Comparison of Bayesian Lasso -Tobit quantitative regression and the new pre distribution with application

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Abstract

In this document, we introduce a new hierarchy for the previous distribution A prior distribution for coefficient estimates in a Tobit Quantile Regression (TQR) model by using the Standard Exponential (SME) scale mixture. where (SME) is considered a good alternative to the Laplace distribution in the Bayesian lasso method to implement variable selection and coefficient estimation in (T.Q.R.Model). Compared with other existing methods in the same field, we use many simulated scenarios and real data to examine the effectiveness of our proposed method. Both simulated scenarios and real dataset examples show that our proposed method performs well compared to other methods. Keywords: Bayesian New Lasso, Prior Distribution, Tobit Quantile Regression, Stander Exponential Scale Mixture .

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I. Introduction

Since its pioneering work on zero-censored data (James Tobin (1958)) Tobit Regression Model (T.R.Model) became very important, it has been used in many scientific fields such as psychology, medicine, finance and social sciences. TR This model focuses on evaluating the relationship between a censored dependent variable and a set of independent variables. But T.R. the model has the following form:

$$y_i = \begin{cases} y_i^* = a + \beta_p x_i' + e_i & if\ y_i^* > 0 \\ 0 & if\ y_i^* \le 0 \end{cases} \quad \dots\dots\dots\dots\dots\dots.[1]$$

where

y_i *is dependent variables and*, y_i^* *is latant variable* , a *is intercept term*, β_p *are unknown parameters*

x_i' *are independen variablese*$_i$ *is random erorr*

In the T.R .model covariates are observable, but(y_i^*) is not (Greene, W. (1999)).The T.R .model almshouses different mathematical formulas follows.

$$y_i = \max(y_i^*, 0) \;\ldots\ldots\ldots\ldots\ldots\ldots..[2]$$

$$where \qquad y_i^* = a + \beta_p x_i' + e_i \;\;, e_i \sim N(0, \sigma_I^2)$$

The classical T.R .model is associated with a number of regressionassumptions.Therefore,theclassicalT.R.modelishighlysensitivetooutliersin the data set .Therefore, the classical T.R .model is not robust. (Wooldridge, J. (2002)).It is also very sensitive to Heteroskedastic error team (Long, J. S., & Ervin, L. H. (2000).The T.R. model also suffers from a number of econometric techniques problems (Sune Karlsson, A. (2014)),but the use of the Tobit quantile regression model (T. Q. R. Model)may go beyond these problems .This is a good statistical model for evaluating the relationship between a left-censored dependent variable and a set of independent variables at particular quantic eleven .It was proposed by (Powell (1986)). Many independent variables are in some T.Q.R model .Q .R model .Left-censored dependent variable shave differ interrelation ships with these independent variables ;in the Tobit Q Reg model, independent variables some time shave a small impact . Therefore, in this model, some independent variables are at risk. Excluding important independent variables is difficult problem .To solve this problem ,variable selection can be performed(VS) Recently ,researchers have identified new methods for implementing variable selection in regression models. These methods are of good quality and do not take much time to achieve VS because the process is automated .lasso (least absolute shrinkage and selection operator) (Tibshirani,(1996)), SCAD (Fan and Li,(2001)), and elastic net approach are some of these methods .

Bayesian lasso was described by (Park and Casella, 2008) in a classical regression model .Most of these methods were used in the T.Q. R Model. (Alhamzawi, (2013)) used Bayesian methods and proposed an adaptive lasso in the T.Q. R. Model. (Alhamzawi and Yu,(2014))proposed Bayesian method using g-prior distribution with ridge parameters for coefficient estimation in T. Q. R .Model , Using Bayesian framework, (Alhamzawi, (2014))proposed an elastic net penalty in the T. Q. R. Model .To achieve Bayesian lasso in regression models, most approaches in the field of Bayesian lasso use scaled mixture of normal distributions(SMN)in the penalty in the T.Q. R. Model. However,(Mallick and Yi

