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Using Genetic Algorithm to Estimate the Parameters of the Gumbel Distribution Function by Simulation

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Abstract

In this research, the focus was on estimating the parameters on (min-Gumbel distribution), using the maximum likelihood method and the Bayes method. The genetic algorithmmethod was employed in estimating the parameters of the maximum likelihood method as well as the Bayes method. The comparison was made using the mean error squares (MSE), where the best estimator is the one who has the least mean squared error. It was noted that the best estimator was (BLG_GE).

Keywords: Genetic algorithm, Gumbel Distribution, likelihood Function , loss Function

1.Introduction:

The Gumbel distribution is considered one of the important distributions because of the wide applications that deal with the phenomena that occur irregularly and take extreme behavior, for example, volcanoes, storms and other natural phenomena.

1.1 Gumbel distribution

Gumbel distribution [1] [5] ,is an important distribution in statistics. It has many practical applications and is one of the value distributions Extreme value distributions. The term extreme value is called maximum value have identified three types (families) of extreme distributions. Each type represents a family of several distributions, and they are respectively:

1). (Type I) is the Gumbel distribution
2). (Type II) is the Frehet- type distribution
3). (TypeIII) is the Weibull-type distribution

The Gumbel distribution is the most widely used distribution as it has two types, the (max- Gumbel distribution) and (min- Gumbel distribution)

In our paper, we will work on the (min- Gumbel distribution)

The probability function (PDF) for this distribution is:

$$f(x) = \alpha\,\beta\,x^{-(\alpha+1)} exp(-\beta x^{-\alpha})\ , x > 0, \alpha, \beta > 0 \ldots\ldots(1)$$

The cumulative distribution function(CDF) is:

$$F(x)=1-exp(-\beta X_i^{-\alpha})\quad ,x>0,\alpha,\beta>0 \ldots\ldots(2)$$

2. Estimation methods

2.1Maximum likelihood estimation

The likelihood is the greatest possibility estimator is what makes the possibility function at its maximum limit [2] [4] [5] [7], and it can be obtained by deriving the logarithm of the possibility function and equating it to zero, so if (x) is the overhead Gumbel distribution, it will be as follows:

The likelihood function of (α, β) is:

$$L(\alpha,\beta) = \prod_{i=1}^{n}\left[\alpha\,\beta X_i^{-(\alpha+1)} exp(-\beta X_i^{-\alpha})\right] \ldots\ldots\ldots\ldots(3)$$

The log-likelihood function can be written as:

$$ln\,L = n\,ln\,\alpha + n\,ln\,\beta - (\alpha+1)\sum_{i=1}^{n} ln(X_i) - \beta\sum_{i=1}^{n} X_i^{-\alpha} \ldots\ldots(4)$$

Differentiating equation (5) and setting it equal to zero, we will get:

$$\frac{\partial \ln L}{\partial \alpha} = \frac{n}{\beta} - \sum_{i=1}^{n} ln(X_i) + \beta\sum_{i=1}^{n} X_i^{-\alpha} ln(X_i) = 0 \ldots\ldots(5)$$

$$\frac{\partial \ln L}{\partial \beta} = \frac{n}{\beta} - \sum_{i=1}^{n} X_i^{-\alpha} = 0 \ldots\ldots(6)$$

The maximum likelihood estimates of (α, β) can be obtained:

$$\hat{\alpha}_{ML} = \frac{n}{\sum_{i=n}^{n} ln(x_i) - \beta\sum_{i=1}^{n} X_i^{-\alpha} ln(X_i)} \ldots\ldots\ldots\ldots(7)$$

$$\hat{\beta}_{ML} = \frac{n}{\sum_{i=1}^{n} X_i^{-\alpha}} \ldots\ldots\ldots\ldots(8)$$

2.2Bayesian estimation

In Bayesian estimation, we depend on the loss functions is LINEX [2] and can be expressed as:

$$L(\Delta) \propto \exp(k\Delta - k\Delta - 1), k \neq 0 \ldots\ldots..(9)$$

where ∆=(θ̂-θ),and (θ)̂is an estimate of θ

The posterior expectation of the LINEX loss function is:

$$E_\theta[L(\theta^{-\theta})] \propto exp(k\hat{\theta})\, E_\theta[exp(-k\theta)] - k\left(\hat{\theta} - E_\theta(\theta)\right) - 1, \ldots\ldots..(10)$$

