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Poisson Regression Analysis for Risk Classification and Derivation of Mortality Rate Estimation in a Life Insurance Company (Case Study of a Life Insurance Company in Indonesia)

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***Abstract*—This study aims to classify risk and derive the best estimate mortality rate for life insurance company PT ABC by using a Poisson regression model. With the Poisson regression model, this study modeled the number of deaths with policy duration, underwriting treatment, extra mortality enactment, and the sum insured amount. The sample data used in this study is the death count of insured males over the age of 18 years during period 2012-2016 in life insurance company PT ABC. After modeling the baseline mortality with a Poisson regression model and then performing exploratory analysis using a Standardized Mortality Ratio (SMR) for classifying risk, the mortality rate estimation based on the risk profile of life insurance company PT ABC is obtained. This estimated mortality rate is used to construct a mortality table. The results of the study showed that mortality rates for three-year policy duration of insured males over the age of 18 years' underwritten insurance policy with sum insured less than IDR 100 million and no extra mortality are greater than mortality rates for zero-year policy duration with the same profile. By getting the mortality rate in accordance with the company's risk profile, life insurance companies are expected to be more precise in determining the required reserves and deriving premiums in line with the risk profile of the insured lives.**

***Index Terms*—mortality rate, Poisson regression model, life insurance**

I. Introduction

According to Actuarial Practices Standard by the Society of Actuaries of Indonesia (Persatuan Aktuaris Indonesia or PAI) published in 2012, the best estimate is an estimate of future experience made by an actuary by utilizing his/her professional judgment, training, and experience with reference to statistical data as well as any other available information that is believed to be neither overstated nor understated [1]. The best estimate assumption is the actuary's best estimate of the parameters associated with the projection of future cash flows. The insurance company's liabilities calculated using the best estimate assumption should reflect a reasonable level of liabilities. In order to assess insurance liabilities, including reserves, options, and guarantees, detailed knowledge of mortality is required.

The best estimation assumption for mortality rate for insurance companies that market their products in Indonesia can use Indonesian mortality tables (Tabel Mortalita Indonesia or TMI) published by Indonesian Life Insurance Association (Asosiasi Asuransi Jiwa Indonesia or AAJI) as the basis for determining premium and life insurance reserves. The use of this table for insurance companies should be verified whether it fits in with the business being run and adjusted if necessary. Best estimate rates might vary strongly between insurance companies due to different risk profiles of the insured lives or a different business mix [2]. Thus, a specific mortality table is needed for each company.

According to Gschlössl, et al., the best estimate assumption usually comes from a certain age and gender [2]. Furthermore, it can also be distinguished by other factors such as smoking habits or the sum insured. Data limitations can be problematic in determining the best estimate of mortality rate with these other factors. Regression analysis is used as a tool to estimate differential mortality to get around the issue.

This paper presents the Poisson regression model as a method for risk classification and the derivation of best estimate mortality rates. Using Poisson regression model, life insurance companies can determine their own best estimate mortality rate according to their risk profiles. By having the best estimate rates based on risk profile, life insurance companies can have a sound basis for pricing, reserving, product development and other actuarial applications. Previous research explained this approach based on life insurance data but not clearly illustrate how to construct the mortality table based on the model result. This paper describes the usage of this approach to Indonesian life insurance PT ABC data and explains the illustration to build a mortality table according to the company's risk profile after modeled with Poisson regression. The present findings demonstrate that the mortality table can be constructed not only based on age and gender– as currently described in TMI – but also based on other significant factors such as sum insured, policy duration, extra mortality, and the underwriting process.

The paper proceeds as follows. In section II, the literature review related to this research is explored. Then, the methodology is presented in section III. Results and discussion are shown in section IV and V, respectively. The final section VI concludes the paper.

II. Literature Review

The classical actuarial approach has already been used to determine mortality rates. In the classical actuarial approach, the best estimate assumption for mortality rate is derived by smoothing crude rates [2]. The idea behind the classical method is to equate the expected number of deaths to the observed number of deaths [3]. The mortality rate is estimated from statistical data of a certain group of lives, e.g. policyholders, which has been under observation for a certain period. The estimator from this method works well if the volume data is large. For sparse data, the estimator does not work satisfactorily. In addition to that, the estimator cannot be used to estimate confidence intervals or to do statistical testing, because the statistical properties of this method are hard to evaluate.

Cox analyzed regression models for mortality rates [4]. His research is relevant to situations where the sampling fluctuations are large enough to be of practical importance. In other words, the application of Cox's research is more likely to be in industrial reliability studies and in medical statistics than in actuarial science.