(2014)) proposed a new for mutation to achieve Bayes lasso in classical regression models suing a scale mixture uniform (SMU) prior of the Laplace distribution . This idea was extended by (Fadel Al-Hussaini (2017))by using a uniform scale mixture(SMU) prior in quantile-point regression via a Bayesian framework. Also, (Fadel Al-Hussaini (2017))used the(SMU) prior distribution in the T.Q.R .Model to obtaining easy to understand and efficient algorithm. (Flaih et al 2020).proposes anew Bayesian lasso based on a combination of new developments in the hierarchical model and anew Laplace distribution measure. It combines the Rayleigh distribution with a normal mixture. (Remah Oday and Fadel Al-Hussaini (2021)) propose new scale mixture of uniform distributions that mixes with the standard exponential distribution in it variance in a quantile regression model with a Bayesian approach .The paper proposes new Bayesian-type lasso in the T. Q. R . model using a scale mixture of uniform distributions mixed with a standard exponential distribution for it variance to ensure that the posterior distribution of the parameter estimates is uniform. The paper is organize din five sections .The first section focuses on Tobit quantile regression

II. Tobit Quantile Regression

Selecting an appropriate regression model from the available data is the most important step in regression modeling. For example, if the dependent variable is censored at particular value ,a censored regression model is the solution .However ,if the censored value is equal to the zero point ,a Tobit regression model is appropriate ;a Tobit regression model becomes in effective if some assumptions are violated. To overcome this difficulty ,the T.Q.R .model is used .Itis shown as follows.

$$y = \max(0, y_i^*) \quad , y_i^* = x_i^{\prime}\beta_p + e_i \dots\dots\dots\dots\dots [3]$$

herey_i^* is called the latent variable and takes unobserved observables ,and(a_p) istheintercept term. $\beta_p$istheunknownparameter$(\beta_{p1}, \beta_{p2}, \dots\dots \beta_{pk})$,and p is the interval(0,1) y_i isthe quantile recognized to be a zerocensored dependent variable.coefficientestimation intheT.Q.R.modelminimized the following loos function.

$$\min_{a_p,\beta_p} = \sum_{i=1}^{n} \rho_p \left(y_i - max\{C, y_i^*\}\right) \dots\dots\dots\dots\dots\dots\dots\dots\dots [4]$$

Equation(4) is not differentiable at the zero point and can besolved by linear programming(Koenker and D'Orey, (1987)). In the T.Q.R model, there are many methods to estimate its parameters .Most of these methods ,however ,are flawed and useless. (Konker and Machado (1999)) and (Yu and Moyeed (2001)) have proposed Bayesian approach to parameter estimation in the T.Q.R .model. The error term ϵof the T.Q.R .Model is very close to the skew-Laplace distribution (SLD).) It has the following probability density function(p.d.f.)

$$f(e_i|\mu,\sigma,p) = \frac{p(1-p)}{\sigma}\ \exp{-\rho_p}\left\{\left(\frac{e_i-\mu}{\sigma}\right)\right\} \ldots\ldots\ldots\ldots\ldots\ldots.[5]$$

when $\mu = 0$ and $\sigma = 1$ then, pdf to e_i is:

$$f(e_i|\sigma,p) = p(1-p)\exp\left(-\rho_p\{(e_i)\}\right)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[6]$$

The random variable (e_i) is have mean $E(e_i) = \frac{1-2p}{p(1-p)}$ and variance,

$$\text{var}\ (e_i) = \frac{1-2p+2p^2}{p^2(1-p)^2}$$

The joint distribution of $y = (y_1, \ldots, y_n)'\ given\ X = (x_1, \ldots, x_n)'$ is:

$$\begin{aligned}&(y|X,\alpha,\beta_p,\sigma,p)\\ &= p^n(1-p)^n exp\left\{-\sum_{i=1}^{n}\rho p(y_i - max\{0, x_i'\beta_p + e_i\}\right\}\ldots\ldots\ldots\ldots..[7]\end{aligned}$$

(Kozumi and Kobayashi, (2011))transformation ,the SLD Is scale-mix normally distributed(SMN). Therefore ,the dependent variable in the T.Q.R .model takes the following equation

$$f(y_i^*|\alpha_p, x_i', p, \beta_p, m_i) = \left[\frac{1}{\sqrt{4\pi m_i}}\right]^n e^{-\sum_1^n \frac{\left(y_i^*-x_i'\beta_p-(1-2p)m_i\right)^2}{4m_i}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [8]$$

Equation(8) is a very important equation in Gibbs sampling of the posterior distribution of the coefficient estimates of the T.Q .R model.

