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FITTING OF ROBUST FUZZY REGRESSION ESTIMATOR

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Abstract

According to Bang Yong Sohn (1997) is used in M estimator for finding the robust linear regression. The deficiency of robust M estimation is that it does not consider data distribution and is not a function of the whole data because it utilises the median as the weight value. This paper is mainly focus on to detect (Identified) and eliminate the irregular data with the help of a robust estimator concept. It is known as the Robust Fuzzy Regression Estimator (RFRE). A numerical example indicates that utilising residuals based on RFRE-estimators, irregular data may be recognised, and the suggested robust fuzzy regression is most resistant to these spots. The accuracy of the proposed method has been studied through simulation study with existing algorithms.

Keywords: Fitting, Robust regression, Fuzzy, S- Estimator, Fuzzy intervals, Type-I error.

Introduction

Certain assumptions underpin traditional parametric approaches. One crucial assumption is that the data under consideration are regularly distributed. This assumption is seldom satisfied in practise. Another crucial assumption underpinning basic parametric testing is that population variances are equal. Researchers frequently assert that traditional parametric tests are resistant to breaches of the assumptions of normality, obviating the necessity for other techniques. Robust statistics limit Type I error while still preserving statistical power. In contrast, statements that conventional parametric tests are resilient frequently only take Type I error into account, not power. The results of fuzzy linear regression and least squares are very sensitive to irregular data. This type of regression to despoiled data set.

Chum.O & Matas, (2002), developed a novel approach called Randomized ransac with T(d,d) test. They created a doubly linear adaptive regression model by combining two linear models, such as a spread regression model and a centre regression model. Forstner and Ruwiedel, (1992), developed new fuzzy linear regression methods. He has generalised the kind of single Ordinary equation in linear regression models by employing fuzzy data for the variables in order to account for the physical ambiguity of the relevant objects.

According to Haralick.R.M, (1990), researchers have created fuzzy linear regression (FLR) and the extension of numerous FLR models (Jolion,J.M., Meer,P., and Bataouche,S, 1991). Kumarand and Hanson,A, (1989) proposed the least squares approach for fitting a fuzzy vector, which is sensitive to outliers. Meer.P Mintz,D., Rosenfeld,A., and Kim,D.Y, (1991), created a fuzzy least squares regression model that minimises new fuzzy distance. Myatt.D Torr,P., Nasuto,S., Bishop,J., and Craddock, (2002), developed a hybrid approach for fuzzy least squares regression by adding the smallest fuzziness condition into traditional least squares regression. A hybrid fuzzy least squares regression model was

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created Threshold.
The least-squares fitting criterion and the weighted fuzzy arithmetic mean were used. According to Muthukrishnan and Ravi, (2016), Ravi and et. Al., (2018a), (2018b) robust regression estimator approaches were first utilised in computer vision to improve the effectiveness of feature extraction algorithms at the bottom of the vision hierarchy (Li,S.z, 1966). These methods allow for the incorporation of data points that differ from the underlying model; these points are commonly referred to as outliers.
Most robust regression estimators can take up to 50% outliers. Even when outliers constitute a bigger proportion of the data, a strong robust regression estimator should be able to find the fit. Furthermore, the estimator should be able to mitigate the impacts of all outlier types, including clustered, uniformly distributed, and pseudo-outliers.
The multiple robust regression approaches, including those referred to as resistant regression techniques on occasion, show how new techniques evolved in response to the flaws of previous ones in an evolutionary manner. A few regression classes are R-estimators, M-estimators, GM-estimators, S-estimators, L-estimators, MM-estimators, and other closely related robust regression estimators. However, because more recent advances in robust regression have built on them, basic descriptions of some of these approaches are still provided, even if they should be considered obsolete.

In this work, the robust fuzzy linear regression RFLR based on S-estimators and the tool for irregular data detection were tested using simulation with error tolerance. Section 2 provides a brief explanation of the most prevalent existing estimators. Section 3 describes the proposed RFRE strategy and computation algorithm. A simulation study is conducted using MATLAB software to evaluate the performance of the proposed method, and the results are reported in section 4. The study's summary and conclusion are discussed in the final part.

Preliminaries

The notion of statistical technique stability is known as robust statistics. It investigates how changes in modelling assumptions impact known approaches and, if necessary, develops new or superior ones. Two frequent modelling assumptions are normality and the independence of random errors. There are intricate theories with major practical implications for both, and normality, in particular, may be replaced by any other feasible parametric model. One of the simplest approaches to estimate regression model parameters that are less vulnerable to outliers than least squares estimates is to use least absolute deviations. Even in that instance, the extreme outliers may still have a major impact on the model, prompting research into even more trustworthy approaches.

