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Geometric processes and its extensions

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Outline



Background

Literature review

New models and their performance

Future research

Recurrent event data analysis



Analysis of recurrent events data:



- Applications
 - modelling of insurance claims/warranty claims: times between claims
 - modelling of the outbreak of an epidemic disease: the number of cases
 - modelling of time between failures of technical systems (software or hardware)

Challenges

- 1. Common difficulties in reliability engineering:
 - Lacks of failures, technical systems are normally reliable and do not have many failure data
 - Censoring: when the observation period ends, not all units have failed some are survivors
- 2. Recurrent event data analysis is also widely studied in the healthcare sector, in which
 - the effect of covariates is the focus and
 - they have more data available for modelling

Recurrent event data analysis



Recurrent events:



Notations:

$$S_n = \sum_{i=1}^{\infty} X_i$$

$$Y_t = \sum_{n=1}^{\infty} \chi \{S_n \le t\} = \sup\{n : S_n \le t\}$$

$$m(t) = E[Y_t]$$

Questions in reliability mathematics:

- 1. What are the distributions of the gap times, i.e., the distributions of X_i ?
- 2. How many events occurred within a given time, i.e., How can we estimate m(t)?



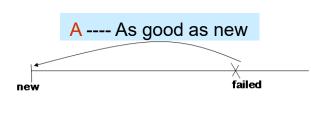
Literature review

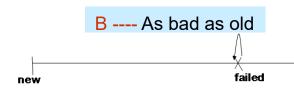
Existing modelling methods

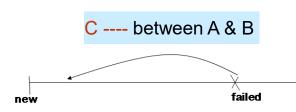


- Parametric methods, for example
 - Renewal process (RP): replacement, repaired as good as new
 - Nonhomogeneous Poisson process (NHPP): minimal repair
 - Virtual age models
 - Geometric process

Non-parametric methods



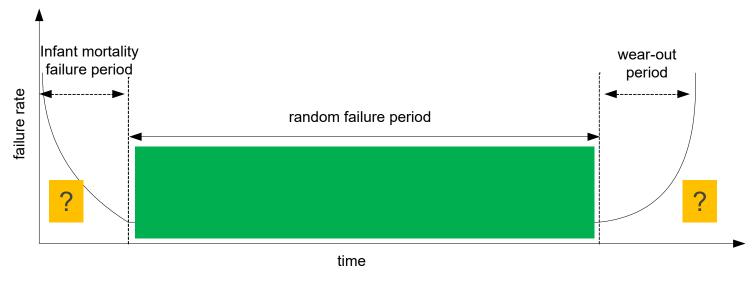




Renewal process



• Given a sequence of non-negative random variables $\{X_k, k = 1, 2, ...\}$, if they are Independent and identically distributed, then $\{X_k, k = 1, 2, ...\}$ is called a **renewal process** (RP).



Geometric process



• Given a sequence of non-negative random variables $\{X_k, k=1,2,...\}$, if they are independent and the cdf of X_k is given by $F(a^{k-1}x)$ for k=1,2,..., where a is a positive constant, then $\{X_k, k=1,2,\cdots\}$ is called a **geometric process** (GP) (Lam, 1988).