III. Hierarchical Prior Distribution

(Tibshirani, (1996)) gave good in formation for researcher slinked to the Bayesian variable selection framework. If the researcher achieves variable selection with a Bayesian approach ,then the Laplace prior distribution (L.P.D.) for regression must be used.

$$e^{-\sigma\lambda|\beta|} = \int_{z>\sigma|\beta|}^{\cdot} \lambda e^{-\lambda\beta}\, d\beta \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [9]$$

When σ is a positive quantity, λ is known as the shrinkage parameter (λ ≥0).Bayesian variable selection methods employ an alternative representation to the Laplace prior density distribution .This is because using the Laplace prior distribution directly is very difficult to obtain a good Gibbs sampler To solve this problem, many researchers have used the transformation of(Andrews and Mallows (1974)).

$$\frac{\sigma\lambda_j}{2}\, e^{-\sigma\lambda|\beta|} = \int_0^{\infty} \frac{1}{\sqrt{2\pi s_j}} e^{\left(-\frac{\beta_j^2}{2s_j}\right)} \frac{\lambda_j^2}{2} e^{\left(-\frac{s_j\lambda_j^2}{2}\right)} ds_j \ldots\ldots\ldots\ldots\ldots [10]$$

Here ,the Laplace prior density function can be reformulated as two functions. The first function can be specialized to the prior of the β_j parameter,which isnormallydistributedwith mean 0 and variance (s_j):Yue and Hong, (2012)use a Bayesian TQR model with group lasso penalty and(Alhamzawi, (2013))use a Bayesian framework to adaptive lasso in TQR models.

Also (Alhamzawi, (2014)) proposed a Bayesian elastic net penalty in the T. Q. R. Model .In this paper, we plan to employ another transformation on of the Laplace prior density :a scale mixture of uniform distributions mixed with a standard exponential distribution.

$$e^{-\sigma\lambda|x|} = \int_{m>\sigma|x|}^{\cdot} \lambda e^{-\lambda m}\, dm$$

$$\frac{\sigma\lambda}{2} e^{-\sigma\lambda|x|} = \int_{m>\sigma|x|}^{,} \frac{\sigma\lambda}{2}\, \lambda e^{-\lambda m} dm$$

$$\lambda w = m$$

$$= \int_{m>\lambda\ |x|}^{,} \frac{\sigma\lambda}{2}\, \lambda e^{-m} \frac{1}{\lambda}\, dm$$

$$\frac{\sigma\lambda}{2}\, e^{-\sigma\lambda|x|} = \int_{m>\sigma\lambda|x|}^{,} \frac{\sigma\lambda}{2}\, e^{-m} \quad dm \ldots\ldots\ldots\ldots\ldots\ldots\ldots [11]$$

Now by letting $\boldsymbol{x} = \boldsymbol{B}$ in **(3.7),** we get

$$\frac{\boldsymbol{\sigma\lambda}}{\mathbf{2}}\ \mathbf{e}^{-\sigma\lambda|\mathbf{B}|} = \int_{\mathbf{m}>\sigma\lambda|\mathbf{B}|}^{'} \frac{\boldsymbol{\sigma\lambda}}{\mathbf{2}}\ \mathbf{e}^{-\mathbf{m}} \quad \mathbf{dm} \ldots\ldots\ldots\ldots\ldots.[\mathbf{12}]$$

See(Remah Oday and Fadel Al-Hussaini 2021)for details .We shall use the hierarchical prior distribution resented in the above system of equations in the T.Q.R. model .The resulting Bayesian hierarchical T.Q.R .model for mutations as follows.