Tukey's (1960) and Hampel's (1971, 1974) seminal works trace back to the nineteenth century. The topic of robust statistics research has grown significantly over the last five decades, as indicated by a huge number of published books and papers, some of which are listed below: Huber (1964, 1981), Maronna (1976), Rousseeuw and Yohai (1984), Hampel et al. (1986), Rousseeuw and Leroy (1987), Stewart (1999), Wang and Suter (2004), Wilcox (2005), Cizek (2006), Huber and Ronchetti (2009), Wilcox (2012), Jureckova et al. (2013), and Xanthopoulos et al. (2013).

After Huber's seminal work from 1960, robust statistics had many years of rapid growth and encountered ever-more challenging issues, both conceptually and computationally. A large number of reliable procedures have been made available for wider usage in the scientific community because to the quick development of computer technologies.

Huber (1973) was the first to suggest M-estimation in the context of regression. Outliers in the response variable were resistant to the method, but not those in the explanatory variables. When there are outliers in the explanatory components, the approach has no benefit over least squares. In order to

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overcome the lack of opposition, a variety of M-estimation alternatives were released in the 1980s.Two prominent robust estimating strategies are S-estimation (Rousseeuw and Yohai, 1984) and MM-estimation (Yohai, 1987), a derivative of the M estimation method.
The S-estimator, developed by Rousseeuw and Yohai, (1984), is used to produce regression estimates for M-scales. The next phase in the approach is to find a very trustworthy and robust S-estimate that minimises an M-estimate of the residuals' scale (Steinand, A., and Werman, M (1992), Salibian,M., and Yohai,V.J (2006), Susanti, Y., and Pratiwi,H, (2011)). The estimated scale is then kept while a nearer M estimate of the parameters is found (Susanti,Y., Pratiwi,H., and Liana,T, (2009), Susanti,Y., Pratiwi,H., Sulistijowati, S and Liana, (2014)). The MM estimate attempts to combine the efficacy of M estimating with the durability and resistance of S estimation.

The robust statistics were first utilised in computer vision at the bottom of the vision hierarchy to improve the performance of the feature extraction approach. These strategies permit the incorporation of data points that depart from the putative model; these data points are known as "outliers." In general, if an estimator delivers arbitrarily bad results, the attention will be on a small group of outliers in the data set (Zhuang,X., Wang,T., and Zhang,P , 1992).
Many robust statistical techniques have been utilised to address computer vision difficulties. Several authors have studied robust statistics in the field of computer vision. Fischler and Bolles (1981), Hampel et al. (1986), Miller and Stewart (1996), Torr and Murray (1997), Torr and Zisserman (2000), Myatt (2002), Wang and Suter (2003), Matas and Chum (2005), Wang (2008, 2010), Jianjum et al.

M-Estimator (ME)

Generalising Maximum Likelihood Estimation to the Minimization of Huber (1964) suggested

$$\sum_{i=}^{n} \rho\left(X_{i,}\theta\right) = \min, \theta \in \Theta \quad (1)$$

where ρ is a function with certain properties. The solutions is,

$$\hat{\theta} = arg_{\theta}\min\left(\sum_{i=1}^{n} \rho(x_{i,}\theta)\right), \theta \in \Theta \quad (2)$$

Redescending M-Estimator (RME)

Andrews (1972) proposed the redescending M-estimator, which is a popular -model M-Estimator.

Under extremely extensive regularity criteria, the M-estimator is consistent and asymptotically normally distributed with asymptotic variance.

$$v(\psi, \varphi) = \frac{\int \psi^2 \varphi \, dx}{\left(\int \psi' \varphi \, dx\right)^2} \quad (3)$$

where φ is the mixture model distribution and the negative value of $\psi'(x)$. It combines with large positive value of $\psi^2(x)$ of outliers to x.

GM-Estimator (GME)

Mallows (1973, 1975) was studied the generalized M-estimator. The GM estimators is defined by,

$$\sum_{i=1}^{n} w_i(x_i)\, \psi(.) x_i = 0 \quad (4)$$

where $\psi(.) = \frac{e_i}{\sigma\, v(x)}$ and ψ are the score function and the weights w and v initially depends on the model matrix X from an initial OLS regression fitted to the data but are updated iteratively.

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LMS and LTS Estimators

Rousseeuw (1984) developed the Least Median of Squares (LMS) and Least Trimmed Squares (LTS) estimators.

This leads to LMS regression, which is written as,

$$\min_{b} \underset{i}{med} (y_i - x'_i b)^2 \quad (5)$$

S-Estimator (SE)

Rousseeuw and Yohai proposed the S-estimator in 1984. In reaction to the M-estimator's low breakdown point, Hampel (1975) considered the amplitude of the residuals.

