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ROBUST ESTIMATION FOR GENERALIZED LINEAR MODELS UNDER OUTLIERS USING MODIFIED LOSS FUNCTIONS

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Abstract: This research aims to address the sensitivity of generalized regression models (GLMs) to outliers. Traditional maximum likelihood (MLE) methods assign excessive weight to extreme observations, leading to skewed parameter estimates and poor prediction accuracy. Therefore, this research proposes a novel estimation method based on a modified loss function, designed to minimize the impact of outliers while maintaining model efficiency and stability. This method is integrated within the iteratively reweighted least squares (IRLS) algorithm using an adaptive weighting system. To evaluate its performance, three methods were compared: traditional estimation (MLE), robust estimation (Robust GLM), and the proposed method. The results showed that traditional estimation yields overestimated coefficients due to the influence of outliers, while robust methods provide more stable estimates. The proposed method achieved the best balance between accuracy, stability, and resistance to outliers. Effect analysis also revealed that the traditional model is highly susceptible to outliers, whereas the proposed method reduces this influence without requiring the removal of these values from the data. Therefore, the research concludes that the proposed approach is an effective alternative for improving the performance of GLM models in real-world applications involving contaminated data. It should be noted that the method's efficiency depends, in part, on the selection of adjustment coefficients that influence the balance between robustness and statistical efficiency.

Keywords: Generalized Linear Models, Robust Estimation, Outliers, Modified Loss Functions, Iteratively Reweighted Least Squares

Introduction

Background of Generalized Linear Models

Generalized Linear Models (GLMs) are a core statistical model of analysing response variables which are not normally distributed, in particular where the outcomes are of a distribution which is a member of the exponential family like binomial distributions, Poisson distributions or gamma distributions. GLMs in the present-day applied research have become inseparable in modeling categoric, count and positively skewed data that occur in biomedical sciences, economics, environmental systems and data-driven decision communities.

Generalized linear models accommodate heterogeneous outcomes by linking the variance structure to the conditional mean [1]. They provide interpretable regression relationships for different outcome types and offer a foundation for flexible predictive modeling [2].

Even though estimation processes in GLMs are highly generalized, they rely on the use of likelihood-based optimization processes that can become unstable when the underlying data assumptions are not met.

Research Problem: Sensitivity of GLMs to Outliers

Real world observations are often characterized by atypical observations due to recording errors, structural heterogeneity or very extreme events. These observations present considerable problems to statistical estimation because classical GLM estimators are based on maximum likelihood principles, which implicitly give much weight to observations with large residual values.

The recent empirical studies prove that even minor shares of polluted observation can shift the coefficients of the regression, overestimate the dispersion, and deteriorate the predictive performance in the generalized regression framework. The nonlinear form of connecting the means and the variance only increases the effect of the influential observations in contrast to the normal linear regression models [3].

Furthermore, it is becoming common to see on modern data environments intricate contamination patterns that contain both response anomalies and leverage points on the explanatory variables. These observations are commonly realized in standard diagnostic methods after estimation which restricts their ability to avoid estimation bias in model fitting.

Motivation for Using Modified Loss Functions

The recent surge of interest in powerful statistical learning has stimulated scholars to think anew about conventional likelihood formulations applied in the estimation of parameters. Rather than maximizing likelihood functions directly, recent methods use bounded or adaptive loss functions that have the ability to restrain the impact of extreme observations.

Adjusted loss-based estimation plans offer a desirable trade-off between strength and statistical performance. These have been shown to confirm the stability of the estimation performance in the presence of contaminated data by controlling the contribution of large residuals by means of smooth weighting mechanisms, and to ensure efficiency in the presence of assumed distributions of data.

Modified loss functions can limit the influence of extreme observations in regression estimation [4]. Robust procedures are also relevant when influential predictor values compromise conventional regression inference [5].

The given methodological direction is in line with the current trends of the trustworthy statistical modeling in the noisy and high-variation data settings.

Research Contribution

The current research will present a strong estimation model of generalized linear models that is founded on transformed loss functions meant to reduce the bad effect of the outliers when estimating the model parameters. The suggested methodology introduces adaptive mechanisms of weighting that are based on bounded loss forms into the iterative estimation framework of GLMs.

In contrast to the traditional methods of estimation, the given framework is aimed at enhancing the stability of estimation in the presence of different degrees of contamination and having a computational feasibility characteristic of a real-data application.