$$\boldsymbol{y_i} = \boldsymbol{max}(\boldsymbol{y_i^*}, \mathbf{0})$$

$$\boldsymbol{y_i^*} \sim \boldsymbol{N}(\alpha_p - x_i' \beta_p - (1-2p)m_i, \boldsymbol{2m_i})$$

$$p|\boldsymbol{\sigma} \sim\ \boldsymbol{\sigma^n e^{-\sigma \sum_{i=1}^{n} p_i}}$$

$$\boldsymbol{m} \sim\ \left(\frac{\mathbf{1}}{\sqrt{\mathbf{2}\boldsymbol{\pi}}}\right)^{\boldsymbol{n}}\ \ \boldsymbol{exp}\left(-\frac{1}{2}\sum_{i=1}^{n} \boldsymbol{m_i}^{\mathbf{2}}\right) \ldots\ldots\ldots\ldots \textbf{[13]}$$

$$\mathbf{B}|\boldsymbol{\sigma}, \boldsymbol{\lambda} \sim\ \boldsymbol{uniform}(-\frac{\mathbf{1}}{\boldsymbol{\sigma\lambda}}, \frac{\mathbf{1}}{\boldsymbol{\sigma\lambda}})$$

$$\boldsymbol{m} \sim \boldsymbol{standard\ exponential}$$

$$\boldsymbol{\sigma} \sim\ \boldsymbol{\sigma^{a-1} e^{-b\sigma}}$$

$$\boldsymbol{\lambda} \sim\ \boldsymbol{\lambda^{c-1} e^{-d\lambda}}$$

where the parameters σ and λ each have a gamma prior distribution and fixed hyper parameters (a, b, c, d).. These fixed hyper parameters have small values (a =0.1,b=0.1,c=0.1and d=0.1) .

IV. Posterior distribution inferences

Using the Bayesian hierarchical model (13),the Gibbs sampler algorithm can be improved as follows

- **The Full Conditional Posterior Distribution of $\boldsymbol{y}$:**

Let ψ(.)denotes to a degenerate distribution, where the variable y_i^* has a Full conditional distribution, written as following.

$$y_i^*|y_i,m_i,,\mathrm{B}\sim\left\{\begin{array}{ll}\{\psi(.), & if\ y_i>0;\\ \left\{\left[\frac{1}{\sqrt{4\pi\sigma^{-1}m_i}}\right]^n e^{-\sum_1^n\frac{(y_i^*-x_i'\beta_p-(1-2p)m_i)^2}{4\sigma^{-1}m_i}}\right\} & I(y_i^*\le 0), otherwise\end{array}\right. \quad \dots\dots[14]$$

- **The full conditional posterior distribution of $\boldsymbol{m_i}$ is general inverse Gaussian**

$m_i\sim GIG(\gamma,\vartheta)$,where $\gamma=\frac{\sigma(y_i^*-x_i'\beta_p)^2}{2p}$ $,\vartheta=\frac{\sigma(1-p)^2}{p^2}+2\sigma$

- **The full conditional posterior distribution $\boldsymbol{w_j}$ is truncated standard exponential**
- **The full conditional posterior distribution $\boldsymbol{\beta}$ is multivariate normal posterior distribution with mean $\boldsymbol{\mu^t}$ and variance $\boldsymbol{D^{-1}}$ where**

$$D^{-1}=\sum_{i=1}^n\frac{x_ix_i^t}{\sigma^{-1}\theta m_i}+\left(\frac{\mathbf{1}}{\mathbf{3\sigma^2\lambda^2}}\right)\ \textbf{then } D=\left[\sum_{i=1}^n\frac{x_ix_i^t}{\sigma^{-1}\theta m_i}\right]^{\mathbf{-1}}+\mathbf{3\sigma^2\lambda^2},$$

Then the mean $\mu^t=D*\sum_{i=1}^n\frac{x_i(x_i\beta+\theta m_i)}{\sigma^{-1(1-\theta)m_i}}$ **.**

- **The full conditional posterior distribution of $\boldsymbol{\sigma}$ is gamma distribution with parameters $(\boldsymbol{a}+\frac{\mathbf{3n}}{\mathbf{2}})$ and $\left(\sum_{\mathbf{1}}^{\boldsymbol{n}}\left[\frac{(\boldsymbol{y_i^*-x_i'\beta_p-pm_i})^{\mathbf{2}}}{(\mathbf{1-2p})\boldsymbol{m_i}}+\boldsymbol{m_i}\right]+\boldsymbol{b}\right)$.**
- **The full conditional distribution of $\boldsymbol{\lambda_j}$ is truncated gamma distribution**.

