

# Modeling COVID-19 Pandemic Data with New Pareto Model

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## ABSTRACT

This paper aims to find a statistical model for the COVID-19. We used an efficient and superior model for fitting the COVID 19 mortality. A new Extended-Pareto distribution (NE-P) is found. The maximum likelihood method is utilized to obtain the estimator of the parameters. A simulation was carried out using different sample sizes and different values of the parameters. In addition, the goodness of fit test statistics was calculated for proposed model compared with the baseline model to find out that our new model is the best for modeling data COVID-19.

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*Keywords: A new Extended-Pareto distribution, COVID 19 mortality, The maximum likelihood method, Goodness of fit.*

## 1 Introduction

19 Probability distributions are often used in reliability tests for data modeling  
20 which is an important aspect of statistical work in a wide range of scientific and  
21 technological fields. Over the last decades, a considerable amount of research  
22 was devoted to the creation of lifetime models and several generalization or  
23 transformation methods have been proposed. These generalizations are  
24 obtained either by adding one or more shape parameters or changing the  
25 functional form of distributions to make them more flexible for modeling many  
26 lifetime data. One of the most important of these distributions is Pareto  
27 distribution (PD) which has attracted the attention of researchers for example,  
28 Jayakumar et al. [1] presented a new four parameter distribution called New

29 Generalized Pareto distribution, which was a generalization of the classical  
 30 Pareto distribution. Boumaraf et al. [2] used nonlinear optimization methods to  
 31 find the estimators of beta Pareto distribution.

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33 The probability density function (PDF) of Pareto distribution is given by:

$$34 \quad g(x) = \frac{\beta}{x^{\beta+1}} ; x \geq 1 ; \beta > 0 . \quad (1)$$

35 and the cumulative distribution function (CDF) is:

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$$37 \quad G(x) = 1 - x^{-\beta} ; x \geq 1 , \beta > 0 . \quad (2)$$

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39 where  $\beta$  is the scale parameter.

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41 Furthermore, there were many authors who were interested to introduce new  
 42 models: Ibrahim et al. [3], Bantan et al. [4], in [5], the authors studied a new  
 43 extended (NE-X) family of distributions. The PDF of NE-X distribution is given  
 44 by:

$$45 \quad f(x) = \frac{2\theta^2 g(x)G(x)(1-G^2(x))^{\theta-1}}{(1-(1-\theta)G^2(x))^{\theta+1}} ; \theta > 0 ; x \in R . \quad (3)$$

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47 The CDF of NE-X distribution is:

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$$49 \quad F(x) = 1 - \left( \frac{1-G^2(x)}{1-(1-\theta)G^2(x)} \right)^{\theta} ; \theta > 0 ; x \in R . \quad (4)$$

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51 Depending on Equations (1) , (2) and the family in [5], we deduced a new  
 52 distribution called it a New Extended-Pareto Distribution (NE-P). The PDF  
 53 and CDF of NE-P distribution with two parameters( $\theta, \beta$ ) is obtained  
 54 respectively as:

$$55 \quad f(x) = \frac{2\theta^2(\beta x^{-(\beta+1)})(1-x^{-\beta})(1-(1-x^{-\beta})^2)^{\theta-1}}{(1-(1-\theta)(1-x^{-\beta})^2)^{\theta+1}} ; \theta > 0 , \beta > 0 ; x \in R . \quad (5)$$

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57 And

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$$59 \quad F(x) = 1 - \left( \frac{1-(1-x^{-\beta})^2}{1-(1-\theta)(1-x^{-\beta})^2} \right)^{\theta} ; \theta > 0 , \beta > 0 ; x \in R \quad (6)$$

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61 **2 Maximum Likelihood Estimation Method**

62 This section presents the maximum likelihood estimator of the NE-P  
 63 distribution parameters  $(\theta, \beta)$ . If  $x_1, x_2, \dots, x_n$  is a random sample from NE-  
 64 P distribution, the log-likelihood function is  $L(\underline{x})$  can be obtained as:

$$\begin{aligned}
 65 \quad L(\underline{x}) &= (2\theta^2\beta)^n \prod_{i=1}^n x_i^{-(\beta+1)} \prod_{i=1}^n (1 - x_i^{-\beta}) \prod_{i=1}^n \left(1 - (1 - x_i^{-\beta})^2\right)^{\theta-1} \\
 66 \quad &\times \prod_{i=1}^n \left(1 - (1 - \theta)(1 - x_i^{-\beta})^2\right)^{-(\theta+1)}. \tag{7}
 \end{aligned}$$