The Bayes estimator of , denoted by θ̂_BL under LINEX loss function, is the value which minimizes equation (10)

$$\theta_{BL} = -\frac{1}{k} ln\{E_\theta[exp(-k\theta)]\} \ldots\ldots\ldots(11)$$

2.3 Genetic Algorithm

The genetic algorithm (GA) is one of the research methods based on natural selection and natural genetics. The genetic algorithm is classified as one of the Evolutionary Algorithm, which is based on simulating the work of nature from Darwin's perspective. This algorithm works as a random search method for the purpose of finding optimal or close to optimal solutions by achieving the principle of fitness and using natural biological mechanisms such as genetics, mating and genetic mutation. Good characteristics of successive generation processes, optimum progeny production, and repeat genetic cycles to improve off spring with new phases and patterns [3] [6] .

The speed of the algorithms was taken advantage of genetic in giving results and transcending many stages in the solution that cannot be bypassed by using traditional methods to reach the optimal solution . In our research, the genetic algorithm was employed to estimate the parameters of the Gumbel distribution and for the two methods of maximum likelihood and Bayes method.

Steps of the genetic algorithm

The genetic algorithm consists of the following steps:

i. Initialization: It is the first step in the genetic algorithm, where a set of random solutions is generated in the form of chromosomes, and the length of the chromosome and the way it is represented depends on the nature of the problem. to be resolved. Usually, there are several hundreds or thousands of possible solutions. Traditionally, chromosomes are generated randomly to give a full range of possible solutions for search space. One of the ways to represent chromosomes is binary encoding. In this type, chromosomes are represented to form a series of numbers that includes zero and one only

ii.Selection: This process is applied to all successive generations, as a set of chromosomes is selected according to a certain percentage for the purpose of producing and generating a new generation.

iii. Reproduction, which is the process of generating and producing a new generation of individuals that have been selected and selected through the selection process, then the crossover process and genetic mutation to produce offspring to form the new generation . iv.Termination Conditions

The genetic algorithm ends and stops when one of the following factors occurs

- **Finding the optimal solution.**
- **Access to the number of generations required.**
- **Reaching a certain value, such as the cost of production.**
- **Falling into the Local Minimum and not being able to get out of it.**

The experimental aspect

The simulation method is considered one of the best methods in solving complex problems that cannot be solved in the external reality. Also, this method is referred to in the absence of appropriate statistical data, noting that this method saves a lot of effort and money and this is done through the following steps:

i.Determine sample sizes:

Five sample sizes were selected is: (20,30,50,80,100)

ii.. Generating random numbers:

Random numbers were generated U_i that follow a uniform distribution within the period(0,t).

$$U_i \sim U(0,1) \qquad , i = 1, 2, \ldots, n$$

U_i: it represents a continuous random variable that is generated using an electronic calculator according to the following formula:

$$U = RND \ldots\ldots (12)$$

iii. Transfer data:

Converting the data generated in equation (12) that follows the uniform distribution $U(0,1)$ into data that follows the Gumbel distribution through the use of the distribution function (cdf) as follows:

Hence:

$$u = 1 - \exp(-\beta x^{-\alpha}) \ \ldots\ldots (13)$$

iv.Comparison Criterion.

The formula for mean squares of error was relied upon to find out the best model in the following (table):

$$MSE(\hat{S}) = \frac{\sum_{i-1}^{R}\left(y_i - \hat{y}\right)^2}{R}$$

Since:

$\hat{y}$: estimated model

R: the number of replications for each experiment, which was equal to 100.

v.Results and Discussion:

Using Matlab program, the results were obtained in the following tables MSE, has been adopted for comparison by using the simulation method.