V. APPLIED SIDE

In this simulation scenarios, The effectiveness of our suggested method is assessed using simulation study. We will compare our suggested method (b Lasso.T.Q.R.Model) with others methods such as : (bayesian adaptive elastic net T. Q. R.Model) bAnet'. And

(Bayesian new lasso Tobit quantile regression) These methods are assessed using two criteria , first is Root Mean Square Error(RMSE) had computed by using two criteria , first is Root Mean Square Error(RMSE) had computed by

$RMSE=\sqrt{\frac{x'\widehat{\beta}-x'\beta}{N}}$ (N is the number of simulation) and the second criteria is standard division (S.D). in this simulation the true model ($y_i=\max(0,y_i^*)$) has been used.

Where $y_i^* = x'\beta_p + e_i$. where latent variable y_i^* is scaling for it, We take into consideration two simulated examples:

First example (very sparse case): $\beta = (1,0,0,0,0,0,0,0)'$ and second example (dense case): $\beta = \underbrace{(0.85, \dots \dots, 0.85)}_{8}'$,

The variable X is distributed multivariate normal with mean vector from 0 and variance and co-variance. Where $X \sim N_K(\underline{0}, \Sigma_x)$, $(\Sigma_x)_{hl} = 0.5^{|h-l|}$

the residuals term are generated from three different residual distributions . They are standard normal $e_i \sim N(0,1)$, student t-distribution with three degrees of freedom, $e_i \sim t_{(3)}$, and standard Laplace $e_i \sim Laplace(0,1)$. In this paper, we will use three quantile levels ($low\ quantile\ level\ p_1 = 0.15, intermediate\ quantile\ level\ p_2 = 0.60, and\ high\ quantile\ level\ p_3 = 0.99$.

table (I) the RMSE and SD are summarised for three methods under study , and first simulation -very sparse case.

Quantile level	Methods residual distributions	Bayesian lasso Tobit quantile regression	Bayesian new lasso Tobit quantile regression	BAnet
$\boldsymbol{p_1 = 0.15}$	$e_i \sim N(0,1)$,	0.6443 (0.2736)	0.9342 (0.4763)	0.9562 (0.4963)
	$e_i \sim t_{(3)}$	0.7362 (0.3762)	0.8713 (0.3549)	0.9037 (0.4241)
	$e \sim Laplace(0,1)$.	0.4539 (0.1798)	0.5982 (0.1641)	0.6814 (0.1950)
$\boldsymbol{p_2 = 0.60}$	$e_i \sim N(0,1)$,	0.8351 (0.3863)	0.9061 (0.3993)	1.0923 (0.5721)
	$e_i \sim t_{(3)}$	0.7282 (0.4571)	0.9821 (0.5604)	1.2781 (0.6035)
	$e_i \sim Laplace(0,1)$.	0.7363 (0.2832)	0.8911 (0.4824)	1.2711 (0.5814)
$\boldsymbol{p_3 = 0.99}$	$e_i \sim N(0,1)$,	0.9015 (0.5812)	0.9782 (0.4742)	1.2541 (0.6721)
	$e_i \sim t_{(3)}$	0.9216 (0.5710)	0.8684 (0.3539)	1.2411 (0.7252)
	$e_i \sim Laplace(0,1)$.	0.9462 (0.491)	1.1127 (0.1640)	1.4514 (0.6752)

form table (I) the RMSE and SD are summarised for three methods under study.

- table (I) reveals our proposed method (b Lasso.T.Q.R.Model) performance appears to be fairly good in comparison with (bAnet) and (b new.L.T.Q.Reg). The RMSE and SD had generated in our suggested method is much smaller than RMSE and SD are generated in existing methods for three residual distributions.
- table(I) The Root Mean Square Error (RMSE) and standard division (SD) for first simulation .

