

The Impact of Outliers on Linear Regression Models: Detection and Correction Strategies

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Article History

Received: May, 07, 2025

Revised: May, 23, 2025

Accepted: June 07, 2025



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Doi: <https://doi.org/10.58840/fbcv732>

Abstract:

Outliers can significantly distort the results of linear regression models, leading to misleading conclusions and reduced predictive performance. This study investigates the impact of outliers on three regression techniques—Ordinary Least Squares (OLS), Huber Regression, and RANSAC—by comparing their behavior on both clean and contaminated datasets. Using simulated data with a 5% contamination rate, we evaluated each model based on key metrics, including slope, intercept, Mean Squared Error (MSE), and Coefficient of Determination (R^2). Our findings reveal that OLS is highly sensitive to outliers, showing a dramatic increase in MSE and a substantial drop in R^2 despite minimal changes in coefficients. Huber Regression offers slightly improved resilience by down-weighting the influence of extreme values, but still suffers from performance decline. RANSAC demonstrates the most robustness, with the smallest drop in R^2 and an active reconfiguration of regression parameters to exclude outlier influence. The results underscore the necessity of incorporating outlier detection and correction strategies in regression modeling, especially in real-world datasets prone to noise. The study provides practical insights for researchers and practitioners seeking to improve the reliability and interpretability of regression models under non-ideal data conditions.

Keywords: *Outliers, Linear Regression, Robust Regression, Huber Regression, RANSAC, Model Accuracy, Mean Squared Error (MSE)*

1. Introduction

Linear regression is one of the most widely used statistical tools for modeling relationships between variables in disciplines ranging from economics and engineering to healthcare and the social sciences. Its popularity stems from its simplicity, interpretability, and the ease with which it can be implemented (Dash et al., 2023). However, one of the major vulnerabilities of linear regression lies in its sensitivity to outliers—data points that deviate markedly from the overall pattern of the data. These anomalies can distort estimates, reduce predictive accuracy, and lead to invalid inferences if not properly addressed (Fang et al., 2022).

Outliers can arise for a variety of reasons, including measurement errors, data entry mistakes, natural variability in the population, or rare but valid events. Regardless of their origin, their presence can disproportionately affect the slope and intercept of regression lines, inflate standard errors, and violate assumptions such as homoscedasticity and normality of residuals. In particular, outliers can have high leverage or large residuals, making them influential enough to shift the regression line in a way that does not represent the general trend of the data. As such, the identification and treatment of outliers is a critical step in ensuring the reliability of regression models (Stefan & Schönbrodt, 2023).

The impact of outliers is especially significant in small datasets, where each individual data point carries more weight in the overall estimation. In such cases, even a single influential observation can significantly alter the results. This is problematic not only for parameter estimation but also for hypothesis testing, where incorrect standard errors can lead to inaccurate confidence intervals and misleading p-values. Consequently, the need for systematic detection and correction of outliers becomes essential for producing statistically valid results (Wang et al., 2022).

Several statistical techniques have been developed to identify outliers in regression contexts. Graphical methods such as scatterplots, boxplots, and residual plots provide intuitive visual cues for identifying extreme values. More advanced diagnostic tools include leverage statistics, Cook's distance, Mahalanobis distance, and standardized residuals, all of which help quantify the influence of individual data points on the model. These methods are particularly useful in high-dimensional datasets, where visual inspection becomes impractical (Twumasi & Twumasi, 2022). Once outliers are detected, the next step is deciding how to handle them. Common strategies include data transformation, robust regression techniques (such as least absolute deviations or M-estimators), and exclusion of extreme values. However, each approach carries trade-offs. Exclusion may lead to loss of valuable information, while transformations can complicate interpretation. Robust regression offers a balanced solution by reducing the influence of outliers without discarding data, but it requires more computational effort and methodological understanding (Shan, 2025). This paper explores the multifaceted impact of outliers on linear regression models, focusing on detection methods and correction strategies. Through simulation and case studies, we aim to demonstrate how outliers can bias model outcomes and how targeted interventions can mitigate these effects, ultimately improving model robustness and inference validity.

2. Literature Review

Linear regression has long been a fundamental technique in statistical modeling, offering straightforward insights into relationships between independent and dependent variables. However, its assumptions of linearity, homoscedasticity, and normality of residuals make it highly

susceptible to outliers. Outliers can distort regression coefficients, standard errors, and goodness-of-fit measures, often rendering statistical conclusions invalid (Monereo-Sánchez et al., 2021). This literature review explores the significance of outliers in regression analysis, established detection methods, and modern correction strategies, as documented in empirical and theoretical research.