Note: the abbreviations are given in the following tables:

-ML: Maximum likelihood

-BLG: Bayes LINEX General

-ML_GE: Maximum likelihood _ Genetic

-BLG_GE: Bayes LINEX General_ Genetic

vi. The initial values

The initial values in the simulation for α and β are (0.5,1.0,1.5,2.0)

Table 1: Average estimates and corresponding α (MSE) for α when (k=1, a1=1, a2=2)

n	Estimator↓α→	0.5	1.0	1.5	2.0
20	α- ML	0.2214(0.0776)	1.9956(0.9912)	0.0857(1.9999)	0.1037(3.5958)
	α- BLG	0.3386(0.0260)	1.9957(0.9914)	0.6734(0.6832)	0.5104(2.2188)
	α- ML_GE	0.2881(0.0022)	1.3669(0.0067)	0.8409(0.0217)	0.1181(0.1771)
	α- BLG_GE	0.3352(0.0014)	1.3686(0.0066)	0.9512(0.0151)	0.4101(0.1264)
	Best	α- BLG_GE	α- BLG_GE	α- BLG_GE	α- BLG_GE
30	α- ML	0.0737(0.1818)	0.0533(0.8962)	0.0429(2.1231)	0.0340(3.8650)
	α- BLG	0.5180(0.0006)	0.8090(0.0365)	1.2306(0.0726)	2.3498(0.1223)
	α- ML_GE	0.0941(0.0082)	0.7714(0.0017)	0.0556(0.0695)	0.0488(0.1269)
	α- BLG_GE	0.3892(0.0003)	0.9658(0.0001)	0.7863(0.0170)	0.9869(0.0342)
	Best	α- BLG_GE	α- BLG_GE	α- BLG_GE	α- BLG_GE
50	α- ML	0.0559(0.1972)	0.0535(0.8959)	0.0458(2.1146)	0.0542(3.7861)
	α- BLG	0.4048(0.0091)	0.4299(0.3250)	0.5278(0.9451)	0.4302(2.4643)
	α- ML_GE	0.2002(0.0018)	0.3914(0.0074)	0.2677(0.0304)	0.3603(0.0538)
	α- BLG_GE	0.2385(0.0014)	0.4100(0.0070)	0.2867(0.0294)	0.3674(0.0533)
	Best	α- BLG_GE	α- BLG_GE	α- BLG_GE	α- BLG_GE
80	α- ML	0.0307(0.2202)	0.0638(0.8764)	0.1138(1.9216)	0.0531(3.7902)
	α- BLG	0.5105(0.0001)	0.2353(0.5848)	0.1888(1.7193)	0.2759(2.9725)
	α- ML_GE	0.0548(0.0025)	0.8818(0.0003)	0.3521(0.0165)	1.388(0.0093)
	α- BLG_GE	0.2811(0.0006)	0.8896(0.0002)	0.3589(0.0163)	1.1396(0.0091)
	Best	α- BLG	α- BLG_GE	α- BLG_GE	α- BLG_GE
100	α- ML	0.0192(0.2311)	0.0109(0.9783)	2.0208(0.0785)	3.9038(0.0242)
	α- BLG	0.7150(0.0462)	2.3532(1.8312)	1.7373(0.1819)	2.1758(0.5249)
	α- ML_GE	4.4192(0.1536)	0.7471(0.0006)	0.7159(0.0061)	1.1735(0.0069)
	α- BLG_GE	4.4193(0.1533)	0.8043(0.0004)	0.9378(0.0032)	1.1736(0.0068)
	Best	α- BLG	α- BLG_GE	α- BLG_GE	α- BLG_GE

Table 2: Average estimates and corresponding β (MSE) for β when (k=1, a1=1, a2=2)