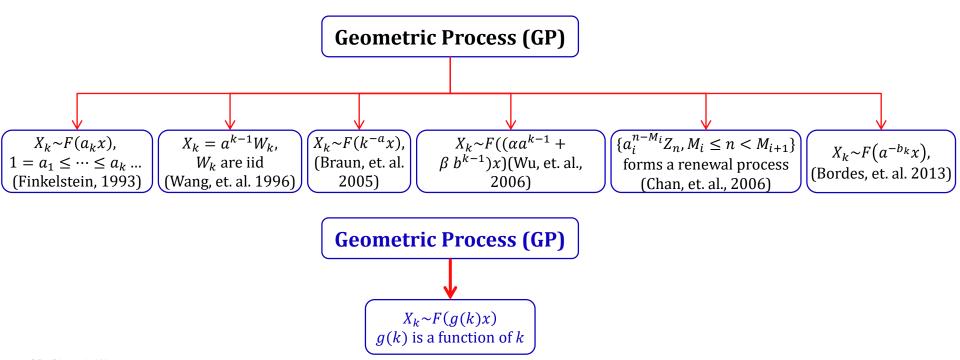
Remarks

- If a > 1, then $\{X_k, k = 1, 2, \dots\}$ is stochastically decreasing.
- If a < 1, then $\{X_k, k = 1, 2, \dots\}$ is stochastically increasing.
- If a=1, then $\{X_k, k=1,2,\cdots\}$ is a renewal process (RP).
- If $\{X_k, k = 1, 2, ...\}$ is a GP and X_1 follows the Weibull distribution, then the shape parameter of X_k for k = 2, 3, ... remains the same as that of X_1 .

Literature review



• The GP has been extensively studied since its introduction in 1988 (Lam, 1988), mainly due to its elegance and convenience in deriving mathematical properties in applications



Motivation for the doubly geometric process (DGP)



The process $\{X_k, k = 1, 2, ...\}$ with $X_k \sim F(g(k)x)$ has the following restrictive implications

• **Invariance of the CV** (coefficient of variation): Given a GP $\{X_1, X_2, ...\}$, then

$$CV_k = \frac{\sqrt{V(X_k)}}{E(X_k)} = \frac{\sqrt{E(X_1^2) - (E(X_1))^2}}{E(X_1)}$$

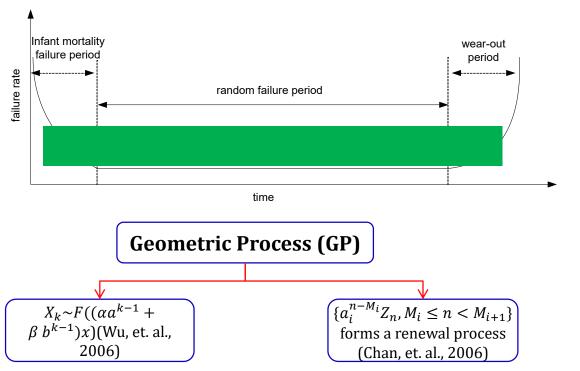
• Invariance of the shape parameter: Suppose $X_1 \sim 1 - \exp\{-\left(\frac{x}{\theta_1}\right)^{\theta_2}\}$, then

$$F(g(k)x) = 1 - \exp\left\{-\left(\frac{x}{\theta_1(g(k))^{-1}}\right)^{\theta_2}\right\}$$

Literature review



• Monotonicity of the GP: from the remarks, the GP $\{X_k, k = 1, 2, ...\}$ change monotonously, either increasing or decreasing



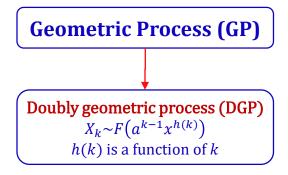


Doubly geometric processes and double ratio geometric processes

Doubly geometric process



• Given a sequence of non-negative random variables $\{X_k, k = 1, 2, ...\}$, if they are independent and the cdf of X_k is given by $F(a^{k-1}x^{h(k)})$ for k = 1, 2, ..., where a is a positive constant, then $\{X_k, k = 1, 2, ...\}$ is called a **doubly geometric process** (GP) (Wu, 2018).



Examples



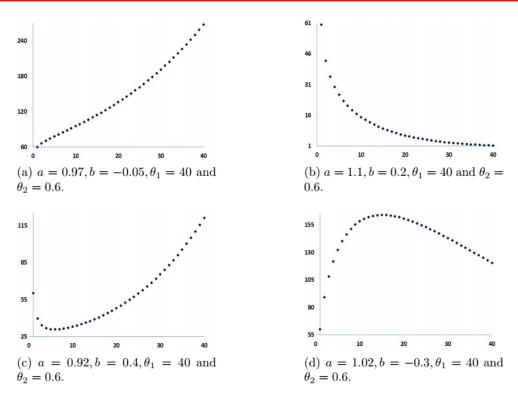


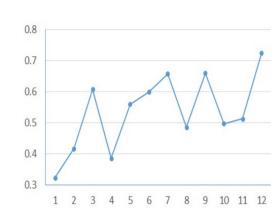
Figure 1: DGPs with different parameter settings: the Y-axes are $\mathbb{E}[X_k]$ and the X axes are k, $F(x) = 1 - e^{-(\frac{x}{\theta_1})^{\theta_2}}$, $h(k) = (1 + \log(k))^b$.