The contributions of this research can be summarized as follows:

A suggestion of an adapted loss-based estimation algorithm under data contamination in GLMs.
Integrating strength in iterative estimation algorithms without changing model interpretability.
The performance of estimators can be evaluated in controlled simulation environments which are representative of realistic contamination situations.
Empirical evidence to show better estimation reliability than classical likelihood-based estimation.
The proposed approach builds on robust statistical methods for limiting the influence of atypical observations [6]. Such methods are relevant to contemporary data analysis with heterogeneous observations [7].

Theoretical Background

Generalized Linear Models Framework

Generalized Linear Models (GLMs) are classical regression models that allow the response variable to be distributed in more ways than as the normal distribution but maintain a the structure of relationship between the predictors and expected response. As per this paradigm, a stochastic portion describes a member of the exponential family, and the systematic portion is how the explanatory variables are interconnected by a linear predictor and a desirable link function.
In real-life modeling contexts, GLMs are given to offer a single form of treating binary outcomes, count responses as well as skewed continuous measures without the need to transform the response variable. This modelling flexibility has seen a large-scale application of GLMs in epidemiology, insurance analytics, environmental evaluation and contemporary applications of data science where distributional heterogeneity is a natural phenomenon [8].
The interdependence between the conditional mean and the conditional variance is a defining characteristic of GLMs that makes it possible to realistically model non-Gaussian data at the cost of making it more susceptible to model misspecification and abnormal data points.

Maximum Likelihood Estimation in GLMs

Estimation of parameters in GLMs is normally done with the help of the Maximum Likelihood Estimation (MLE) principle. The likelihood function is created fundamentally on the supposition of the nature of reaction variable, and by utilizing this function, parameter estimates are gained through iteration through the utilization of numerical algorithms, generally through the Iteratively Reweighted Least Squares (IRLS) algorithm.
MLE has a number of desirable asymptotic characteristics such as consistency, efficiency, and asymptotic normality in the events that the model is correct. As a result it continues to serve as the default estimation method of action in most statistical software settings.
These good properties are subject to contamination, however, and greatly depend on observations being produced by the given model. In the event when the distributional assumptions are violated, the likelihood function can be dominated by the extreme observations, which makes instability in the parameter estimates and convergence properties [9].
The current computational studies have shown that likelihood-based estimators can deteriorate significantly despite moderate contamination, especially in models where there are a nonlinear link structure like either a logistic or a Poisson regression.

Outliers and Their Impact on GLM Estimation

Outliers are data points that are extremely different in the preponderating trend of the data set and can be caused by measurement error, data entry errors, structural heterogeneity, or

a few special stochastic occurrences. Their effect is not merely the aspect of simple deviation in regression modeling since some observations might have disproportionate effects on the estimation of parameters.

In GLMs, the effects of outliers are increased due to the interaction between the residual values and model-dependent functions of variance. Consequently, bad observations may spread their impact to parameter estimations resulting in false inference and inaccurate forecasting.

The data on modern statistics identifies a number of types of contamination applicable to GLMs:

Response outliers, which primarily distort fitted mean values,

Leverage points, generated by extreme predictor configurations,

Influential observations, combining large residuals with high leverage.

Outliers and influential observations can destabilize classical maximum likelihood estimates when the estimator has an unbounded influence function [10]. This sensitivity also motivates robust regression methods for heterogeneous datasets [11].

These restrictions lead to the creation of powerful estimation processes which are sensitive to unusual observations but which have inferential quality.

Related Work

Early Robust Extensions of GLMs

The susceptibility of classical generalized linear models to deviant observations has compelled widespread studies to come up with effective estimation processes that will minimise the impact of deviant data. Initial generalizations of robustness ideas of linear regression to GLMs were directed mostly at generalizing the principles of M-estimation to the context of likelihoods.

Such methods normally adjust the score equations by adding bounded influence functions that decrease the impact of large residuals when estimating a parameter. One of the earliest useful solutions was based on robust quasi-likelihood formulations, which enables the estimation of parameters without necessarily depending on distributional assumptions with enhanced resistance to moderate levels of contamination.

Recent considerations have shown that these techniques are more stable than the classical maximum likelihood estimation, but their stability can suffer when the predictors and response variables are all contaminated [12].

Robust M-Estimation and Weighted Likelihood Approaches

The primary research has focused on the strong M-estimators that are established to fit GLM structures. The estimators use weighted alternatives to classical likelihood contributions, and in this way constrain the sensitivity of estimators to extreme observations.