n	Estimator↓β→	0.5	1.0	1.5	2.0
20	β – ML	0.2656(0.5393)	0.4684(0.2826)	0.1814(0.6701)	0.1900(0.6561)
	β – BLG	0.2177(0.6120)	1.9913(0.9828)	0.0598(0.8839)	0.0819(0.8428)
	β - ML_GE	0.3993(0.0180)	0.6796(0.0051)	0.6784(0.0052)	0.2688(0.0267)
	β - BLG_GE	0.2948(0.0249)	1.3542(0.0063)	0.8060(0.0019)	0.1101(0.0396)
	Best	β - ML_GE	β - ML_GE	β - BLG_GE	β - ML_GE
30	β - ML	0.1671(0.6937)	0.1295(0.7577)	0.1245(0.7665)	0.1070(0.7975)
	β - BLG	0.0555(0.8921)	0.0316(0.9379)	0.0204(0.9596)	0.0115(0.9771)
	β - ML_GE	0.2417(0.0288)	0.5382(0.0071)	0.1870(0.0220)	0.1674(0.0231)
	β - BLG_GE	0.0857(0.0418)	0.7261(0.0025)	0.0471(0.0303)	0.0369(0.0309)
	Best	β - ML_GE	β - BLG_GE	β - ML_GE	β - ML_GE
50	β - ML	0.1239(0.7676)	0.1309(0.7554)	0.1226(0.7698)	0.1417(0.7367)
	β - BLG	0.0436(0.9148)	0.0420(0.9178)	0.0323(0.9365)	0.0427(0.9164)
	β - ML_GE	0.3143(0.0094)	0.4050(0.0071)	0.4216(0.0067)	0.4276(0.0066)
	β - BLG_GE	0.1984(0.0128)	0.3992(0.0072)	0.2698(0.0107)	0.3646(0.0081)
	Best	β - ML_GE	β - ML_GE	β - ML_GE	β - ML_GE
80	β - ML	0.1070(0.7974)	0.1384(0.7423)	0.1920(0.6529)	0.1307(0.7556)
	β - BLG	0.0216(0.9572)	0.0563(0.8906)	0.1088(0.7943)	0.0450(0.9120)
	β - ML_GE	0.1761(0.0085)	0.4646(0.0036)	0.3923(0.0046)	0.4999(0.0031)
	β - BLG_GE	0.0475(0.0113)	0.8736(0.0002)	0.3547(0.0052)	1.1354(0.0002)
	Best	β - ML_GE	β - BLG_GE	β - ML_GE	β - BLG_GE
100	β - ML	0.0779(0.8503)	0.0556(0.8918)	0.1693(0.6901)	0.0924(0.8238)
	β - BLG	0.0120(0.9761)	0.0042(0.9916)	0.0731(0.8591)	0.0173(0.9657)
	β - ML_GE	0.6007(0.0016)	0.4329(0.0032)	0.4438(0.0031)	0.4872(0.0026)
	β - BLG_GE	4.4188(0.1169)	0.7331(0.0007)	0.7049(0.0009)	1.1702(0.0003)
	Best	β - ML_GE	β - BLG_GE	β - BLG_GE	β - BLG_GE

Table 3: Average estimates and corresponding α (MSE) for α when (k=-1, a1=1, a2=2)

n	Estimator↓α→	0.5	1.0	1.5	2.0
20	α- ML	0.0134(0.2368)	0.2821(0.5154)	0.0348(0.1468)	0.0169(0.9328)
	α- BLG	1.5465(1.0953)	0.2999(0.4901)	0.8555(0.4154)	1.3701(0.3968)
	α- ML_GE	0.0578(0.0098)	2.0923(0.0597)	0.0790(0.1010)	1.2614(0.0273)
	α- BLG_GE	1.3573(0.0367)	2.0914(0.0596)	0.7257(0.0300)	1.2615(0.0272)
	Best	α- ML_GE	α- BLG_GE	α- BLG_GE	α- BLG_GE
30	α- ML	0.0010(0.2490)	0.0584(0.8867)	0.0256(0.1740)	0.0111(0.9558)
	α- BLG	3.5146(0.0879)	0.4278(0.3274)	0.8150(0.4693)	1.3854(0.3777)
	α- ML_GE	0.4106(0.0003)	0.3604(0.0136)	0.2021(0.0562)	0.4509(0.0800)
	α- BLG_GE	0.4550(0.0001)	0.3829(0.0122)	0.2689(0.0505)	0.4929(0.0757)
	Best	α- BLG_GE	α- BLG_GE	α- BLG_GE	α- BLG_GE
50	α- ML	0.0506(0.2019)	0.0201(0.9603)	0.0042(0.2374)	0.0691(0.7285)
	α- BLG	0.3319(0.0283)	0.6859(0.0987)	1.7514(0.0632)	0.2638(0.0144)
	α- ML_GE	0.1233(0.0028)	0.2191(0.0122)	1.8675(0.0026)	0.2717(0.0597)
	α- BLG_GE	0.2331(0.0014)	0.2496(0.0113)	1.8676(0.0027)	0.2910(0.0584)
	Best	α- BLG_GE	α- BLG_GE	α- ML_GE	α- BLG_GE
80	α- ML	0.0639(0.1902)	0.0069(0.9862)	0.0577(0.0803)	0.0502(0.8017)
	α- BLG	0.2015(0.0891)	1.0332(0.0011)	0.2164(0.6475)	0.2395(0.0993)
	α- ML_GE	0.4326(0.0001)	0.4532(0.0037)	0.0590(0.0260)	0.7961(0.0181)
	α- BLG_GE	0.4403(0.0002)	0.4587(0.0036)	0.2683(0.0190)	0.8212(0.0174)
	Best	α- ML_GE	α- BLG_GE	α- BLG_GE	α- BLG_GE
100	α- ML	0.0684(0.1863)	0.0179(0.9645)	0.0168(0.2000)	0.0481(0.8098)
	α- BLG	0.1723(0.1074)	0.4464(0.3065)	0.4711(0.0586)	0.2080(0.2111)
	α- ML_GE	0.4749(0.0001)	0.7048(0.0009)	0.3482(0.0133)	0.8856(0.0124)
	α- BLG_GE	0.4844(0.0002)	1.1000(0.0001)	0.3546(0.0131)	0.8918(0.0123)
	Best	α- BLG	α- BLG_GE	α- BLG_GE	α- BLG_GE