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68 And the log-likelihood function is given as follows

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$$\begin{aligned}
 70 \quad l = \log(L) &= n \log(2) + n \log(\theta^2) + n \log(\beta) - (\beta + 1) \sum_{i=1}^n \log x_i \\
 71 \quad &+ \sum_{i=1}^n \log(1 - x_i^{-\beta}) + (\theta - 1) \sum_{i=1}^n \log(1 - (1 - x_i^{-\beta})^2) \\
 72 \quad &- (\theta + 1) \sum_{i=1}^n \log(1 - (1 - \theta)(1 - x_i^{-\beta})^2). \tag{8}
 \end{aligned}$$

73 Differentiating (8) with respect to each of the parameters  $\theta$  and  $\beta$  gives

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$$\begin{aligned}
 75 \quad \frac{\partial \log L}{\partial \theta} &= \frac{2n}{\theta} + \sum_{i=1}^n \log(1 - (1 - x_i^{-\beta})^2) - (\theta + 1) \\
 76 \quad &\times \sum_{i=1}^n \frac{(1 - x_i^{-\beta})^2}{(1 - (1 - \theta)(1 - x_i^{-\beta})^2)} - \sum_{i=1}^n \log(1 - (1 - \theta)(1 - x_i^{-\beta})^2), \tag{9}
 \end{aligned}$$

$$\begin{aligned}
 77 \quad \frac{\partial \log L}{\partial \beta} &= \frac{n}{\beta} - \sum_{i=1}^n \log x_i + \sum_{i=1}^n \frac{x_i^{-\beta} \ln x_i}{1 - x_i^{-\beta}} - 2(\theta - 1) \\
 78 \quad &\times \sum_{i=0}^n \frac{x_i^{-\beta} \ln(x_i)(1 - x_i^{-\beta})}{1 - (1 - x_i^{-\beta})^2} + 2(1 - \theta^2) \sum_{i=0}^n \frac{x_i^{-\beta} \ln(x_i)(1 - x_i^{-\beta})}{(1 - (1 - \theta)(1 - x_i^{-\beta})^2)}. \tag{10}
 \end{aligned}$$

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80 There isn't a closed form answer to this equations for  $(\theta, \beta)$ . As a result, the  
 81 equations can be solved numerically using a method like the Newton-Raphson  
 82 method to determine the Maximum Likelihood Estimate  $\hat{\theta}_{MLE}$  and  $\hat{\beta}_{MLE}$ .

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### 86 3 Simulation Study

87 In this section, the simulation result for the ML method is given when two  
 88 parameters are unknown based on complete samples. for various sample  
 89 sizes and parameter values, the parameter values are selected as  $\beta =$   
 90  $2.8, \theta=1.5$  and  $n = 25, 100, 250, 450,$  and  $1000$  This process is repeated  $N =$   
 91  $500$  times . Furthermore, performance of different estimators is considered in  
 92 terms of their biases and mean square errors (MSEs) that given, respectively,  
 93 by

$$94 \quad \text{Bias}(\hat{\lambda}) = E(\hat{\lambda}) - \lambda \quad \text{and} \quad \text{MSE}(\hat{\lambda}) = E(\hat{\lambda} - \lambda)^2.$$

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Table 1: Mean, MSEs and Bias for the parameter estimates when  $\beta_0 = 2.8, \theta_0=1.5$ .

<b>N</b>		<b>MLE</b>	<b>MSE</b>	<b>BIAS</b>
<b>25</b>	$\hat{\beta}$	3.37488	0.76493	0.574879
	$\hat{\theta}$	1.67533	0.627229	0.17533
<b>100</b>	$\hat{\beta}$	3.00401	0.638085	0.204005
	$\hat{\theta}$	1.67228	0.622801	0.17228
<b>250</b>	$\hat{\beta}$	3.00453	0.27286	0.204525
	$\hat{\theta}$	1.579	0.185657	0.0790023
<b>450</b>	$\hat{\beta}$	2.94519	0.339871	0.145187
	$\hat{\theta}$	1.55915	0.151468	0.059146
<b>1000</b>	$\hat{\beta}$	2.89381	0.069541	0.0938141
	$\hat{\theta}$	1.53192	0.05152	0.0319226

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100 We can see when sample size increases, the mean squared error and bias  
 101 decrease. Therefore, the maximum likelihood method works very well to  
 102 estimate the parameters of NE-P distribution.