The S-estimate is the solution that defines the minimal likely dispersion of the residual scale.

$$\frac{1}{n}\sum_{i=1}^{n} \rho(.) = \hat{\omega} \quad (6)$$

R-Estimator (RE)

Let Ri indicate the residuals' rank (ei). The R-estimator attempts to reduce the sum of the scores of the ranked residuals. The R-estimator was proposed by Jaeckel (1972). It is based on dispersion metrics derived from linear combinations of ordered residuals.

$$\min \sum_{i=1}^{n} a_n(R_i) e_i \quad (7)$$

W-Estimator (WE)

The W-estimator is an alternative to M-estimators. Every W-estimator has a unique weight function known as w (.).

$$\sum_{i=1}^{n} w\,(r_{i)} r_i = 0 \quad (8)$$

L-Estimator (LE)

Any estimator that is calculated from a linear combination of order statistics is an L-estimator.

$$T_n = \sum_{i=1}^{n} C_{ni} h\,(X_{n:i}) + \sum_{j=1}^{k} a_j h^* \left(X_{n:[np_j]+1}\right) \quad (9)$$

where $c_{ni}\ and\ a_j$ are given coefficients $0<p_1<\ldots.<p_k<1$ and h(.) and h*(.) are given functions. The coefficients are generated by bounded weighted function.

Robust Fuzzy Regression Estimator (RFRE)

Rousseeuw and Yohai invented the S-estimator in 1984, based on the residual scale of M estimation. M estimate is not a function of the entire data because it uses the median as the weights. The S-estimator based Robust Fuzzy Regression estimator (RFRE) is proposed as a unique technique that substitutes the median for the S-estimator based residual standard deviation.

According to Salibian and Yohai (2006), S-estimator is defined by, $\hat{\omega} = \min\beta\ \hat{\Lambda}_S\ (e_1,e_2,...,e_n)$ with determining minimum robust scale estimator $\hat{\Lambda}_S$.

$$\bar{\beta}_S = \min_{\beta} \bar{\sigma}_S(e_1, e_2, ..., e_n)$$

Let consider $\{X_1, X_2, ..., X_N\}$ the collection of all data points (inliers and outliers). Assume that the first data point is X_0. Given a model that requires a minimum of n data points to instantiate its free parameters and a set of S_1 data P with more points than n (P≥n), randomly choose a subset of n data

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points from P and instantiate the model. Use the instantiated model M_1 to determine the subset S_1^* of points in P that are within some error tolerance of M_1. The set S_1^* is called the consensus set of S_1.If > t, S_1 use S_1^*, which is a function of the estimate of the number of gross errors in p, use to estimate a new model M_1^*.

If S_1< t, pick a new subgroup S_2 at random then continue as before. After a specified number of trials, if no consensus set with t or more members has been discovered, either solve the model using the largest consensus set found or cease looking. Without loss of function, the noise in the photo is Gaussian on each image coordinate, with a uniform standard deviation Λ and a zero mean. As a result, the joint probability density function of the outliers is,

P(x,y,z) =

$$\begin{cases} \frac{1}{4t^2\Lambda\sqrt{2\pi}} exp\left(\frac{-z^2}{2\Lambda^2}\right) + (1-\gamma)\frac{1}{v}, & -t < x < t, -t < y < t, -t < z < t \\ 0, & otherwise \end{cases} \quad (10)$$

M estimation is a dependable regression estimation strategy defined as,

$\hat{\beta} = \dot{\varphi}_n(x_1, x_2 \dots \dots x_n)$ then $E[\dot{\varphi}_n(x_1, x_2 \dots \dots x_n)] = \dot{\varphi}$

Equation (10) shows that the estimator $\dot{\varphi}^{\wedge} = \dot{\varphi}_n(x_1, x_2 \dots \dots x_n)$ is an unbiased and has minimum variance, so M estimator has the smallest variance estimator compared to other estimators of variance.

$$var(\dot{\varphi}) \geq \frac{\tilde{\dot{\varphi}}^2}{nE\left(\frac{d}{d\dot{\varphi}} In\, f(x_i, \dot{\varphi})\right)^2}$$

where $\hat{\beta}$ is other linear and unbiased estimator for $\dot{\varphi}$.The principle is to minimize the residual functionρ,

$\widehat{\dot{\varphi}_s} = \min_{\dot{\varphi}} \rho\left(y_i - \sum_{j=0}^{k} x_{ij}\, \dot{\varphi}_j\right)$.