Data analysis

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Table 1: Time between warranty claims of 22 identical items (unit: day).

Shipments Months	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	CV
1	10	8	13	7	8	16	9	6	7	15	11	9	13	7	9	6	13	10	9	5	0.323
2	7	4	8	6	9	6	1	8	8	9	11	10	10	9	7	8	1	3	9	12	0.417
3	11	7	15	3	4	3	3	13	9	13	6	4	3	5	5	6	3	2	8	5	0.607
4	8	3	12	6	7	6	11	9	9	7	10	7	8	11	6	5	8	5	6	17	0.385
5	4	3	4	2	8	6	7	15	7	9	10	5	2	6	4	14	3	7	10	13	0.559
6	11	8	5	10	4	5	7	8	1	6	11	1	3	4	3	9	4	5	16	13	0.599
7	7	7	22	3	5	14	12	5	4	7	9	4	4	6	17	4	13	3	6	5	0.658
8	11	8	4	5	4	12	6	10	3	4	8	3	5	12	9	10	3	11	4	4	0.486
8	4	3	16	7	1	8	3	6	1	5	6	4	4	12	5	2	4	5	5	6	0.660
10	2	5	9	4	3	10	11	8	1	12	8	6	10	7	2	3	9	10	6	9	0.497
11	5	4	8	4	7	12	1	9	5	8	4	7	3	2	3	5	13	8	7	6	0.513
12	4	5	2	6	1	7	6	10	4	3	12	2	2	17	4	13	6	1	9	5	0.724



• The AICc of DGP is 630.090 and that of GP is 630.242

Reliability data: Time between

failure data

Reliability data

The least squares method

The maximum likelihood method

Table 2: The datasets, including TBF(Time between failures).

No.	Dataset	N_0	References
1	Hydraulic system (LHD3)	25	Kumar and Klefsjö (1992)
2	Propulsion diesel engine failure data	71	Ascher and Feingold (1984)

Table 3 Comparison of the performance of the GP and the DGP based on the least squares method

No.	Pa	rameters of the l	DGP	Parameter	rs of the GP	$RMSE_{DGP}$	$RMSE_{GP}$
	â	\hat{b}	μ̂	â	μ̂		
1	0.944	0.499	531.406	1.0382	209.841	111.729	144.431
	(0.0559)	(0.174)	(109.390)	(0.0315)	(67.652)		
2	0.909	0.488	147.624	0.972	56.702	65.670	69.810
	(0.0607)	(0.280)	(62.664)	(0.0181)	(20.486)		

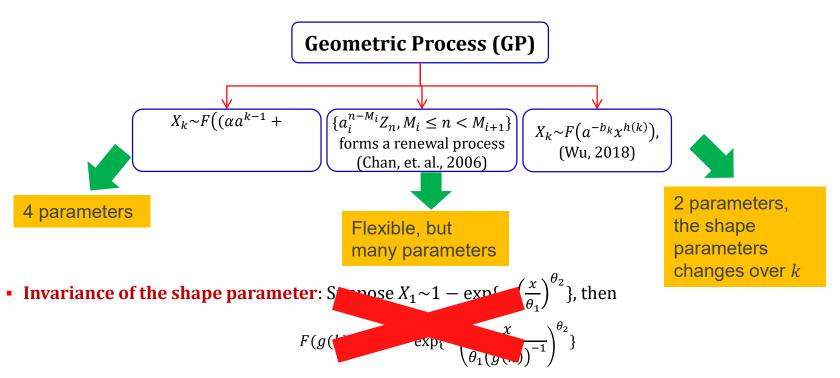
Table 4 Comparison of the performance of the GP and the DGP based on the maximum likelihood method