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## 106 **4 Real Data Applications**

107 In this section, we provide the application with real data sets to assess the  
 108 flexibility of NE-P distribution comparing with the base line Pareto distribution.  
 109 The parameters are estimated using maximum likelihood method.  
 110 Mathematica (V.11.0) is used for computation. Moreover, we consider the  
 111 model selection criteria, including Akaike information criterion (AIC), Bayesian  
 112 information criterion (BIC), consistent Akaike information criterion (CAIC), and  
 113 Hannan-Quinn information criterion (HQIC). They are defined as follows:

$$114 \quad AIC = -2l(\hat{\theta}) + 2k$$

$$115 \quad CAIC = AIC + \frac{2k(k+1)}{n-k-1}$$

$$116 \quad HQIC = -2\log l(\hat{\theta}) + 2k \log(\log(n))$$

117 (See Whittaker and Furlow [6]).

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## 119 **5 Daily mortality cases of COVID-19:**

120 In this section, we will study the data number of daily mortality COVID-19  
 121 cases will be compared with (PD).

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### 123 **5.1 Data set 1:**

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125 The first data represents a COVID-19 mortality rates data belongs to Italy of  
 126 59 days, that is recorded from 27 February to 27 April 2020. The data is taken  
 127 from (Almongy et al. [7]) as follows:

128 4.571, 7.201, 3.606, 8.479, 11.410 ,8.961, 10.919, 10.908, 6.503 ,18.474,  
 129 11.010 ,17.337, 16.561, 13.226, 15.137 ,8.697 ,15.787 ,13.333 ,11.822  
 130 ,14.242 ,11.273, 14.330, 16.046, 11.950, 10.282, 11.775 ,10.138 ,9.037  
 131 ,12.396 ,10.644, 8.646 ,8.905, 8.906, 7.407, 7.445, 7.214, 6.194, 4.640 ,5.452  
 132 ,5.073, 4.416, 4.859 ,4.408 ,4.639 ,3.148 ,4.040 ,4.253 ,4.011 ,3.564, 3.827,  
 133 3.134, 2.780, 2.881, 3.341, 2.686, 2.814, 2.508, 2.450 ,1.518.

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**Table 2:** Descriptive statistics for data set 1.

n	Min	$Q_1$	Median	Mean	$Q_3$	Max	Skewness	Kurtosis
59	1.518	4.04	7.44	8.15	11.41	18.474	0.45	2.12

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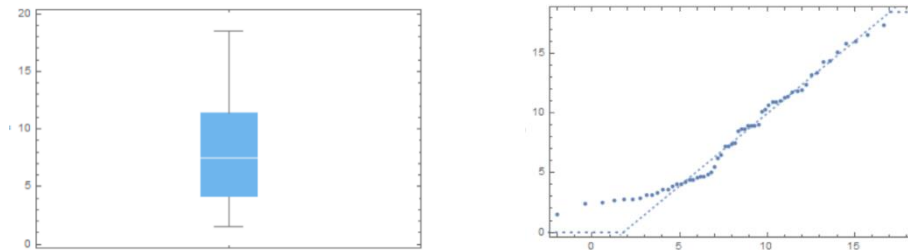
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**Figure 1.** PP plot of the NE-P distribution and the box plot for data set 1.

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**Table 3.** Parameter estimation for various distributions depending on data set 1.