We have to solve

$$\min_{\dot{\varphi}} \sum_{i=1}^{n} \rho\,(u_i) = \min_{\dot{\varphi}} \sum_{i=1}^{n} \rho\left(\frac{e_i}{\widehat{\sigma_s}}\right) = \min_{\dot{\varphi}} \sum_{i=1}^{n} \rho\left(\frac{y_i - \sum_{j=0}^{k} x_{ij}\dot{\varphi}_j}{\widehat{\sigma_s}}\right)$$

Where $\widehat{\Lambda_s} = \sqrt{\frac{1}{nk}\sum_{i=1}^{n} \omega_i {\varepsilon_i}^2}$ and ω_i

$$= \omega_\sigma(u_i) = \frac{\rho(u_i)}{{u^2}_i} \quad (11)$$

The initial estimate is,

$$\widehat{\Lambda_s} = \frac{median|e_i - median(e_i)|}{0.6745} \text{ and } u_i = \frac{\varepsilon_i}{\sigma_s} \quad (12)$$

For ρ function we use the Tukey's bi-square objective function

$$\rho(u_i) = \begin{cases} \frac{{u_i}^2}{2} - \frac{{u_i}^4}{2c^2} + \frac{{u_i}^6}{6c^4}, & |u_i| \leq c \\ \frac{c^2}{6}, & |u_i| > c \end{cases} \quad (13)$$

Furthermore we look for first partial derivative the solution is obtained by differentiating to $\dot{\varphi}$ so that $\widehat{\dot{\varphi}_s}$ to $\dot{\varphi}$ so that

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$\sum_{i=1}^{n} x_{ij} \emptyset \left(\frac{y_i - \sum_{j=0}^{k} x_{ij} \dot{\omega}_j}{\widehat{\sigma_s}}\right) = 0$, j=0,1,2,……k

where $\emptyset = \rho^{|}$, x_{ij} is i-th observation on the j-th independent variable and x_{i0}=1. The function $\emptyset$is a function as derivative of ρ is,

$$\emptyset(u_i) = \rho^{|}(u_i) = \begin{cases} u_i \left[1 - \left(\frac{u_i}{c}\right)^2\right]^2 , & |u_i| \le c \\ 0 , & |u_i| > c \end{cases} \quad (14)$$

The usual choice is c= 2.58 and k= 0.199 for 50% breakdown and about 28% asymptotic efficiency. So the equation (14) becomes,

$\sum_{i=1}^{n} x_{ij} w_i \left(y_i - \sum_{j=0}^{k} x_{ij} \dot{\omega}\right) = 0$, (15)

j=0,1,……k

where$w_i$is an iteratively reweighted least square (IRLS) weighted function in the bi-square family with score function is

$$\omega_i(u_i) = \begin{cases} \left[1 - \left(\frac{u_i}{c}\right)^2\right]^2 , & |u_i| \le c \\ 0 , & |u_i| > c \end{cases}$$

Solve the above equation by using IRLS method, assuming that there is an initial estimate $\dot{\omega}_0$, $\emptyset_0$ and $\widehat{\sigma_i}$ is a scale estimate. If j is numbers of parameters then, $\sum_{i=1}^{n} x_{ij} \emptyset_0 \left(\frac{y_i - \sum_{j=0}^{k} x_{ij} \dot{\omega}^0}{\widehat{\sigma_s}}\right) = 0$ (16)

j=0,1,2,……k

The matrix notation of the equation (16) can be written as

$(X' \emptyset_i X)^{-1} X' \emptyset_i Y$ (17)

where $\emptyset_i$ is a n x n matrix with its diagonal elements are the iteratively reweighted. Equation (17) is known as iteratively reweighted least squares (IRLS) equation. Solution for this equation gives an estimator for$\dot{\omega}$. This is given by,

$$\widehat{\dot{\omega}} = (X' \emptyset_i X)^{-1} X' \emptyset_i Y)$$

Experimental Study

The suggested RFRE estimator, as well as the most used robust estimators, has been evaluated in a simulated setting. Under the premise that ax+by+c=0 and $a^2+b^2=1$, the simulation was ran with n=100, n=500, and n=1000 samples. The number of inliers is estimated utilising numerous algorithmic methods, including ME, RME, GME, LMS, LTS, SE, RE, WE and LE in the RFRE technique. Furthermore, with a fixed threshold (t) = 2, the same experiment was repeated with different contamination (ε) levels, including 0%, 1%, 3%, 5%, 10%, 20%, 30%, and 40%. The findings are summarised in Table 4.1.