No.	Estin	nated paran	neters of the D	OGP	Estimate	d parameters o	of the GP	$AICc_{DGP}$	$AICc_{GP}$	$AICc_{PL}$
	â	\hat{b}	$\hat{\theta}_1$	$\hat{ heta}_2$	â	$\hat{\theta}_1$	$\hat{ heta}_2$			
1	0.884 (0.0938)	0.638 (0.352)	449.165 (337.92)	0.789 (0.227)	1.0147 (0.0230)	168.807 (58.139)	1.0287 (0.159)	301.376	304.182	311.851
2	0.899 (0.0714)	0.502 (0.349)	147.636 (103.569)	0.964 (0.281)	0.983 (0.0151)	73.070 (19.461)	1.295 (0.182)	318.030	319.445	323.094

GP-like models that can describe non-monotonic trends



There are GP-like models that can describe non-monotonic trends



Requirements of a new GP-like model



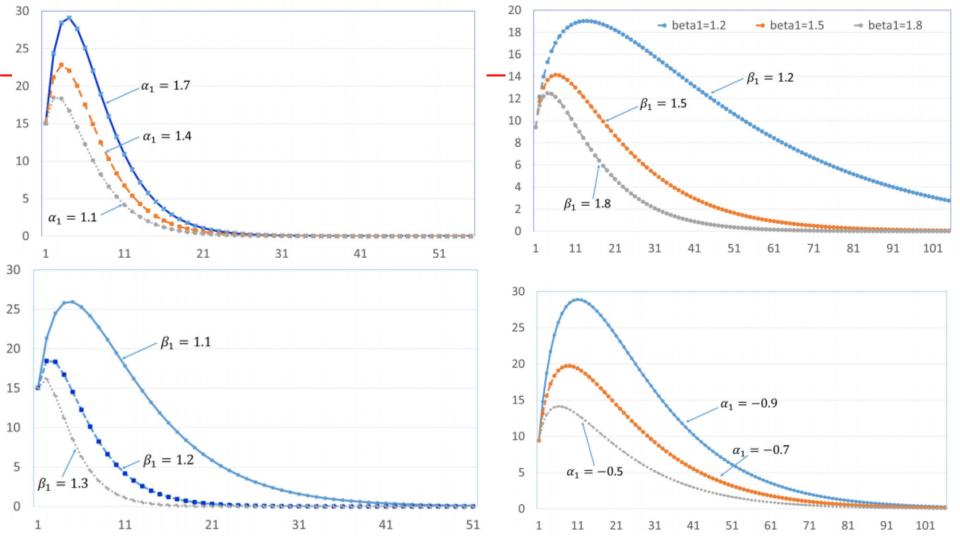
- We require a model satisfying three conditions
 - A parsimonious model: with fewer parameters
 - Be able to describe non-monotonic trends
 - If X_1 follows the Weibull distribution, the distributions of X_k (for k=2,3,...) have the same shape parameter as that of X_1

• DRGP: Given a sequence of non-negative random variables $\{Z_k^D, k = 1, 2, ...\}$, if they are independent and the cdf of Z_k^D is given by $F_k^D(t) = 1 - \exp\{-\int_0^t b_k h(a_k u) du\}$ for k = 1, 2, ..., where a_k and b_k are positive parameters (or ratios) and $a_1 = b_1 = 1$. $\{Z_k^D, k = 1, 2, ...\}$ is called the **double-ratio geometric process** (DRGP) (Wu, 2021)