Renshaw analyzed excess mortality using the generalized linear interactive modeling (GLIM) [5]. He showed the potential of these methods for actuaries when the databases are relatively small and the importance to get the right mortality factor is high. The newer approach to model extra mortality using the generalized linear model (GLM) had been researched by England and Haberman [6]. This approach provides a more dynamic method of constructing and testing models than the traditional approach [6].

According to De Jong and Heller, the GLM is used to assess and quantify the relationship between a response variable and explanatory variables [7]. The modeling differs from ordinary regression modeling in two important respects. First, the distribution of the response need not be normal or close to normal and maybe explicitly non-normal. Second, a transformation of the mean of the response is linearly related to the explanatory variables. The GLM is important in the analysis of insurance data. With insurance data, the assumptions of the normal model are frequently not applicable.

When the response variable is a count, the Poisson regression model is often used as the response distribution. The Poisson regression model is commonly used for premium rating in non-life insurance [2]. This technique is not very well known by practitioners in life insurance. Haberman and Renshaw (1996) described the versatility of generalized linear models in actuarial science which can be used as non-life insurance and life insurance model [8].

Gschlössl, et al. analyzed the usage of a Poisson regression model to derive the mortality rate in life insurance [2]. He showed that Poisson regression allows for the incorporation of insured lives' specific covariates like for example age, gender, amount insured, smoking habits, etc. within one model. Furthermore, Poisson regression provides statistical tests in order to verify the significance of each factor on the estimated risk. Confidence intervals are obtained for the estimated effect of each risk factor by which the uncertainty of the estimates can be assessed. Hence, best estimate rates depending on the risk profile of the insured lives together with confidence intervals can be derived. Gschlössl, et al. applied this approach to the insurance portfolio in Germany over a five-year period to illustrate the usefulness of the Poisson regression model [2]. This paper used Poisson regression to model PT ABC life insurance data to derive mortality rate estimation according to the company's risk profile.

III. Research Methodology

To classify risk and derive the best estimate mortality rates, this paper uses the Poisson regression model. In general, it is assumed that n individuals aged x is observed. Central exposure-to-risk, $er_x = \Sigma_i^n \tau_i$, and the number of deaths recorded among individuals aged x, $d_x = \Sigma_i^n \delta_i$ where δ_i taking the value 1 if individual i dies and 0 otherwise, can be calculated. The force of mortality likelihood for individuals aged x, $\mathcal{L}\left(\mu_x\right)$, is assumed to be proportional with Poisson likelihood is based on the assumption $D_x \sim Poisson\left(er_x \mu_x\right)$. Therefore, the GLM framework is employed in this study.

Variables of interest consist of the dependent variable and independent variables. The dependent variable is the number of deaths for each individually aged x, where $x = 18, 19, \cdots, 85$. The independent variables are product type, policy duration, underwriting process, extra mortality, and sum insured.

First, the baseline mortality rate is estimated by Poisson regression for death counts. At this stage, the only independent variable is age x. All of the other covariates are disregarded. For each age x, the death counts of the different cells are aggregated into D_x, and the corresponding exposures into er_x. The model is

$$\ln\left(\mu_x^b\right) = \beta_0 + \beta_1 x \tag{1}$$

From this model, the baseline mortality is $\mu_x^b = \exp\left(\beta_0 + \beta_1 x\right)$.

Based on the estimated baseline mortality, an exploratory analysis is conducted using standardized mortality ratio. The standardized mortality ratio is calculated by dividing the actual number of deaths at age x by the number of deaths expected according to the estimated baseline mortality. The standardized mortality ratio can either be considered depending on age x, which is denoted as SMR_x, or depending on a global level, which is denoted by SMR. The standardized mortality ratios for different subgroups of insured lives are computed in order

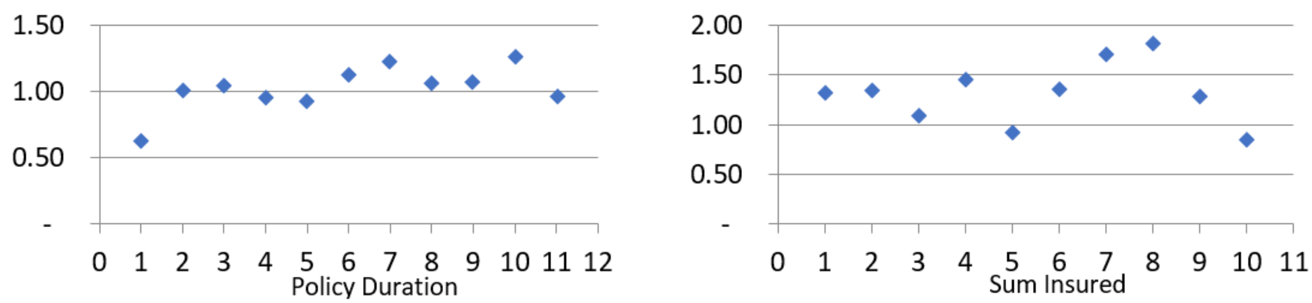

Fig. 1. Graph of global SMR by policy duration and by sum insured.