2.1. Significance and Sources of Outliers

Outliers are data points that differ substantially from the overall distribution of a dataset. As Rousseeuw and Leroy (1987) noted, outliers can emerge from recording errors, data entry mistakes, or genuine but rare population characteristics. In the context of linear regression, their presence becomes especially problematic when they exert undue influence on model parameters—a concept formalized through the idea of leverage and influence (Sura, 2024). Tax et al. (2022) emphasized that outliers not only misrepresent underlying trends but can also invalidate model assumptions. For instance, a high-leverage point far from the centroid of the predictor space can severely affect the slope of the regression line, leading to biased estimates and underestimated standard errors.

2.2. Theoretical Implications for Regression Models

Standard linear regression, which minimizes the sum of squared residuals, is inherently sensitive to extreme values. One or more outliers can drastically affect the direction and magnitude of the estimated coefficients. According to Belsley, Kuh, and Welsch (1980), this is particularly dangerous when the outlier has both high leverage and a large residual, classifying it as an "influential point." In small samples, even a single outlier can distort regression results significantly. Hampel et al. (1986) showed that traditional regression models lose their robustness in datasets with non-normal error distributions and moderate contamination rates. Thus, identifying and mitigating the influence of such points becomes central to trustworthy regression modeling (Tremblay, 2025).

2.3. Outlier Detection Methods

The literature distinguishes between graphical and analytical techniques for identifying outliers. Yin & Liu (2022), graphical tools include:

- **Boxplots** for detecting outliers in univariate distributions.
- **Scatterplots** and **residual plots** for visualizing anomalies in bivariate and multivariate contexts.
- **Q-Q plots** to assess deviations from normality.

While useful, graphical methods become less effective in high-dimensional data or large samples, where more formal statistical techniques are preferred. Among the most commonly used diagnostic statistics are:

Leverage (hat values): Quantifies the extremity of predictor values; high-leverage points lie far from the average in the predictor space (Mohammad, 2023).

Standardized and studentized residuals: Assess whether a residual is large compared to others.

Cook's Distance: Measures the effect of deleting a data point on fitted values. Values above 1 typically indicate influential outliers (Han et al., 2022).

DFBETAs and DFFITS: Estimate the impact of deleting a point on individual regression coefficients and fitted values, respectively.

These measures have been widely validated and incorporated into regression diagnostic frameworks in software packages such as R, SPSS, and Stata.

2.4. Robust Statistical Techniques

The limitations of traditional least squares estimation have led to the development of robust regression techniques. These methods aim to reduce sensitivity to outliers without entirely excluding data points. One approach is Least Absolute Deviations (LAD), which minimizes the sum of absolute residuals rather than squares. LAD is more resistant to extreme values but less efficient when the error distribution is truly normal (Mahmod et al., 2024).

M-estimators, introduced by Huber (1981), modify the loss function to downweight the influence of outliers. They provide a compromise between least squares and LAD methods, maintaining efficiency while enhancing robustness.

RANSAC (Random Sample Consensus) is another robust approach that repeatedly samples subsets of data to fit models and identifies inliers as those points that best support the model (Fischler & Bolles, 1981). While computationally intensive, it is widely used in computer vision and machine learning.

Studies comparing robust regression methods indicate that M-estimators and other iteratively reweighted algorithms provide better performance in the presence of contamination (Niu et al., 2022). However, they also note the trade-off between robustness and computational complexity, especially in large datasets.

2.5. Data Transformation and Exclusion

Another strategy involves transforming the dependent or independent variables to reduce skewness and mitigate outlier influence. Common transformations include log, square root, and Box-Cox transformations (Thompson, 2025). While effective, these methods can complicate interpretability and are not always appropriate. Some researchers advocate for removal of outliers, especially when they are determined to be errors or artifacts. However, this approach can be controversial. Barnett and Lewis (1994) caution that excluding valid but rare observations may lead to biased estimates and loss of information. Therefore, the decision to exclude an outlier must be justified contextually, ideally based on domain knowledge, and confirmed by sensitivity analyses. Best practices recommend comparing regression results with and without the outlier to assess robustness.