An equivalent definition



- Lemma: Given a sequence of non-negative random variables $\{Z_k^D, k=1,2,...\}$, if they are independent and the cdf of $a_k^{-1} Z_k^D$ is given by $F_k^D(t) = 1 \left(1 F_1^D(a_k t)\right)^{\frac{b_k}{a_k}}$ for k=1,2,..., where a_k and b_k are positive parameters (or ratios), and $a_1=b_1=1$. Then $\{Z_k^D, k=1,2,...\}$ is a double-ratio geometric process.
- [Monotonicity] Suppose h(t) is a monotonously increasing function in t, $\{Z_k^D, k = 1, 2, ...\}$ is a DRGP, then
- If both a_k and b_k are increasing in k, then the DRGP is stochastically decreasing;
- If both a_k and b_k are decreasing in k, then the DRGP is stochastically increasing; and
- If both a_k (or b_k) is increasing in k and b_k (or a_k) is decreasing, then the DRGP may not be stochastically monotonic.







No.	Dataset	n	Description	Reference
1	LHD3	25	failures of a load-haul-dump (LHD) machine	Kumar and Klefsjö (1992)
			deployed at Kiruna mine, Sweden	
2	LHD11	28	failures of a load-haul-dump (LHD) machine	Kumar and Klefsjö (1992)
			deployed at Kiruna mine, Sweden	
3	Calvert Cliffs	23	diesel generator failure data from power plant	Kvam et al. (2002)
			"Calvert Cliffs"	
4	Pump D	30	reliability data collected from a main pump	Percy and Alkali (2007)
			(A) at an oil refinery	

Test for non-monotonic trend.

No.	p-value from the Ljung-Box test	p-value from V_1	p-value from V_4
1	0.886	0.00866	0.0216
2	0.899	0.0159	0.0114
3	0.509	0.0194	0.0276
4	0.107	0.00874	0.00180

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Table 5: AICc values of the models

No.	EGP	DGP	TGP	DRGP-I	DRGP-II	DRGP-III	DRGP-IV
1	310.198	301.345	309.431	307.040	305.281	300.228	300.228
2	328.790	323.711	324.103	325.802	324.983	321.312	321.312
3	224.545	221.461	222.055	221.490	222.299	219.632	219.632
4	297.200	300.939	298.127	306.622	308.924	295.031	295.031

Table 6: Parameters

No.	DRGF	P-III ($\hat{a}_k = k^a$	$\hat{b}_k = \hat{b}_k$	$\hat{\beta}_1^{k-1}$)	DRGP-IV $(\hat{a}_k = \hat{\beta}_2^{k-1} \text{ and } \hat{b}_k = k^{\hat{\alpha}_2})$					
	$\widehat{\alpha}_1$	$\widehat{eta_1}$	$\widehat{ heta}_1$	$\widehat{\theta}_2$	$\widehat{\alpha}_2$	\widehat{eta}_2	$\widehat{ heta}_1$	$\widehat{\theta}_2$		
1	6.942	0.848	1.231	553.510	1.603	0.490	1.231	553.510		
	(5.502)	(0.0621)	(0.200)	(308.283)	(0.671)	(0.287)	(0.200)	(340.652)		
2	14.233	0.891	1.085	347.046	1.205	0.254	1.085	347.046		
	(27.230)	(0.0555)	(0.166)	(251.771)	(0.617)	(0.660)	(0.165)	(251.777)		
3	-29.898	0.855	0.960	92.937	1.192	50.442	0.960	92.937		
	(144.543)	(0.0861)	(0.182)	(106.597)	(0.935)	(920.240)	(0.176)	(106.516)		
4	-8.996	1.281	1.297	4.629	-2.673	2.304	1.297	4.629		
S	(4.827)	(0.0787)	(0.185)	(2.985)	(0.689)	(1.0352)	(0.186)	(2.985)		

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Contributions and further research



Contributions

- the DGP can model a stochastic process with varying CV
- the DGP can model recurrent event processes where $F_k(x)$'s have different shape parameters over k's, which can be done by neither the GP-like models nor other repair models such as reduction of age models
- the DGP and DRGP can model not only monotonously increasing or decreasing stochastic processes, but also processes with complicated failure intensity functions such as the bathtub shaped curves and the upside-down bathtub shaped curves

Further research

 Both the DGP and DRGP have the limitation that they are parametric models, a Bayesian nonparametric method is under development

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