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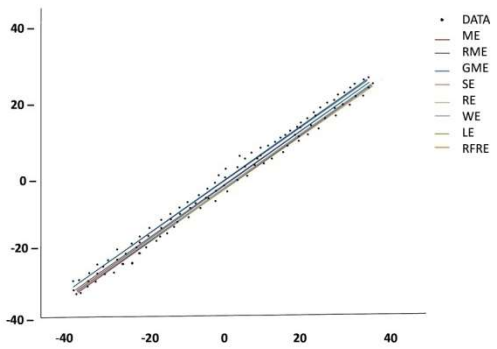
Table 4.1: Estimated inliers under RFRE with other Estimator procedures

n=100								
Error / Methods	**0.00**	**0.01**	**0.03**	**0.05**	**0.10**	**0.20**	**0.30**	**0.40**
Real Model	100	99	97	95	90	80	70	60
ME	98	96	93	93	88	76	69	59
RME	97	95	94	91	86	75	67	59
GME	97	94	93	92	87	76	69	58
SE	96	95	93	93	86	75	68	58
RE	95	93	91	90	87	76	67	57
WE	95	94	93	92	88	76	67	58
LE	97	95	94	93	88	77	68	59
RFRE	99	97	96	94	88	79	70	60
n=500								
Error / Methods	**0.00**	**0.01**	**0.03**	**0.05**	**0.10**	**0.20**	**0.30**	**0.40**
Real Model	500	495	485	475	450	400	350	300
ME	480	470	462	463	438	395	341	204
RME	477	469	461	448	422	391	343	290
GME	478	471	462	460	432	395	340	286
SE	473	471	460	452	427	387	341	290
RE	471	470	391	462	432	366	340	291
WE	475	472	420	466	436	370	342	293
LE	477	473	428	467	438	374	344	294
RFRE	482	475	468	471	445	398	348	296
n=1000								
Error / Methods	**0.00**	**0.01**	**0.03**	**0.05**	**0.10**	**0.20**	**0.30**	**0.40**
Real Model	1000	990	970	950	900	800	700	600
ME	949	952	927	940	847	759	682	581
RME	951	951	913	907	843	759	676	568
GME	944	948	919	931	861	755	691	590
SE	933	950	926	905	865	751	671	583
RE	939	951	910	927	841	758	670	582
WE	941	953	912	931	846	762	675	589
LE	944	956	918	941	851	764	681	591
RFRE	954	964	936	948	867	766	697	596

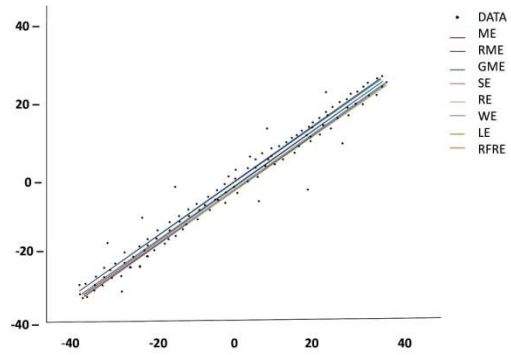
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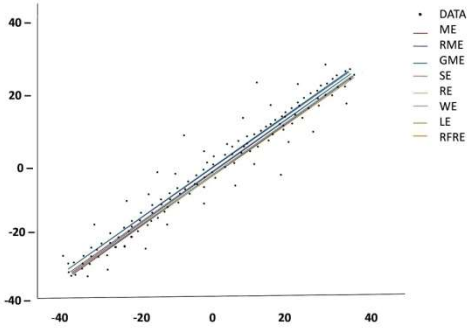
The data Simulated in TLS MATLAB toll box. It is randomly generated data based on the sample size. It is also to fix the threshold values in the tool box.