Note: Standard deviation in parentheses Another way to check the efficiency of estimation with our method is to follow plots and histograms. Figure 1 shows a flow chart showing the stability of the MCMC algorithm over all iterations.

Figure (1) shows trace plots of the parameter estimation in very sparse case

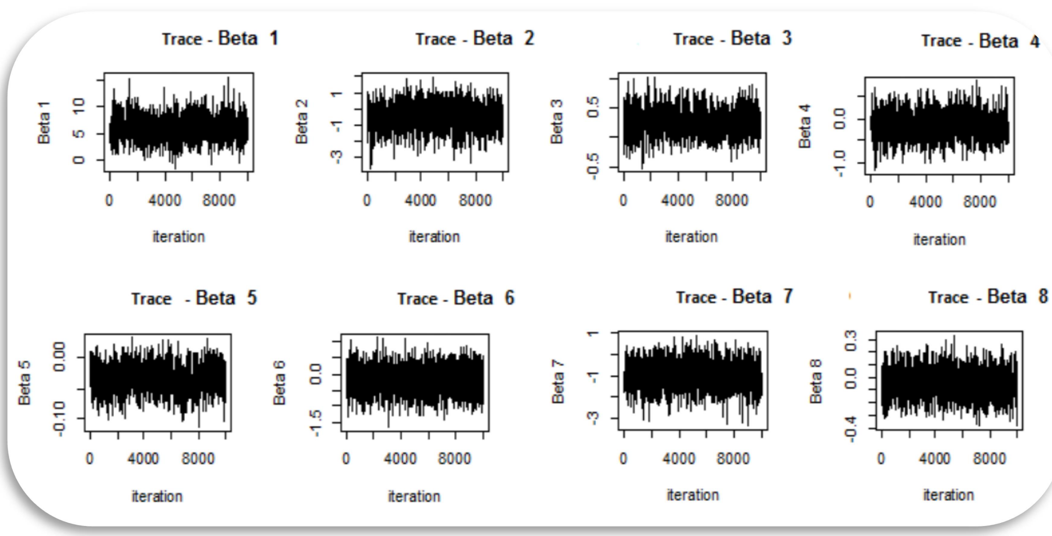
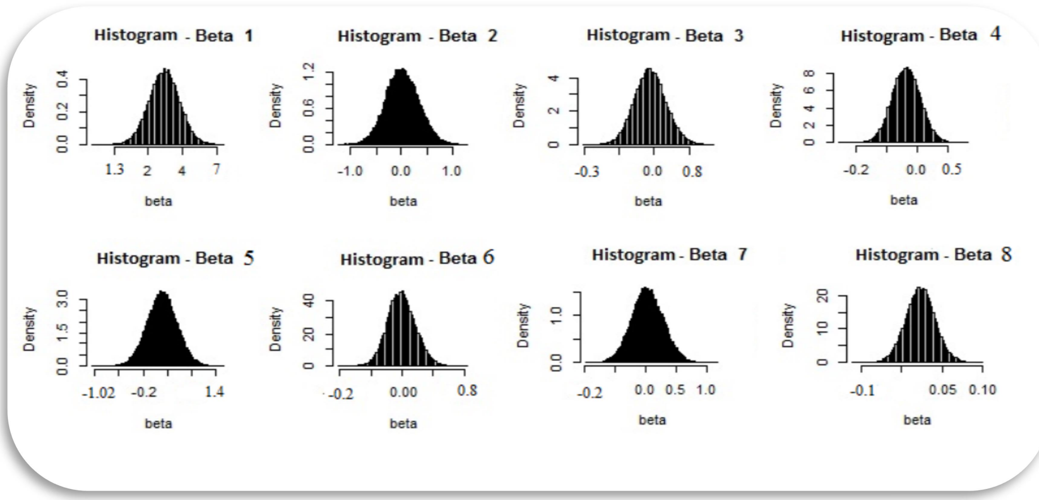