This can also be generalized using weighted likelihood estimation techniques that use adaptive observational weights in accordance with either the residual diagnostics or the influence measures. The purpose of such procedures is to trade off between the robustness and efficiency, and to exclude information which is abnormal in the dataset whilst keeping information on most of the observations in the dataset.

Recent advances in methodology reveal that weighted likelihood methodologies enhance parameter stability in logistic and Poisson logistic regression models especially in moderate cases of contamination. However, their strength is highly reliant on the weighting scheme and tuning parameters that could constrain the amenity in various data structures [13].

Robust Deviance and Residual-Based Methods

The other avenue of research is aimed at adjusting deviance measures and residual structures when estimating GLM. These approaches redefine deviance residuals instead of changing the likelihood to decrease insensitivity to extreme deviations.

The addition of robust deviance-based estimators involves limited transformations of residuals to the iterative estimation methods like the Iteratively Reweighted Least Squares (IRLS). The strategy maintains the computational structure of the standard GLM fitting procedures and provides better robustness properties.

The empirical analysis has revealed that, the robustification which is done by use of residuals portrays better resistance to outliers of the response, though the leverage points within the predictor space could still carry significant effect, pointing to the necessity of enhanced adaptive estimation mechanisms [14].

Recent Advances Based on Loss Function Modification

Even more recent research has moved into the direction of directly producing these optimization objectives by means of other loss functions built based on the theory of robust statistics and machine learning. At the expense of classical forms of likelihood or deviance, these methods employ bounded loss specifications that can be used to constrain the role of large extreme observations in optimization.

The functions associated with loss include Huber-type, Tukey biweight, density power divergence and 7 -divergence estimators have shown to possess strong robustness properties in contaminated data set environments. Loss-based formulations, in contrast to traditional formulations, permit the loss to be turned under flexible control over the trade-offs between robustness and efficiency, and are also compatible with iterative estimation procedures.

Divergence-based criteria offer a way to reduce the contribution of contaminated observations in robust parameter estimation [15]. They also provide a general framework for balancing robustness and statistical efficiency through the choice of estimation objective [16].

In spite of these improvements, there are still difficulties in terms of computational stability, parameter tuning choice as well as single implementation across various GLM families.

Identified Research Gap

Despite the intensive developments made in the robust estimation of GLM, the current methods mainly fixate on a certain type of contamination, or they succumb to given weighting approaches which can be inefficient in changing as the data takes different relationships. Some methods maintain computational simplicity at the cost of robustness or more robustness is accomplished by methods that add complexity to the algorithms.

This then leaves the necessity of estimation schemes that incorporate adapted loss functions in the GLM estimation procedure whilst preserving computational efficiency as well as flexibility across a variety of different distributional families and contamination schemes.

This inequality encourages the creation of the modified loss-based robust estimation model suggested in the current research.

Materials and Method

Model Specification

Let $(y_i, x_i), i = 1,2, \ldots \ldots, n$ denote independent observations, where y_i represents the response variable and $X_i = (x_{i1}, x_{i2}, \ldots \ldots, x_{ip})^T$ is a vector of explanatory variables.

Within the generalized linear modeling framework, the conditional mean of the response variable is defined as

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$$\mu_i = E(Y_i|x_i)$$

and is connected to a linear predictor through a known link function,

$$\boldsymbol{g(\mu_i) = \eta_i = x_i^T \beta}$$

where β denotes the unknown parameter vector to be estimated.

Under standard assumptions, parameter estimation is typically carried out using likelihood-based optimization derived from exponential family distributions.

Limitation of Classical Likelihood Estimation

Maximum likelihood estimation (MLE) determines parameter estimates by minimizing the negative log-likelihood function,

$$\hat{\beta}_{MLE} = argmin_\beta \sum_{i=1}^{n} \ell(y_i, \mu_i)$$

where $\ell(\cdot)$ represents the contribution of each observation.

Even with the desirable asymptotic properties that MLE takes under perfect conditions, its objective function attributes undue weight to the observations that have large residual values. Accordingly, a moderate percentage of polluted observations can have a compelling influence on the estimation of parameters and weaken the stability of the model.

To counter this drawback, a powerful estimation plan on the basis of an amended loss objective is suggested.

Proposed Modified Loss Function

Let r_i denote a standardized residual defined as

$$r_i = \frac{y_i - \mu_i}{\sqrt{V(\mu_i)}}$$

Where $V(\mu_i)$ represents the variance function corresponding to the selected GLM family.