to get the first idea of possible risk factors on mortality. The calculation for both standardized mortality ratio is as follows.

$$SMR_x = \frac{d_x}{\widehat{d}_x} = \frac{d_x}{er_x\widehat{\mu}_x^b} \tag{2}$$

$$SMR = \frac{\Sigma_{x=18}^{85} d_x}{\Sigma_{x=18}^{85} \widehat{d}_x} = \frac{\Sigma_{x=18}^{85} d_x}{\Sigma_{x=18}^{85} er_x\widehat{\mu}_x^b} \tag{3}$$

After getting the possible risk factors on mortality, the covariates in mortality rates are included by means of a Poisson regression analysis. The model is as follows.

$$\ln(\mu_i) = \beta_0 + \beta_1 \ln\left(\mu_i^b\right) + \Sigma_{j=2}^{r+1}\beta_i x_{ij} \tag{4}$$

where μ_i^b: baseline mortality rate for cell i and x_{ij}: binary variables coding the covariates for cell i. The categorical covariate with k levels is created by $k-1$ binary variables x_{ij} taking the value 1 if observation i is in level j and 0 otherwise.

The goodness of fit testing is performed to ensure that the death count data has Poisson distribution. Other statistical testing conducted include parameter significance testing, multicollinearity testing, and overdispersion testing. After all testing are done and the model is fit, mortality rate estimation for PT ABC depending on the risk profile of its policyholders is derived.

IV. Results

Data used in this research is the death claim of PT ABC from 2012 until 2016. Based on the company profile, policyholders with unit link product are the majority: higher than 99%. Other products, which are endowment and term insurance, have a portion of less than 1%. So, the focus on this research is on unit link product. The sample is taken from male policyholders aged older than 18 years old who purchased the unit link product. The death count of the sample is modeled using (1) after being tested that it has Poisson distribution.

From the sample data, it is known that most of the death claims were submitted by male policyholders within the age of 40 and 50 years. Both Kolmogorov-Smirnov statistic (KS) and Anderson-Darling statistic (AD) for Poisson has the lowest value (KS: 0.0664, AS: 16.663) compared to other distributions: Negative Binomial (KS: 0.06664, AS: 16.789), Uniform (KS: 0.09259, AS: 938.44), Geometric (KS: 0.49912, AS: 1513.3), and Logarithmic (KS: 0.69599, AS: 2861.2). The distribution of the data has been tested statistically and it has Poisson distribution.

Using the GLM framework to model Poisson regression, the baseline mortality model is $\ln\left(\mu_x^b\right) = -8.6997 + 0.0696x$. The standard error of estimated β_0 and β_1 from this model is 0.0683 and 0.0015, respectively. Both p-values of these estimations are less than the significance level of 0.05. The result from this Poisson regression of baseline mortality $\left(\mu_x^b\right)$ is used to calculate the SMR using equation (2) and (3). This ratio was calculated as an exploratory analysis to get the understanding of risk factors that might be related to mortality.

The result of exploratory analysis related to the covariates is as follows.

- Policy duration is categorized from level $0, 1, 2, \ldots 9, 10+$. Age-specific SMRs by policy duration do not reveal any particular structure. Global SMRs by policy duration vary between 63% and 127%.
- The underwriting process only took two levels: 1 if the policy is underwritten and zero otherwise. Age-specific SMRs by the underwriting process do not suggest any clear relationship. The global SMR equals 109.51% for underwriting level 1 and 96.08% for underwriting level 0.
- Since there is no detail on the extra percentage of extra mortality; the extra mortality category is similar to the underwriting process category: 1 if the policy has extra mortality and zero otherwise. Age-specific SMRs by extra mortality do not reveal any particular structure. The global SMR equals 92.97% for extra mortality level 0 and 129.58% for extra mortality level 1.
- The sum insured is classified from the smallest level of less than IDR 100 million as the first category, between IDR 100 million and IDR 150 million as the second category (SA2), between IDR 150 million and IDR 200 million as the third category (SA3), and so on until higher than IDR 500 million as the tenth category for sum insured (SA10). Age-specific SMRs by sum insured do not suggest any clear relationship. The global SMR fluctuated between 86% and 181%.

