. The **intercept** of 68.7127 represents the baseline; it is the predicted score for a student who has engaged in zero hours of study. While the **intercept** is mathematically necessary, it is important to consider whether it makes sense in a real-world context, as some values of **x** may be outside the range of the actual data.

When presenting your findings, it is standard practice to round these coefficients to a reasonable number of **significant figures**, typically two or three decimal places, depending on the required precision. By translating the calculator's raw output into a formatted equation, you make the data accessible to others. This equation allows anyone to understand the trend without having to look at

the original list of numbers, serving as a concise summary of the **empirical evidence** gathered during the study.

Step 5: Predicting Outcomes with the Model

One of the most practical applications of **linear regression** is the ability to make **predictions** for values that were not part of the original dataset. By substituting a specific value for **x** into your regression equation, you can calculate the **expected value** for **y**. For example, if you want to estimate the score for a student who studies for exactly three hours, you would plug "3" into the equation: $68.7127 + 5.5138 * (3)$. The result, **85.25**, provides a data-driven estimate of that student's performance.

This process of predicting within the range of your data is known as **interpolation**. It is generally considered reliable because the model was built using data points in that vicinity. However, one must be cautious when performing **extrapolation**, which is making predictions for **x** values far outside the original range (e.g., predicting the score for 100 hours of study). Relationships that are linear within a certain range may become non-linear or reach a saturation point outside of that range.

In a formal report or academic setting, these predictions are often accompanied by a discussion of the model's limitations. No **linear model** is perfect, and there will always be **residuals**--the differences between the actual observed values and the values predicted by the line. By understanding how to use the equation for prediction, you transition from simply describing the past to forecasting potential future outcomes, which is the ultimate goal of **predictive modeling**.

Step 6: Evaluating the Strength of the Relationship

To determine how much confidence you should place in your **regression model**, you must examine the **coefficient of determination**, or r^2 . In our exam study example, an r^2 value of **0.7199** indicates that approximately 71.99% of the **variance** in exam scores can be explained by the number of hours studied. This suggests a relatively strong relationship, as a large majority of the change in scores is tied directly to the study time. The remaining 28.01% of the variation is due to other factors not included in the model, such as prior knowledge, sleep, or test anxiety.

The **correlation coefficient** (**r**) further clarifies this relationship. If **r** is positive, the variables move in the same direction; if negative, they move in opposite directions. The closer **r** is to 1.0 or -1.0, the more the data points cluster tightly around the **regression line**. On the **TI-84**, if you do not see these values, you must turn on the diagnostics. This is done by pressing **2nd + 0** to enter the **CATALOG**, scrolling down to **DiagnosticOn**, and pressing **ENTER** twice. This ensures that every time you run a **regression**, you receive the full suite of **goodness-of-fit** metrics.

Understanding these metrics prevents the common mistake of over-relying on a weak model. Even if a **slope** is calculated, a very low r^2 value suggests that the linear model does not represent the data well, and any predictions made would likely be inaccurate. By analyzing both the equation and the strength of the fit, you provide a comprehensive and responsible **data analysis** that acknowledges both the trends and the uncertainties inherent in the information.

Advanced Diagnostic Techniques: Residual Plots

For those looking to deepen their analysis, creating a **residual plot** is the next logical step. A **residual** is the difference between an observed **y** value and the **y** value predicted by the **regression line**. By plotting these residuals against the **x** values, you can check the **linearity** assumption. If the **residual plot** shows a random scatter of points around the center line, then a **linear model** is appropriate for the data. However, if a clear pattern--such as a curve--emerges, it indicates that a non-linear model might be a better fit.

The **TI-84** automatically calculates and stores residuals in a list named **RESID** every time you perform a **linear regression**. You can view these values by going back to the **STAT** editor or by creating a new **Stat Plot**. Using **L1** as the **Xlist** and **RESID** as the **Ylist** will generate a visual diagnostic that is essential for advanced statistical verification. This step ensures that your model isn't just a mathematical coincidence but a valid representation of the **distribution** of the data.

Incorporating **residual analysis** elevates your work from basic calculator usage to professional-level **econometrics** or scientific research. It provides a safeguard against **overfitting** and helps identify **outliers** that might be disproportionately influencing your results. For more detailed instructions on this specific technique, you may find additional resources helpful in mastering the graphical capabilities of your device.

Ensure your calculator's **DiagnosticOn** mode is active to see **r** and r^2 .

Always verify that **L1** and **L2** have the same number of data points.

Use **Stat Plot** to visualize your scatter plot before running the **regression**.

The **a** value is your **y-intercept** and **b** is the **slope** in the **LinReg(a+bx)** function.

Additional Resources

To further enhance your skills with the **TI-84**, consider exploring how to visualize these results graphically or how to handle more complex data distributions. Understanding the underlying **calculus** and **linear algebra** that the calculator performs can also provide a deeper appreciation for the **optimization** occurring behind the screen.

[How to Create a Residual Plot on a TI-84 Calculator](#)