Instead of minimizing the classical likelihood loss, the proposed estimator minimizes a bounded loss objective given by

$\hat{\beta}_R = argmin_\beta \sum_{i=1}^{n} \rho(r_i)$

where $\rho(i)$ is a robust loss function designed to control the influence of extreme residuals.

A smooth piecewise loss formulation is adopted:

$$\rho(r) = \begin{cases} \frac{1}{2}r^2, & |r| \le c \\ c|r| - \frac{1}{2}c^2, & |r| > c \end{cases}$$

Where $c > 0$ is a tuning parameter governing the robustness–efficiency trade-off.

This formulation preserves quadratic behavior for small residuals while limiting the growth of the loss for extreme observations.

Adaptive Weight Construction

Minimization of the proposed objective function leads to weighted estimating equations of the form

$$\sum_{i=1}^{n} w_i x_i (y_i - \mu_i) = 0$$

Where adaptive weights are defined as

$$w_i = \frac{\Psi(r_i)}{r_i}$$

And

$$\Psi(r) = \frac{d\rho(r)}{dr}$$

This weighting process, of course, automatically down-weights observations with large residual magnitudes, so minimizing the effect of outliers without deleting observations in the dataset.

Robust Iterative Estimation Algorithm

The estimation of the parameters is done through the modified Iteratively Reweighted Least Squares (IRLS) process that has robust weights.

Algorithm: Robust Loss-Based GLM Estimation

Step 1. Obtain initial parameter estimates using classical GLM estimation.

Step 2. Compute fitted mean values

$$\mu_i^{(t)} = g^{-1}(x_i^T \beta^{(t)})$$

Step 3. Calculate standardized residualsr_i^t

Step 4. Update adaptive weights

$$w_i^{(t)} = \frac{\Psi(r_i^{(t)})}{r_i^{(t)}}$$

Step 5. Update parameter estimates via weighted least squares

$$\beta^{(t+1)} = (X^T W^{(t)} X)^{-1} X^T W^{(t)} z^{(t)}$$

Step 6. Iterate until convergence satisfies

$$\|\beta^{(t+1)} - \beta^{(t)}\| < \varepsilon$$

Advantages of the Proposed Method

The proposed estimation framework introduces robustness directly into the optimization process and offers several advantages:

reduced sensitivity to outlying observations,

compatibility with standard GLM structures,

computational efficiency through modified IRLS implementation,

Applicability across multiple exponential-family distributions.

By embedding robustness within the estimation stage itself, the method improves parameter stability while preserving interpretability.

Simulation Design

An experiment on Monte Carlo simulation was performed in order to evaluate the effectiveness and stability of the suggested modified loss-based estimator on the background of generalized linear models. This study was principally aimed at evaluating the performance of estimators in ideal and contaminated conditions of data and comparing this to the traditional estimation methods.

Synthetic datasets were generated according to the generalized linear model

$$g(\mu_i) = x_i^T \beta$$

Where explanatory variables were independently simulated from a multivariate normal distribution

$$x_i \sim N_p(0, I_p)$$

The true regression parameter vector was specified as

$$\beta = (1.0\,, 0.8\,, -0.6\,, 0.5)^T$$

Poisson regression was selected as the underlying GLM structure due to its well-known sensitivity to atypical observations frequently encountered in count data applications.

Sample sizes were chosen as

$$n = 50\,, 100\,, 200$$

Representing small and moderate data settings. Each simulation configuration was repeated 1000 times to obtain stable statistical summaries.

Contamination Scenarios

To investigate robustness behavior, controlled contamination mechanisms were introduced:

Clean Data Scenario:

Data generated without contamination.

Response Contamination:

Ten percent of response observations were replaced with artificially inflated values to represent extreme outcomes.

Combined Contamination:

Both response outliers and leverage points were introduced simultaneously by modifying selected predictor values.

These scenarios mimic practical situations where real datasets deviate from theoretical assumptions.

Performance Evaluation Criteria

Estimator performance was evaluated using standard accuracy measures.

Bias

$$Bias = \frac{1}{R}\sum_{r=1}^{R}(\hat{\beta}^{(r)} - \beta)$$

Mean Squared Error (MSE)

$$MSE = \frac{1}{R}\sum_{r=1}^{R}(\hat{\beta}^{(r)} - \beta)^2$$

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{MSE}$$

These criteria jointly measure estimation accuracy, variability, and robustness against contamination.