Table 4: Average estimates and corresponding β (MSE) for β when (k=-1, a1=1, a2=2)

n	Estimator↓β→	0.5	1.0	1.5	2.0
20	β - ML	0.0578(0.8877)	0.2822(0.5153)	0.1005(0.8091)	0.0731(0.8592)
	β - BLG	0.0186(1.0375)	0.2917(0.5017)	0.0034(0.0068)	0.0112(0.0225)
	β - ML_GE	0.1802(0.0336)	0.8132(0.0017)	0.2365(0.0291)	0.7288(0.0037)
	β - BLG_GE	0.0441(0.0457)	2.0785(0.0582)	0.0746(0.0428)	1.2541(0.0032)
	Best	β - ML_GE	β - ML_GE	β - ML_GE	β - BLG_GE
30	β - ML	0.0081(0.9839)	0.1356(0.7473)	0.0817(0.8433)	0.0536(0.8957)
	β - BLG	0.0050(0.0111)	0.0341(0.9329)	0.0004(0.0009)	0.0113(0.0227)
	β - ML_GE	0.3981(0.0121)	0.3955(0.0122)	0.3277(0.0151)	0.4352(0.0106)
	β - BLG_GE	0.4246(0.0110)	0.3667(0.0134)	0.2007(0.0213)	0.4691(0.0094)
	Best	β - BLG_GE	β - ML_GE	β - ML_GE	β - BLG_GE
50	β - ML	0.1273(0.7616)	0.0746(0.8563)	0.0272(0.9463)	0.1528(0.7178)
	β - BLG	0.0355(0.9302)	0.0049(0.9903)	0.0041(0.0082)	0.0557(0.8916)
	β - ML_GE	0.2688(0.0107)	0.3292(0.0090)	0.5980(0.0032)	0.3498(0.0085)
	β - BLG_GE	0.1181(0.0156)	0.2180(0.0122)	1.8717(0.0152)	0.2725(0.0106)
	Best	β - ML_GE	β - ML_GE	β - ML_GE	β - ML_GE
80	β - ML	0.1397(0.7402)	0.0432(0.9155)	0.1386(0.7420)	0.1347(0.7487)
	β - BLG	0.0553(0.8924)	0.0002(0.0005)	0.0484(0.9056)	0.0399(0.9218)
	β - ML_GE	0.4305(0.0041)	0.4562(0.0037)	0.2015(0.0080)	0.4617(0.0036)
	β - BLG_GE	0.4373(0.0040)	0.4585(0.0035)	0.0535(0.0112)	0.7838(0.0006)
	Best	β - BLG_GE	β - BLG_GE	β - ML_GE	β - BLG_GE
100	β - ML	0.1538(0.7161)	0.0719(0.8613)	0.0704(0.8642)	0.1265(0.7630)
	β - BLG	0.0616(0.8805)	0.0102(0.9797)	0.0090(0.9820)	0.0405(0.9207)
	β - ML_GE	0.4181(0.0034)	0.4451(0.0031)	0.3726(0.0039)	0.4680(0.0028)
	β - BLG_GE	0.4810(0.0027)	0.6925(0.0009)	0.3503(0.0042)	0.8791(0.0001)
	Best	β - BLG_GE	β - BLG_GE	β - ML_GE	β - BLG_GE