Model	Parameters		LL	AIC	CAIC	HQIC
	$\hat{\theta}$	$\hat{\beta}$				
NE-P	0.31	2.31	-190.47	384.94	385.15	386.56
PD		0.52	-211.25	424.50	424.57	425.31

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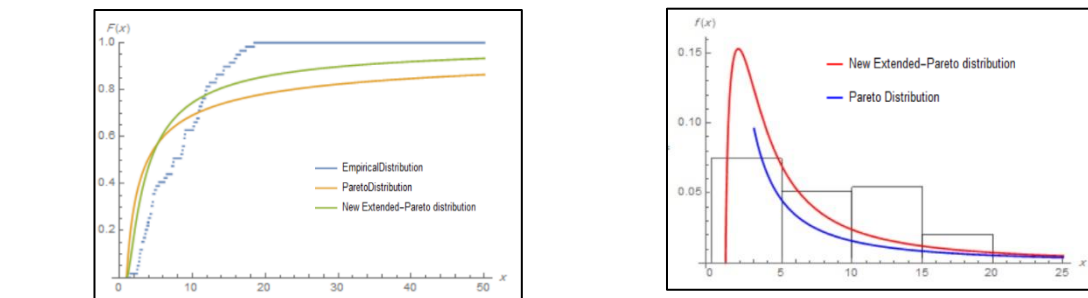
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**Figure 2.** Plots of the fitted CDF (left) and the histogram with fitted PDF (right) of the NE-P model for data set 1.

## 5.2 Data set 2:

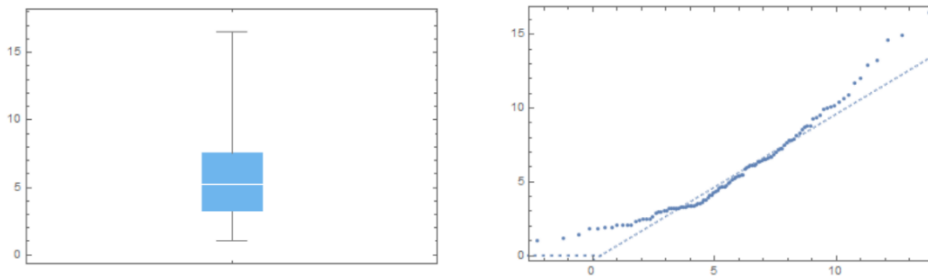
The second data set of data of COVID-19 mortality numbers in Mexico of 108 days, that is recorded from 4 March to 20 July 2020. The data is taken from Nagy et al. The data is taken from (Almongy et al. [7]) as follows:

170 8.826, 6.105, 10.383, 7.267, 13.220, 6.015, 10.855, 6.122, 10.685, 10.035,  
 171 5.242, 7.630, 14.604, 7.903, 6.327, 9.391, 14.962, 4.730, 3.215, 16.498,  
 172 11.665, 9.284, 12.878, 6.656, 3.440, 5.854, 8.813, 10.043, 7.260, 5.985,  
 173 4.424, 4.344, 5.143, 9.935, 7.840, 9.550, 6.968, 6.370, 3.537, 3.286, 10.158,  
 174 8.108, 6.697, 7.151, 6.560, 2.988, 3.336, 6.814, 8.325, 7.854, 8.551, 3.228,  
 175 3.499, 3.751, 7.486, 6.625, 6.140, 4.909, 4.661, 1.867, 2.838, 5.392, 12.042,  
 176 8.696, 6.412, 3.395, 1.815, 3.327, 5.406, 6.182, 4.949, 4.089, 3.359, 2.070,  
 177 3.298, 5.317, 5.442, 4.557, 4.292, 2.500, 6.535, 4.648, 4.697, 5.459, 4.120,  
 178 3.922, 3.219, 1.402, 2.438, 3.257, 3.632, 3.233, 3.027, 2.352, 1.205, 2.077,  
 179 3.778, 3.218, 2.926, 2.601, 2.065, 1.041, 1.800, 3.029, 2.058, 2.326, 2.506,  
 180 1.923.

181 **Table 4:** Descriptive statistics for data set 2.

n	Min	$Q_1$	Median	Mean	$Q_3$	Max	Skewness	Kurtosis
108	1.041	3.23	5.19	5.75	7.48	16.498	0.98	3.68

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190 **Figure 3.** PP plot of the NE-P distribution and the box plot for data set 2.

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192 **Table 5.** Parameter estimation for various distributions depending on data set 2.