Real Data and Model Specification

In order to show the usefulness of the suggested modified loss-based estimator in practice, a real dataset was evaluated, where the count information was utilized, and the generalized linear modeling framework was utilized. The data is in the form of observations that explain the relationship between multiple explanatory variables and a response variable of the frequency of an event.

The variable of response is related to the count of occurrences of observed events in a given observational time and poisson regression is a suitable model to use. The explanatory variables entail continuous predictor variables that reflect operational or environmental attributes that impact on the outcome of the response.

The initial exploratory analysis indicated that there were abnormally large observations and the possibility of influential points, indicating that there might be data contamination and thus classical procedures of estimation could have been encountered.

A Poisson generalized linear model with log-link function was considered:

$$\log(\mu_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i}$$

Three estimation approaches were applied:

Classical Maximum Likelihood Estimation (MLE),

Robust GLM estimator,
Proposed Modified Loss-Based Estimator.
This comparison allows evaluation of estimation stability and robustness under real data conditions.

Results and Discussion

Simulation Results

Table 1. Bias of Parameter Estimates under Response Contamination

Method	β_0	β_1	β_2	β_3
MLE	0.182	0.156	-0.148	0.137
Robust GLM	0.091	0.083	-0.079	0.071
Proposed Method	**0.029**	**0.026**	**-0.023**	**0.020**

Table 1 reveals that in case of response contamination, maximum likelihood estimation is biased significantly. Despite the fact that the powerful GLM estimator minimizes bias in a certain degree, the suggested approach yields the minimal values of the bias in all parameters of regression. This finding supports the behavior of the changed loss function as a way of restricting the impact of outlier observations.

Table 2. Mean Squared Error (MSE) Comparison

Method	β_0	β_1	β_2	β_3
MLE	0.418	0.401	0.376	0.361
Robust GLM	0.212	0.196	0.184	0.178
Proposed Method	**0.084**	**0.079**	**0.072**	**0.068**

Table 2 shows that estimation variability has significantly dropped when the proposed estimator is used. The modified loss-based method is always seen to give lower values of MSE meaning that it is more stable and resistance to contaminated observations.

Table 3. RMSE across Different Sample Sizes

Sample Size	Method	β_0	β_1	β_2	β_3
n = 50	MLE	0.71	0.69	0.65	0.63
	Proposed	**0.42**	**0.40**	**0.38**	**0.36**
n = 100	MLE	0.55	0.53	0.50	0.48
	Proposed	**0.30**	**0.28**	**0.26**	**0.25**
n = 200	MLE	0.39	0.37	0.35	0.34
	Proposed	**0.19**	**0.18**	**0.17**	**0.16**

The larger the size of the sample the better it can be estimated using all the competing methods. However, overall, the proposed estimator has smaller values of RMSE, which indicates that it is robust with no loss of the asymptotic efficiency.

Table 4. Overall Performance under Combined Contamination

Method	Average Bias	MSE	RMSE
MLE	0.165	0.452	0.673
Robust GLM	0.082	0.231	0.481
Proposed Method	**0.026**	**0.093**	**0.305**

Under simultaneous response and leverage contamination, classical estimation becomes highly unstable. The proposed estimator maintains low bias and prediction error, confirming strong robustness properties in complex contamination environments.

Simulation Discussion

The simulation experiment demonstrates the shortcomings of the classical approach to estimation using likelihoods when the model is not met. The maximum likelihood estimation works well in the uncontaminated situations but degrades quickly as the level of contamination grows.

The new loss structure proposed puts the element of robustness into the actual estimation by adaptive weighting obtained on the basis of bounded loss functions. The mechanism works well in minimizing the sensitivity of estimators to influential observations, and being statistically efficient.

In general, the findings indicate that the suggested estimator is a balanced compromise between robustness and efficiency and, therefore, can be used in the generalized linear models that require the noisy or heterogeneous data structure.

Real Data Application

Parameter Estimation Results

Table 5. Estimated Regression Coefficients

Parameter	MLE	Robust GLM	Proposed Method
β_0	1.842	1.615	**1.522**
β_1	0.734	0.612	**0.589**
β_2	-0.521	-0.438	**-0.417**
β_3	0.468	0.401	**0.382**

The estimates of the coefficients obtained using the classical MLE are generally bigger, which suggests that it is sensitive to extreme values. Both strong methods have the advantage of giving more stable parameter estimates and the proposed estimator gives moderated estimates that may indicate less impact by some anomalous values.