Figure (2) shows Histograms of the parameter estimation in very sparse case



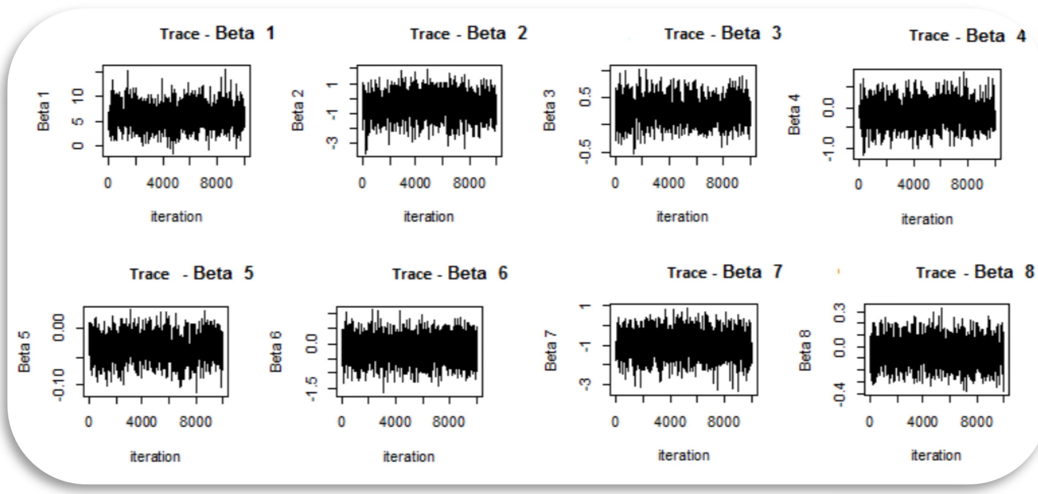
It can be seen from Figure (2) that the parameter estimates are distributed from 1 to 8, and it is obvious that the parameter estimates all obey the normal distribution

table (II)The Root Mean Square Error (RMSE) and standard division (SD) for second simulation

Quantile level	Methods residual distributions	Bayesian lasso Tobit quantile regression	Bayesian new lasso Tobit quantile regression	bAnet
$\boldsymbol{p_1 = 0.15}$	$e_i \sim N(0,1)$,	0.3451 (0.0685)	0.6823 (0.4762)	0.7303 (0.4723)
	$e_i \sim t_{(3)}$	0.3682 (0.1033)	0.5723 (0.3549)	0.6782 (0.4012)
	$e_i \sim Laplace(0,1)$.	0.3428 (0.0894)	0.6522 (0.1640)	0.5072 (0.2682)
$\boldsymbol{p_2 = 0.60}$	$e_i \sim N(0,1)$,	0.4623 (0.1328)	0.5284 (0.2682)	0.8923 (0.3826)
	$e_i \sim t_{(3)}$	0.3518 (0.1624)	0.7633 (0.3714)	0.7824 (0.4934)
	$e_i \sim Laplace(0,1)$.	0.4174 (0.1653)	0.6528 (0.3783)	0.5729 (0.3523)
$\boldsymbol{p_3 = 0.99}$	$e_i \sim N(0,1)$,	0.3782 (0.1482)	0.6572 (0.3893)	0.6341 (0.3763)
	$e_i \sim t_{(3)}$	0.3272 (0.1056)	0.5626 (0.2869)	0.5783 (0.2617)
	$e_i \sim Laplace(0,1)$.	0.3175(0.1783)	0.5079 (0.1640)	0.7853 (0.3591)

Note: Standard deviation in parentheses Another way to check the efficiency of estimation with our method is to follow plots and histograms. Figure 3 also shows a trajectory plot showing the stationary of the MCMC algorithm over all iterations.