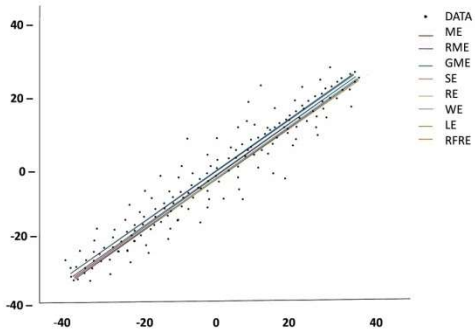
(a) $\varepsilon = 0.00$



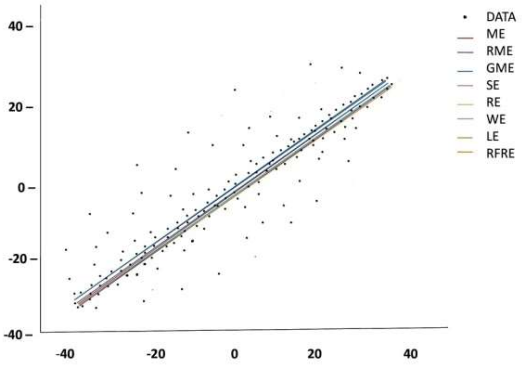
(b) $\varepsilon = 0.01$



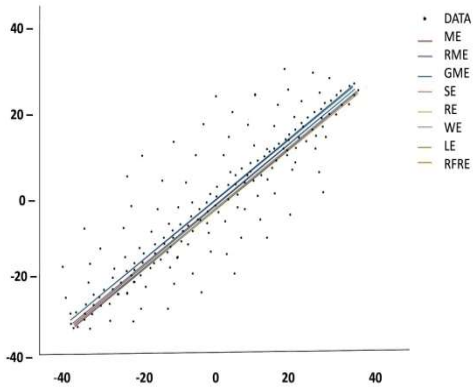
(c). $\varepsilon = 0.03$



(d). $\varepsilon = 0.05$



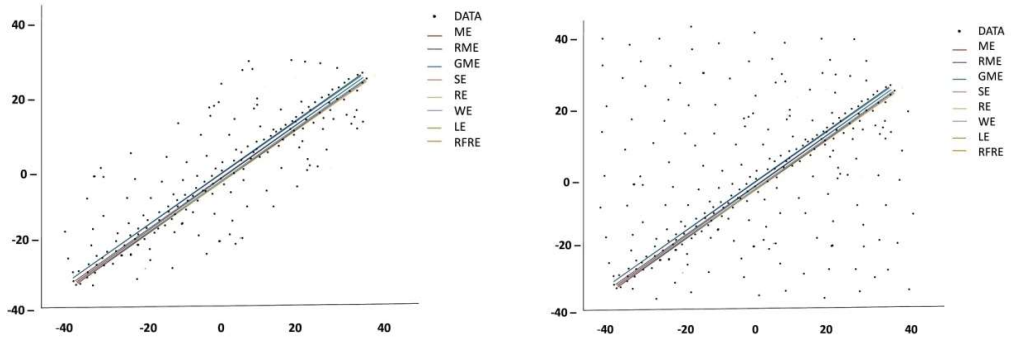
(e) $\varepsilon = 0.10$



(f) $\varepsilon = 0.20$

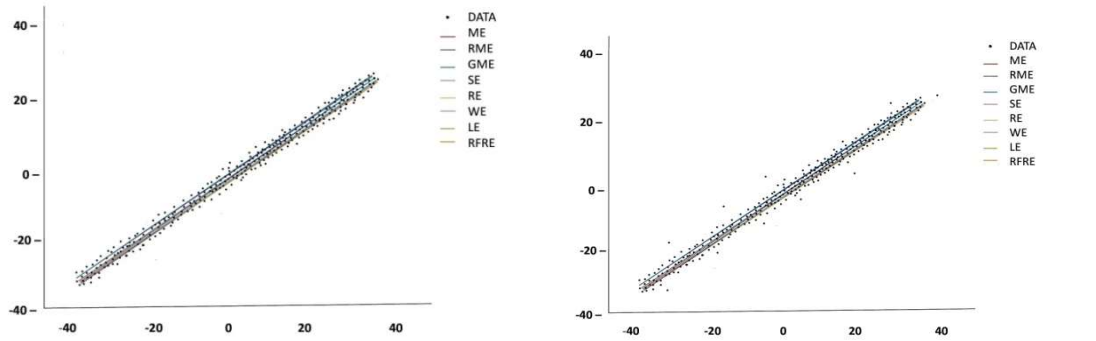
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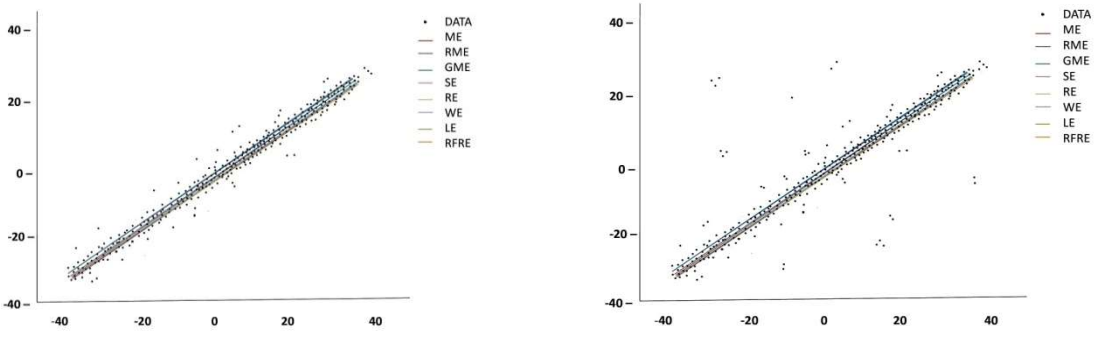