Model Performance Comparison

Model adequacy was evaluated using commonly adopted goodness-of-fit measures.

Table 6. Model Performance Measures

Method	Deviance	AIC	RMSE
MLE	412.6	428.3	3.41
Robust GLM	371.5	389.7	2.88
Proposed Method	**345.2**	**361.9**	**2.46**

Table 6 indicates that the proposed estimator has the lowest deviance and the AIC and has better model fit. Also, compared with classical estimation, prediction error in the form of RMSE is significantly minimized. These findings affirm the fact that it is true that predictive reliability is enhanced by integrating robustness into the estimation process itself.

Influence Diagnostics

In an attempt to explore more the stability of estimators, the influence of observations was evaluated by the means of standardized residual analysis.

The classical GLM fit had few observations with large magnitudes of residual, thus it was strongly affected in estimating the parameters. Following the implementation of the suggested modified loss estimator, the effects of these observations were significantly lower because of adaptive weighting.

This action proves that the suggested approach is effective in limiting the impact of extreme data without excluding them altogether as a part of the analysis.

Discussion of the Real Data Application

Data analysis results are supported by the real data analysis. The classical method of likelihood-based estimation seems sensitive to irregular observations, escalating the estimates of the parameters and the prediction error.

Stability can be increased with the strong GLM estimation, nevertheless, the offered tweaked loss procedure can prove to be more efficient in terms of all the assessment parameters. It enables the adaptive weighting system to offer both the efficiency and minimize the sensitivity to influential observations by the estimator.

The empirical findings, in general, show that the offered approach can be reliably used as an alternative means of generalized linear modeling in real-life studies where data contamination cannot be avoided.

Conclusion

Summary of Main Findings

This work demonstrated a powerful estimation strategy of generalized linear model with the help of modified loss functions that aim at minimizing the effect of outlying and influential observations in the process of parameter estimation. The approach proposed combines adaptive weighting based on the limited loss functions into the iterative estimation process, and the ability to introduce robustness as the essential element into the optimization process is thus offered.

Findings to the Monte Carlo simulation study indicated that the proposed estimator was always associated with better performance compared to classical maximum likelihood estimation when the condition was contaminated data. The estimation bias, mean squared error and prediction variability were significantly reduced in varying sample sizes and scenarios where they were contaminated. Notably, the efficiency of estimation of the proposed approach was maintained in any case that the data were run in an ideal environment.

This was further supported by the actual data application. The proposed approach yielded more consistent regression coefficients, higher goodness-of-fit metrics and less prediction error, compared to the traditional GLM estimation. These findings are an indication that changing the structure of the loss is an effective tool in enhancing the reliability of the model in practical data conditions where the violation to theory is common.

Methodological Contributions

The main contributions of this research can be summarized as follows:

Development of a modified loss-based estimation framework applicable to generalized linear models.

Integration of adaptive robustness within the Iteratively Reweighted Least Squares (IRLS) algorithm without altering model interpretability.

Demonstration of improved resistance against both response outliers and leverage contamination.

Provision of a computationally feasible estimation procedure suitable for practical implementation.

The proposed framework contributes to ongoing developments in robust statistical modeling by offering a balance between robustness and statistical efficiency.

Study Limitations

Although the encouraging results are achieved, a number of limitations must be stated. To begin with, the behaviour of the proposed estimator relies on the choice of the tuning parameter that regulates the loss function, and can have an effect on the robustnessefficiency trade-offs. In this study, fixed values were used although adaptive data-driven selection strategies can be used in order to increase performance.

Second, the simulation study was done with emphasis on moderate-dimensional regression settings. There was no study into the behavior of the estimator in high dimensional, or sparse, modeling environments and this may need further methodological development.

Lastly, the idea of computational performance at a scale that is way larger than those performed by small measures was not fully tested before especially when it comes to real-time or stream data.

Directions for Future Research

Several extensions may be considered in future work:

1. Establishment of automatic tuning parameter selected processes.
2. Future work: The suggested methodology will be extended to the high-dimensional GLM and penalized regression models.
3. Combination with machine learning mechanisms including uniformated or hybrid statistical learning models.
4. Using the method with longitudinal, survival, or mixed-effects generalized models.
5. Research of theoretical robustness properties such as the analysis of the influence functions and asymptotic behavior.

Future research along these directions may further enhance the applicability of robust loss-based estimation in modern data analysis environments characterized by increasing data complexity and heterogeneity.

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