3.Conclusions

1. From Table number(1), average estimates and corresponding MSE for α when (k=1, a1=1, a2=2) ;it was noted that the method(BLG_GE) is the best estimate (least mean square error) for all values of (α) and for different sample sizes, Except for two cases in which the (BLG) estimator has the best (least mean square error) at (α = 0.5) for a sample size is (80 and 100) respectively.

2. From Table number(2), Average estimates and corresponding MSE for β when (k=1, a1=1, a2=2). The following can be observed:

A. the (ML_GE) method is the best estimate (least mean square error) of (β) when (β = 0.5) for different sample sizes.

B. When (β = 1.0) was the best estimate (least mean square error) of (β) is (ML_GE) when the sample size is (20, 50) , and the (BLG_GE) method is the best estimate (least mean square error) for the remaining sample size .

C. When (β = 1.5) was the best estimate (least mean square error) of (β) is (BLG_GE) when the sample size is (20, 100) , and the (ML_GE) method is the best estimate (least mean square error) of (β) for the remaining sample size.

D. When (β = 2) was the best estimate (least mean square error) of (β) is (BLG_GE) when the sample size is (80, 100) , and the (ML_GE) method is the best estimate (least mean square error) of (β) for the remaining sample size.

3. From Table number(3), average estimates and corresponding MSE for α when (k=-1, a1=1, a2=2) . The following can be observed:

A. When (α = 0.5) the (ML_GE) method is the best estimate (least mean square error) of (α) when the sample size is (20, 50) , and the (BLG) method is the best estimate (least mean square error) in the case of a sample size of (100).

B. When (α = 1.0) was the best estimate (least mean square error) of (α) is (BLG_GE) for all sample sizes .

C. When (α = 1.5) was the best estimate (least mean square error) of (α) is (BLG_GE) for sample size (20, 30,80,100); sample size(50) was the best estimator (least mean square error) is (ML_GE).

D. At (α = 2.0), the best estimator (least mean square error) is (BLG_GE) for all sample sizes.

4. From Table number (4), average estimates and corresponding MSE for (β) when (k=-1, a1=1, a2=2) . The following can be observed:

A. The (ML_GE) method is the best estimate (least mean square error) of (β) when (α = 0.5) when the sample size is (20, 50), and the (BLG_GE) method is the best estimate (least mean square error) in the case of a sample size of (30,80,100).

B. When (α = 1.0) was the best estimate (least mean square error) of (β) is (ML_GE) when the sample size is (20,30,50), and the (BLG_GE) method is the best estimate (least mean square error) for sample size (80,100) .

C. When (α = 1.5) was the best estimate (least mean square error) of (β) is (ML_GE) for all sample sizes.

D. When (α = 2.0) was the best estimate (least mean square error) of (β) is (ML_GE) when the sample size is (50), and the (BLG_GE) method is the best estimate (least mean square error) for sample size (20,30,80,100).

4.Recommendations

1.The study showed that the (BLG_GE)(Bayes LINEX General_ Genetic) Estimator is the best for most sample sizes, using the (mean squared error)(MSE) scale. The researcher recommends conducting future research on real data using the (BLG_GE) method.

2. Expand the use of other estimation methods.

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استعمال الخوارزمية الجينية في تقدير معلمات دالة توزيع كامبل بأستخدام المحاكاة

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مستخلص البحث:

في هذا البحث تم التركيز على تقدير معلمات توزيع كامبل للقيم الصغرى بأستخدام طريقة الامكان الاعظم وطريقة بيز وتم توظيف طريقة الخوارزمية الجينية في تقدير معلمات طريقة الامكان الاعظم وكذلك طريقة بيز وتمت المقارنة بأستخدام متوسط مربعات الخطأ , حيث ان هوافضل مقدر لكونه يملك اقل متوسط مربعات خطأ BLG_GE

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