(g) $\varepsilon = 0.30$ (h) $\varepsilon = 0.40$

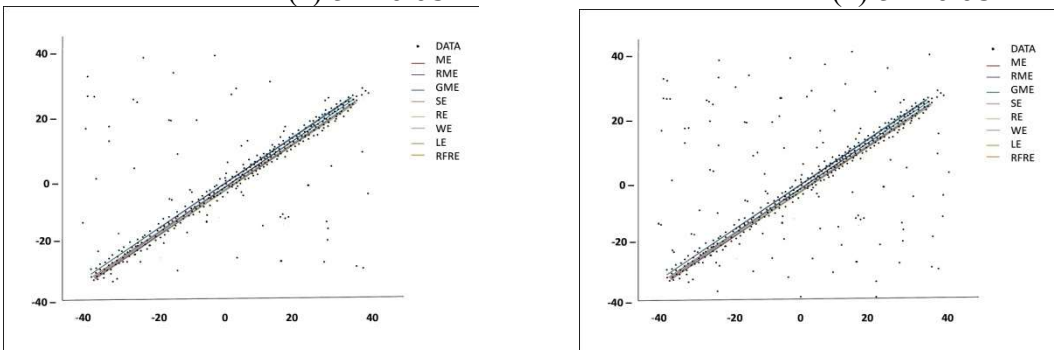
Figure 4.1: Regression fit under RFRE with other Estimator procedures (n=100)



(a) $\varepsilon = 0.00$ (b) $\varepsilon = 0.01$

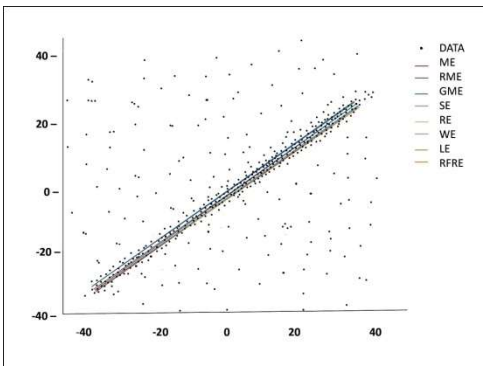


(c) $\varepsilon = 0.03$ (d) $\varepsilon = 0.05$

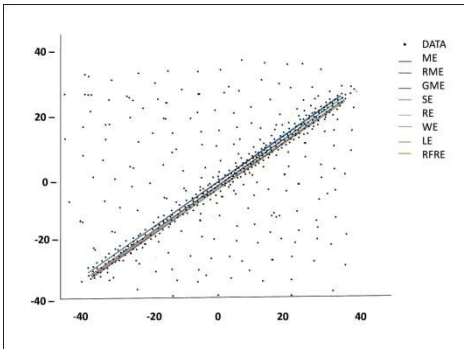


(e) $\varepsilon = 0.10$ (f) $\varepsilon = 0.20$

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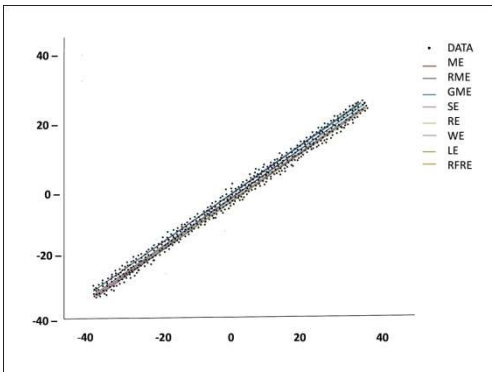


(g) $\varepsilon = 0.30$

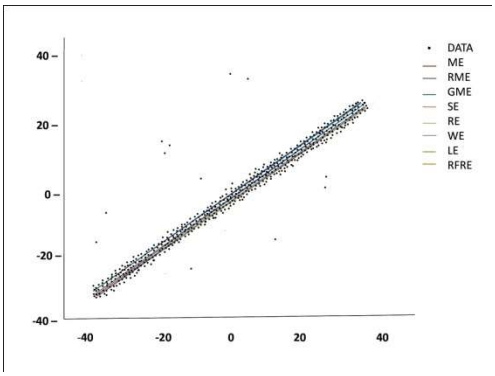


(h) $\varepsilon = 0.40$

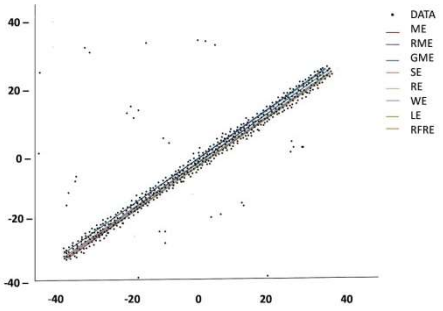
Figure 4.2: Regression fit under RFRE with other Estimator procedures (n=500)