2.6. Impact on Inference and Prediction

The presence of outliers can drastically affect not only coefficient estimates but also the reliability of inferential statistics. They inflate standard errors, widen or narrow confidence intervals inappropriately, and lead to Type I or Type II errors in hypothesis testing (Zhang et al., 2021). Furthermore, outliers reduce the model's predictive accuracy on new data. This is especially problematic in predictive analytics and machine learning applications, where generalization is key. Cross-validation and out-of-sample testing are crucial to identify overfitting caused by influential data points (Surchi, 2025).

2.7. Best Practices and Integrated Approaches

The literature increasingly advocates for integrated approaches to handling outliers. This includes combining detection diagnostics with robust modeling techniques and domain-specific evaluation. For example, in epidemiology, outlier detection is often combined with expert review to determine whether anomalies reflect data entry errors or true but extreme observations (Vittinghoff et al., 2012). In finance, robust methods are preferred due to frequent data irregularities. Recent advancements in machine learning have introduced algorithms that automatically downweight or ignore outliers during training. For instance, gradient boosting frameworks like XGBoost and LightGBM include regularization terms that reduce sensitivity to extreme values (Rahnenführer et al., 2023).

3. Method

3.1. Research Design

This study employed a quantitative, simulation-based research design to systematically evaluate how outliers affect the performance of linear regression models. The approach involved generating controlled datasets with and without outliers, applying both traditional and robust regression techniques, and analyzing the outcomes through diagnostic metrics and statistical testing.

3.2. Data Generation

To maintain control over model parameters and ensure replicability, synthetic datasets were generated using Python's NumPy and Pandas libraries. The primary dataset consisted of 500 observations, modeled using a simple linear equation:

$$Y = \beta_0 + \beta_1 X + \epsilon$$

Where:

- $\beta_0 = 5$ (intercept)
- $\beta_1 = 3$ (slope)
- X values were randomly drawn from a normal distribution: $X \sim N(10, 2)$
- ϵ (error term) followed a normal distribution: $\epsilon \sim N(0, 2)$

Two datasets were created:

1. Clean dataset with no anomalies
2. Contaminated dataset with 5% of the data points altered to include extreme outliers (e.g., $Y = Y + \text{random noise} \times 20$)

3.3. Outlier Detection Techniques

To detect outliers in the contaminated dataset, both graphical and analytical methods were applied:

- Scatterplots and residual plots for initial visual inspection
- Leverage values (hat matrix) to identify observations with extreme X values
- Standardized residuals to assess deviations from predicted values

- Cook's Distance to measure overall influence on the regression model
- Mahalanobis distance to detect multivariate outliers (if multiple predictors are involved)

Thresholds for these diagnostics followed conventional cut-offs:

- Cook's Distance > 1
- Standardized Residuals $> \pm 2$
- Leverage values $> 2(k + 1)/n$, where k is the number of predictors

3.4. Regression Models Tested

To assess the impact of outliers, four types of regression models were applied to both datasets:

1. Ordinary Least Squares (OLS) – baseline method
2. Least Absolute Deviations (LAD) – minimizes absolute residuals
3. Huber M-estimator – balances between OLS and LAD using a robust loss function
4. RANSAC Regression – fits models iteratively using subsets, focusing on inliers

3.5. Evaluation Metrics

The performance of each model was compared using the following metrics:

- Regression coefficients (β_0 , β_1) – to observe distortion
- Mean Squared Error (MSE) – on both training and test splits
- R^2 (Coefficient of Determination) – to evaluate explained variance
- Outlier sensitivity – number of influential points detected by each method
- Prediction accuracy – using k-fold cross-validation ($k = 5$)

In each case, models applied to both clean and contaminated datasets were compared to quantify the effects of outliers.

3.6. Software Tools

All simulations, statistical analyses, and visualizations were conducted using:

- Python (v3.10) with libraries: NumPy, Pandas, Statsmodels, Scikit-learn, Matplotlib, and Seaborn
- SPSS and R were used to confirm some regression diagnostics (e.g., Cook's Distance, DFBETAs)

4. Results and Analysis

Table 1. Impact of Outliers on Model Metrics

Model	Δ MSE	Δ R^2	Δ Slope (β_1)	Δ Intercept (β_0)
Huber	28.78	-0.322	-0.01	+0.10
OLS	28.69	-0.321	0.00	+0.07
RANSAC	28.28	-0.316	+0.27	-2.67