Figure 3 shows trace plots of the parameter estimation in dense case



It can be seen from Figure (4) that the parameter estimates are distributed from 1 to 8, and it is obvious that the parameter estimates obey the normal distribution

VI. Real information

The term "abortion" refers back to the removal or evacuation of a foetus so one can stop a being pregnant. A miscarriage is an abortion that takes vicinity certainly without clinical intervention. They occur in approximately 30 and 40 percent of pregnancies. The abortion manifest via direct oblique factors. In this paper the our data collected from Women's and Children's Hospital / Samawa , where in pattern length is one hundred sixty pregnant women . In this observe there's one based variable (quantity of abortion at one girl) and set of independent variables are :

x_1:is a female's age while pregnant.

x_2:is the lady weight whilst pregnant.

x_3:is a infant sequence while a pregnant female.

x_4:is a blood group whilst pregnant lady.

x_5:is contamination by covid-19 when a pregnant lady.

x_6:is contamination by way of a diabetic whilst a pregnant lady.

x_7:is contamination by means of blood pressure when pregnant lady.

x_8:is an schooling level when pregnant lady.

x_9:is a house when pregnant girl.

x_{10}:is earnings while a pregnant lady.

x_{11}:is foetus size while pregnant female.

x_{12}: foetus distortion when a pregnant woman

The coefficients estimation by three methods under study inserted in bellow table (III)

variables	Bayesian lasso Tobit quantile regression			Bayesian new lasso Tobit quantile regression			**bAnet**		
	$p_1 = 0.15$ (β_p)	$p_1 = 0.60$ (β_p)	$\theta_1 = 0.99$ (β_p)	$p_1 = 0.15$ (β_p)	$p_1 = 0.60$ (β_p)	$p_1 = 0.99$ (β_p)	$p_1 = 0.15$ (β_p)	$p_1 = 0.60$ (β_p)	$p_1 = 0.99$ (β_p)
x_1	0.319	0.543	0.271	0.981	0.732	0.473	0.934	0.845	0.514
x_2	0.292	0.139	0.067	0.781	0.625	0.387	-0.851	-0.706	-0.473
x_3	0.017	0.009	0.000	-0.087	-0.057	-0.038	-0.464	0.412	0.339
x_4	0.003	0.018	0.025	0.066	0.084	0.043	0.743	0.592	0.544
x_5	0.000	0.000	0.000	0.076	0.055	0.000	0.846	0.674	0.064
x_6	0.472	0.157	0.102	-0.796	0.573	-0.283	-0.647	-0.618	-0.564
x_7	0.000	0.000	0.000	0.382	0.308	0.197	0.744	0.473	0.479
x_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
x_9	-0.671	-0.462	-0.244	0.672	0.349	0.368	0.593	0.434	0.454
x_{10}	0.303	0.272	0.152	-0.930	0.762	-0.381	-0.824	-0.535	-0.435
x_{11}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
x_{12}	0.027	0.013	0.007	0.462	0.282	0.184	0.624	0.489	0.297

From the consequences inserted table three , There are every effective and terrible relationships with abortion. In our proposed approach at low and intermediate quantile level 4 impartial variables are not crucial. But in immoderate quantile stage 5 independent variables are no longer vital. Finally, The above estimates is probably used to decide the Root imply squared errors (RMSE) for every technique underneath consideration .

Table (IIII) Root Mean squared errors for the methods under study .

Methods	$p_1 = 0.15$	$p_2 = 0.60$	$p_3 = 0.99$
Bayesian lasso Tobit quantile regressionmodel	1.783	1.179	1.006
Bayesian new lasso Tobit quantile regression	2.070	3.675	3.343
bAnet	2.232	2.835	3.583

From the results in desk IIII, we can observe that our suggested technique (b. Lasso.T.Q.R.Model) has RMSE is a lot smaller than the RMSE generated through both two strategies (b .New.L.T.Q.Reg and bAnet). Consequently, our suggested approach (b Lasso. T.Q.R.Model) plays higher than the other two strategies .

Conclusions

The proposed method successfully improves the prediction accuracy compared to the other two methods .In addition, our proposed method is generated by an efficient and simple MCMC algorithm ,B. Lasso .T.Q.R. Model ,which is a good method for variable selection and coefficient estimation in the Tobit molecular regression model .Simulation experiments show that the proposed Gibbs sampler is efficient in estimating regression coefficients and shrinkage in various examples .Furthermore, simulation results show that our approach is effective even when the actual error term distribution is not SLD. This paper can be extended to Bayesian Russo quantile binary regression and compound tobit quantile regression models.

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