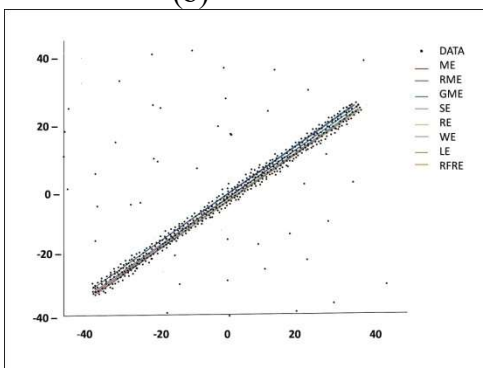
(a) $\varepsilon = 0.00$



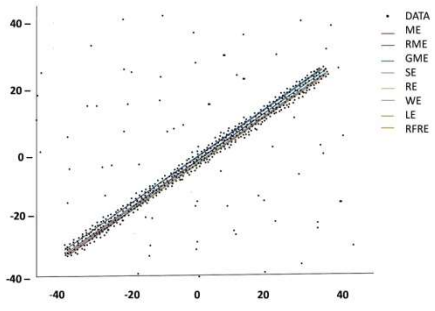
(b) $\varepsilon = 0.01$



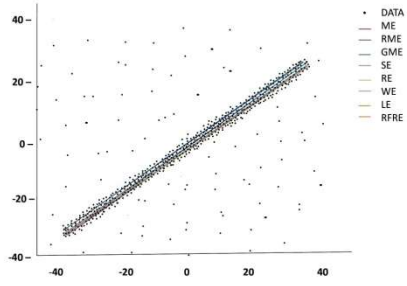
(c) $\varepsilon = 0.03$



(d). $\varepsilon = 0.05$

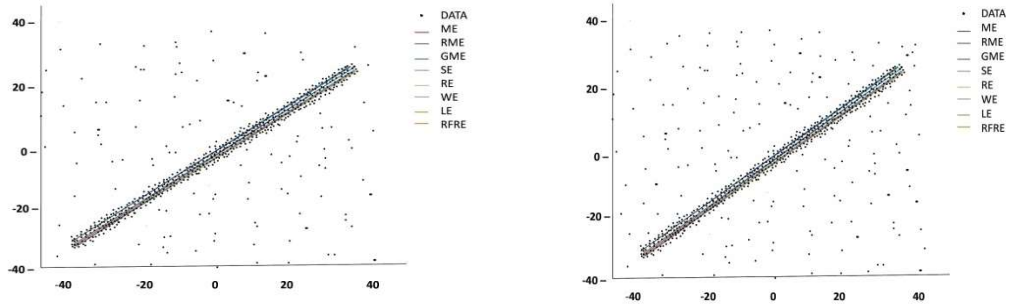


(e) $\varepsilon = 0.10$



(f) $\varepsilon = 0.20$

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(g) $\varepsilon = 0.30$ (h) $\varepsilon = 0.40$

Figure 4.3: Regression fit under RFRE with other Estimator procedures (n=1000)

Figure 4.1 to 4.3 shows the fitting of the Robust Fuzzy techniques with various sample sizes, error rate and the fixed threshold along with the proposed RFRE.

Discussion

It is observed from table and figures, the estimated number of inliers under RFRE algorithm is more than that of the other procedures, ME, RME, GME, SE, RE, WE and LE. Also, it is noted that the proposed RFRE procedure shows the maximum number of inliers over the other existing estimator procedures with/without contaminations.

Conclusion

The first discovering robust methods one is up in their revolutionary possibilities and it is indicating the least squares if flawed. This opens up the possibilities of trying to show robust fuzzy regression methods work better with real data than does ordinary least squares and other existing estimator.

A new estimator called robust fuzzy based regression estimator (RFRE) is proposed and its mathematical aspects. It finds the greater number of inliers of model parameter estimation under a broad range of conditions, due to scale residuals of the hypothesis evaluation step.

The performance of the proposed RFRE has been studied along with the mostly used techniques existing models in the context of model fitting by identifying number of inliers through simulation with various levels of contamination. It is concluded that the proposed RFRE displays more number of inliers than the other procedures. RFRE is an effective tool to detect the true parameters in presence of highly contaminated situation.

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