The tables presented provide a comparative view of how outliers affect different regression models in terms of estimation accuracy and model fit. Specifically, the "Impact of Outliers on Model Metrics" table quantifies the performance shifts between clean and contaminated datasets across three regression methods: OLS (Ordinary Least Squares), Huber Regression, and RANSAC. All three models demonstrated a notable increase in Mean Squared Error (MSE) when trained on the contaminated data. OLS and Huber saw nearly identical rises in MSE (28.69 and 28.78, respectively), while RANSAC experienced a slightly smaller increase (28.28). This suggests that all models became less accurate under the influence of outliers, but RANSAC was relatively more resilient. The drop in R^2 values across all models (roughly -0.32) further confirms a significant reduction in their explanatory power. The lower the R^2 , the less variance in the dependent variable is explained by the model—highlighting the detrimental impact of outliers on regression fit.

Table 2. Regression Model Performance Comparison

Model	Data	Slope (β_1)	Intercept (β_0)
OLS	Clean	2.95	5.56
OLS	Contaminated	2.95	5.63
Huber	Clean	2.92	5.83
Huber	Contaminated	2.91	5.93
RANSAC	Clean	2.93	5.78
RANSAC	Contaminated	3.2	3.11

Changes in coefficients further illustrate how each model responds to contamination. For OLS, the slope (β_1) remained unchanged at 2.95, and the intercept (β_0) increased marginally from 5.56 to 5.63. This consistency is deceptive, as OLS absorbs the effect of outliers without adequately adjusting the model fit, as evidenced by the sharp increase in error metrics. Huber Regression showed a slight reduction in slope (-0.01) and a mild increase in intercept (+0.10), indicating a small but intentional adjustment to reduce outlier impact. In contrast, RANSAC made the most dramatic shift, with the slope increasing from 2.93 to 3.20 and the intercept dropping from 5.78 to 3.11. This reflects its robust nature—it actively excluded or down-weighted outlier data points during model fitting, resulting in a noticeable reconfiguration of the regression line. In summary, these tables show that while OLS and Huber try to accommodate outliers with minimal adjustment, they suffer significant losses in prediction accuracy. RANSAC, although more aggressive in its re-estimation, offers stronger protection against outlier influence by reconfiguring the model structure altogether. This suggests that for datasets prone to contamination, robust techniques like RANSAC may be more appropriate, provided their parameter tuning and computational demands are manageable.

5. Discussion

Linear regression is a cornerstone of statistical modeling, but its vulnerability to outliers is a well-documented limitation (Dash et al., 2023). This study quantitatively examined the effects of outliers on three regression techniques—Ordinary Least Squares (OLS), Huber Regression, and RANSAC—by comparing their performance on clean versus contaminated datasets. The discussion below elaborates on the results, linking them to theoretical expectations and relevant empirical findings in the literature. The sharp rise in Mean Squared Error (MSE) observed across all models when outliers were introduced is a clear indication of performance degradation. OLS showed an increase of 28.69 units in MSE, aligning with classical concerns that OLS, by

minimizing the sum of squared residuals, is disproportionately influenced by extreme values (Hoaglin & Welsch, 1978). Huber regression, although more robust, showed a nearly identical increase in MSE (28.78), suggesting its robustness is more subtle and perhaps insufficient for heavy contamination without further tuning of its tuning constant k (Huber, 1981). RANSAC, known for its outlier-resilient architecture, displayed the smallest increase in MSE (28.28). While all three models were affected, the comparative performance of RANSAC highlights its effectiveness in excluding influential points during model fitting (Fischler & Bolles, 1981). However, it's important to note that RANSAC's performance can be highly variable depending on the number of iterations and subset sampling.

The coefficient of determination (R^2) offers further insight into how much variance is explained by the model. On clean data, all models maintained R^2 values around 0.87, indicating excellent fit. After contamination, R^2 values for all three dropped to approximately 0.55, with Huber Regression experiencing the largest drop (-0.322). This reinforces earlier findings that, while Huber Regression is designed to reduce the weight of outliers, it still allows them to influence the model structure (Wilcox, 2012). The marginally smaller drop in R^2 for RANSAC (-0.316) reflects its robust estimation process, which isolates inliers from outliers and recalculates regression parameters based on the most consistent subset of the data (Torr & Zisserman, 2000). This result supports previous claims that robust methods are essential for maintaining model integrity under noisy conditions (Maronna et al., 2006).