The graph of global SMR by policy duration and by sum insured is shown in Figure 1.

TABLE I
FINAL MODEL

Regression coefficient	Parameter estimate	Standard error	z value	p-value
Intercept (β_0)	-5.4551	0.25154	-21.69	0.000
Natural log of mortality rate (β_1)	0.88912	0.02825	31.47	0.000
Policy duration year 1 (β_2)	0.7454	0.04907	15.19	0.000
Policy duration year 2 (β_3)	-0.5002	0.07975	-6.27	0.000
Policy duration year 3 (β_4)	0.48382	0.05295	9.14	0.000
Policy duration year 4 (β_5)	0.34281	0.05546	6.18	0.000
Policy duration year 5 (β_6)	0.16509	0.05911	2.79	0.005
Policy duration year 7 (β_7)	-0.1692	0.06886	-2.46	0.014
Policy duration year 8 (β_8)	-0.3791	0.07487	-5.06	0.000
Policy duration year 9 (β_9)	-0.6514	0.08589	-7.58	0.000
Policy duration year 10+ (β_{10})	-0.8635	0.10063	-8.58	0.000
Sum insured category 2 (β_{11})	-2.0714	0.13209	-15.68	0.000
Sum insured category 3 (β_{12})	-0.614	0.03616	-16.98	0.000
Sum insured category 4 (β_{13})	-1.3326	0.05342	-24.95	0.000
Sum insured category 5 (β_{14})	-1.6984	0.07189	-23.63	0.000
Sum insured category 6 (β_{15})	-1.8633	0.09269	-20.1	0.000
Sum insured category 7 (β_{16})	-1.893	0.11464	-16.51	0.000
Sum insured category 8 (β_{17})	-2.0353	0.16385	-12.42	0.000
Sum insured category 9 (β_{18})	-2.1084	0.17292	-12.19	0.000
Sum insured category 10 (β_{19})	-2.078	0.25915	-8.02	0.000
Underwritten (β_{20})	1.89977	0.19348	9.82	0.000
Extra mortality (β_{21})	-2.1779	0.25126	-8.67	0.000

After performing the exploratory analysis and the necessary testing, the mortality rate is modeled using the Poisson GLM model (4). The final model can be written as

$$\begin{aligned} \ln(\mu_x) \quad = \quad & \beta_0 + \beta_1 \ln\left(\mu_x^b\right) + \beta_2 I_{(d\in\{1\})} + \beta_3 I_{(d\in\{2\})} + \\ & \beta_4 I_{(d\in\{3\})} + \beta_5 I_{(d\in\{4\})} + \beta_6 I_{(d\in\{5\})} + \\ & \beta_7 I_{(d\in\{7\})} + \beta_8 I_{(d\in\{8\})} + \beta_9 I_{(d\in\{9\})} + \\ & \beta_{10} I_{(d\in\{10\})} + \beta_{11} I_{(a\in\{SA2\})} + \\ & \beta_{12} I_{(a\in\{SA3\})} + \beta_{13} I_{(a\in\{SA4\})} + \\ & \beta_{14} I_{(a\in\{SA55\})} + \beta_{15} I_{(a\in\{SA6\})} + \\ & \beta_{16} I_{(a\in\{SA7\})} + \beta_{17} I_{(a\in\{SA8\})} + \\ & \beta_{18} I_{(a\in\{SA9\})} + \beta_{19} I_{(a\in\{SA10\})} + \\ & \beta_{20} I_{(u\in\{1\})} + \beta_{21} I_{(m\in\{1\})} \end{aligned} \tag{5}$$

where x is the policyholders' age (in years), a is the sum insured, d is the policy duration (in years), m is extra mortality, u is the underwriting process. The reference category from the model is male insured whose policy is not underwritten and has no extra mortality with sum insured less than IDR 100 million, being in zero-year policy duration.

Multicollinearity test result shows that there is no correlation between the independent variables with mean-variance inflation factors (VIF) value equals 1.26. In addition to that, the overdispersion test result shows that there is no overdispersion with its test statistic value equals 1.071. The result from the final regression model can be seen in Table I. With a significance level of 0.05, the regression coefficients for all variables have a p-value less than 0.05 so it can be said that they are statistically significant.