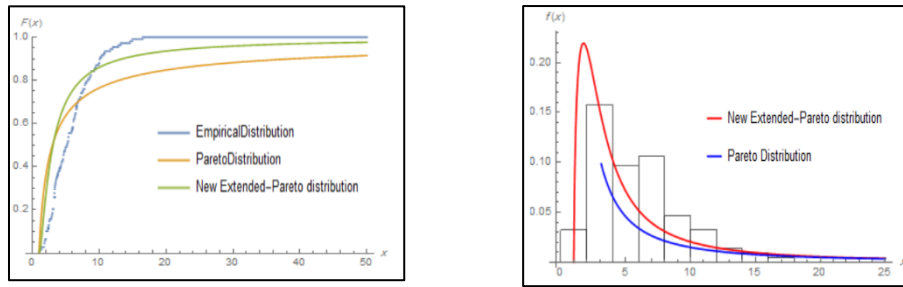
Model	Parameters		LL	AIC	CAIC	HQIC
	$\hat{\theta}$	$\hat{\beta}$				
NE-P	0.33	2.65	-296.84	597.69	597.81	599.87
PD		0.63	-329.82	661.64	661.68	662.73

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205 **Figure 4.** Plots of the fitted CDF (left) and the histogram with fitted PDF (right) of the NE-P model for  
206 data set 2.  
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208 **5.3 Data set 3:**

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210 The third data set of a COVID-19 data belonging to the Netherlands of 30 days,  
211 that is recorded from 31 March to 30 April 2020. This data formed of rough  
212 mortality rate. (see Almongy et al. [7]) The data are as follows:

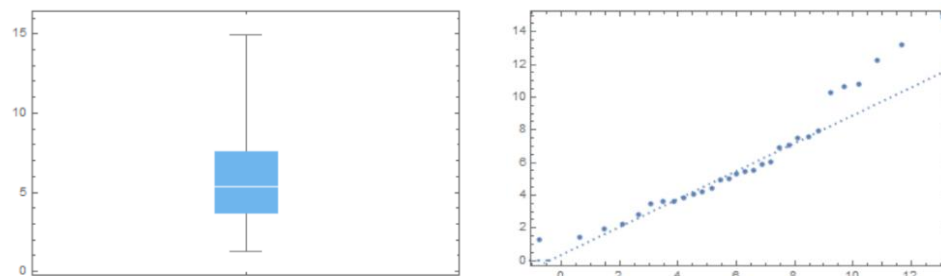
213 14.918, 10.656, 12.274 ,10.289, 10.832, 7.099, 5.928, 13.211, 7.968, 7.584,  
214 5.555, 6.027, 4.097, 3.611, 4.960, 7.498, 6.940, 5.307, 5.048, 2.857, 2.254,  
215 5.431, 4.462, 3.883, 3.461, 3.647, 1.974, 1.273, 1.416, 4.235.

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**Table 6:** Descriptive statistics for data set 3.

n	Min	$Q_1$	Median	Mean	$Q_3$	Max	Skewness	Kurtosis
30	1.273	3.64	5.36	6.15	7.58	14.918	0.83	2.95

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227 **Figure 5.** PP plot of the NE-P distribution and the box plot for data set 3.  
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229 **Table 7.** Parameter estimation for various distributions depending on data set 3 .

Model	Parameters		LL	AIC	CAIC	HQIC
	$\hat{\theta}$	$\hat{\beta}$				
NE-P	0.37	2.32	-85.46	174.93	175.38	175.83
PD		0.60	-94.38	190.76	190.91	191.21

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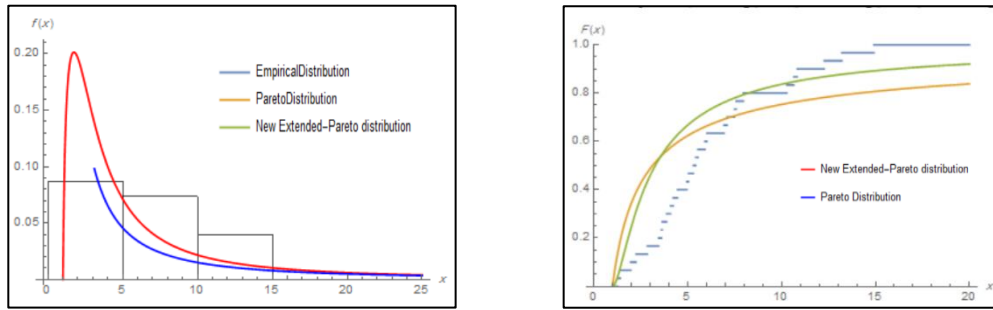
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**Figure 6.** Plots of the fitted CDF (left) and the histogram with fitted PDF (right) of the NE-P model for data set 3.