The regression coefficients (β_0 and β_1) provide another layer of understanding. OLS showed no change in slope and only a minor shift in intercept (+0.07), but this superficial stability is misleading. Because OLS fits all points equally—including outliers—it may yield coefficients that look accurate while producing poor predictions. This behavior has been termed “masking,” where outliers blend into the data due to their alignment along influential directions (Belsley, Kuh, & Welsch, 1980). Huber Regression demonstrated a small shift in slope (-0.01) and intercept (+0.10), consistent with its goal of down-weighting rather than excluding outliers. This modest adjustment may be preferable in domains where complete removal of data points is undesirable, such as medical diagnostics or economics, where each data point may hold important information. In contrast, RANSAC made the most dramatic adjustments, with a slope increase of +0.27 and intercept decrease of -2.67. These shifts illustrate how aggressively RANSAC recalibrates the model based on the most reliable subset of data. Although this often results in improved performance, it also raises concerns about overfitting to the selected inliers, especially when those inliers are few or not representative of the broader population.

This study highlights the classic trade-off between robustness and efficiency. OLS is efficient under ideal conditions (normal distribution, homoscedasticity) but performs poorly under violations. Robust methods like Huber and RANSAC sacrifice some efficiency on clean data in exchange for resilience against contamination. The literature supports this compromise. Koenker and Bassett (1978) found that Least Absolute Deviations (LAD) and similar methods perform well in heavy-tailed error distributions but are less precise under normal conditions. Similarly, RANSAC's robustness depends on parameter tuning, including threshold selection and the number of iterations. In this study, RANSAC was the most adaptable but also the least interpretable in terms of why specific inliers were selected. This has been echoed in machine learning contexts where model transparency is crucial (Chen & Guestrin, 2016).

5. Conclusion

This study explored the influence of outliers on linear regression performance and compared the effectiveness of three models—Ordinary Least Squares (OLS), Huber Regression, and RANSAC—in both clean and contaminated data environments. The results highlight the significant vulnerability of traditional regression techniques like OLS when exposed to even a small percentage of extreme values. While OLS retained stable coefficients, its predictive accuracy and explanatory power were severely compromised, as evidenced by substantial increases in mean squared error (MSE) and reductions in R^2 .

Huber Regression, though designed to reduce the influence of outliers, also suffered performance degradation under contamination, indicating that its robustness is not absolute and must be complemented by proper parameter tuning. In contrast, RANSAC demonstrated superior resilience, actively adjusting its model parameters to account for outlier presence. However, this robustness came with the trade-off of greater shifts in slope and intercept, and reduced interpretability.

Ultimately, the findings affirm that outlier detection and correction are not optional steps but essential components of the regression modeling process. Robust regression techniques, particularly when combined with visualization tools and diagnostic metrics, offer more reliable outcomes in real-world applications where data irregularities are common. Future models must prioritize robustness, transparency, and adaptability to ensure statistical validity in diverse analytical contexts.

6. Implications for Real-World Modeling

In real-world applications such as finance, epidemiology, or climate science, data contamination is common due to instrumentation error, data entry mistakes, or rare but valid anomalies. Rousseeuw and Leroy (1987) argue that ignoring outliers leads to incorrect scientific conclusions, while indiscriminate removal of outliers may cause loss of valuable information. Hence, the choice of detection and correction strategy must be data- and domain-driven.

The findings here suggest that OLS should be avoided in contaminated datasets unless preceded by rigorous outlier diagnostics. Huber Regression may serve as a compromise when moderate contamination is expected, while RANSAC is better suited to datasets with heavy noise, provided interpretability is not paramount.

7. Limitations and Future Research

While this study employed synthetic data to ensure control, real-world datasets often present more complex multivariate relationships and non-linearities. Future work should evaluate the same regression techniques in higher-dimensional contexts and under different types of contamination (e.g., leverage points vs. vertical outliers). Additionally, Bayesian robust regression methods and ensemble-based models such as Gradient Boosted Trees could be explored for their inherent robustness to irregularities.

Moreover, the influence of hyperparameters—especially for Huber and RANSAC—needs deeper investigation. As Maronna et al. (2006) and Hastie et al. (2009) argue, robustness is not absolute; it depends on implementation choices and data structure. Future studies may benefit from an expanded suite of metrics including Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and cross-validated root mean square error (RMSE) to better capture generalizability.

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