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**5.4 Data set 4:**

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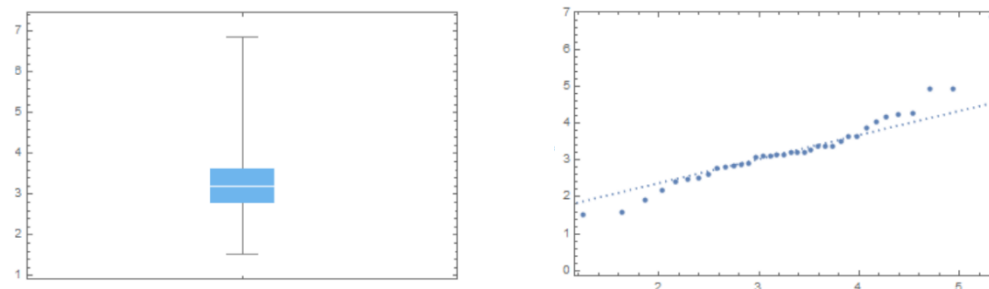
The fourth data set represents a COVID-19 data belong to Canada of 36 days, from 10 April to 15 May 2020 (see Almetwally et al. [8]). These data formed of mortality rate. The data are as follows:

3.1091, 3.3825, 3.1444, 3.2135, 2.4946, 3.5146, 4.9274, 3.3769, 6.8686, 3.0914, 4.9378, 3.1091, 3.2823, 3.8594, 4.0480, 4.1685, 3.6426, 3.2110, 2.8636, 3.2218, 2.9078, 3.6346, 2.7957, 4.2781, 4.2202, 1.5157, 2.6029, 3.3592, 2.8349, 3.1348, 2.5261, 1.5806, 2.7704, 2.1901, 2.4141, 1.9048.

**Table 8:** Descriptive statistics for data set 4.

n	Min	$Q_1$	Median	Mean	$Q_3$	Max	Skewness	Kurtosis
36	1.5171	2.77	3.17	3.28	3.63	6.8686	1.21	6.15

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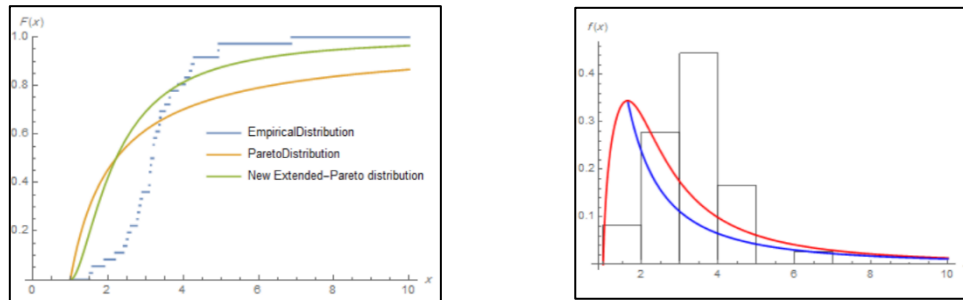
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**Figure 7.** PP plot of the NE-P distribution and the box plot for data set 4.

**Table 9.** Parameter estimation for various distributions depending on data set 4.

Model	Parameters		LL	AIC	CAIC	HQIC
	$\hat{\theta}$	$\hat{\beta}$				
NE-P	0.32	3.75	-68.20	140.41	140.77	141.51
PD		0.87	-82.13	166.27	166.39	166.82

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**Figure 8.** Plots of the fitted CDF (left) and the histogram with fitted PDF (right) of the NE-P model for data set 4.

From Tables 3, 5, 7 and 9, the values of log-likelihood (LL), AIC, CAIC and HQIC are minimum and favorable of NE-P distribution than PD distribution, which indicate that our new model is the best comparing with the competing model.

## 6 Conclusion

We derive a two parameter New Extended -Pareto distribution. The parameters are estimated by method of maximum likelihood. Performances of MLE are tested through simulation study. Finally, four real data applications of COVID-19 are analyzed in to assess the flexibility of new model. The NE-P distribution is better than the PD in modeling data based on the goodness of fit measures.

## 7 References:

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