V. DISCUSSION

According to the result from Table I, the estimated mortality rate based on the company's risk profile is derived. While keeping the same condition for other variables, the mortality rate for fifth policy year is $\exp\left(\widehat{\beta}_6\right) = \exp(0.16509) \approx 1.1795$ or 118% from 0-year policy duration of mortality rate. With the estimated standard of error, confidence interval related to its parameter can be calculated. 95% confidence interval for β_6 is $\left[\exp\left(\widehat{\beta}_6\right) - 1.96 \cdot s.e.\left(\widehat{\beta}_6\right), \exp\left(\widehat{\beta}_6\right) + 1.96 \cdot s.e.\left(\widehat{\beta}_6\right)\right] \approx [1.0637, 1.2953]$. It is noted that the mortality rate for policy in the fifth year is relatively higher than the policy that had just issued, being in the zero-year duration.

For the sum insured category, in particular, for a policy with the amount of sum insured between IDR 150 million and IDR 200 million (SA3), the mortality rate is $\exp\left(\widehat{\beta}_{12}\right) = \exp(-0.614) \approx 0.54117$ or 54% relatively lower than a policy with a sum insured less than IDR 100 million. 95% confidence interval for β_{12} is [0.47028,0.6121].

The underwritten policy has a mortality rate equal to $\exp\left(\widehat{\beta}_{20}\right) = \exp(1.8998) \approx 6.6843$ relative to a mortality rate of policy which is not underwritten. 95% confidence interval for $\beta 20$ is [6.3051,7.0636]. It shows that the underwritten policy has a higher mortality rate than a policy with no underwriting process. This information can be seen as an indication that further evaluation of the underwriting process is needed since the underwriting process might not be effectively conducted to reduced risk from a policy with no underwriting process.

For extra mortality category, a policy with extra mortality has mortality rate $\exp\left(\widehat{\beta}_{21}\right) = \exp(-2.1779) \approx 0.133$ relative to a mortality rate of policy with no extra mortality.

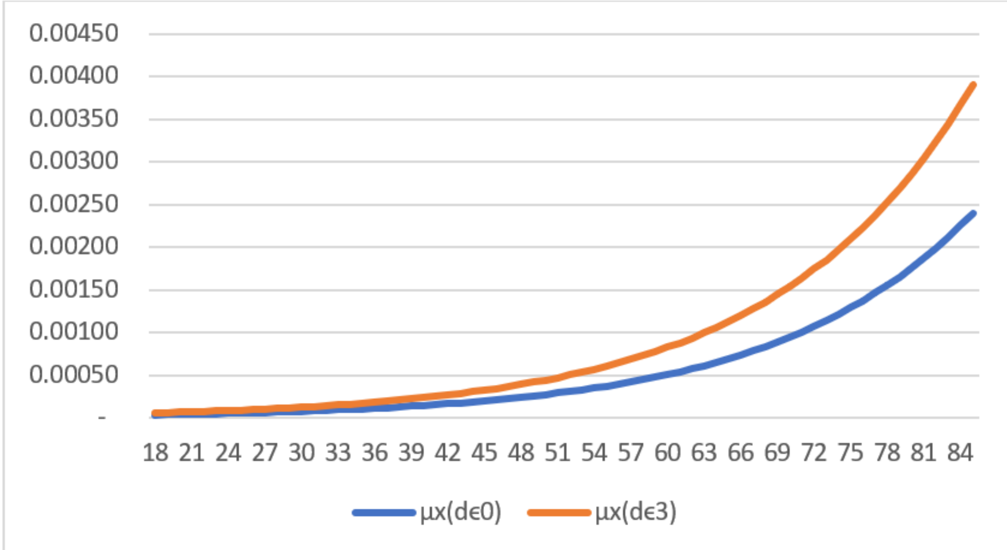

Fig. 2. Graph of the mortality rate for male policyholders whose policy is underwritten, no extra mortality, sum insured less than IDR 100 million and being in zero-year duration ($\mu_x(d \in 0)$) or three-year duration ($\mu_x(d \in 3)$).

It shows that a policy with extra mortality has lower risk than a policy without extra mortality.

The following is an illustration of the usage of a Poisson regression model result to obtain mortality rates. Suppose that there is male policyholder aged 35 who recently bought unit link product of PT ABC with sum insured less than IDR 100 million. His submitted Life Insurance Application Form is underwritten. There is no extra mortality for him. With this information, his mortality rate (μ_{35}) is $\exp\left(\widehat{\beta}_0 + \widehat{\beta}_1 \ln \mu_x^b + \widehat{\beta}_{20} I_{(u \in \{1\})}\right) = \exp\left(-5.4551 + 0.8891\left(-8.69967 + 0.06958(35)\right) + 1.89977\right) = 0.00011$. The graph of this illustration for other ages is described in Figure 2.

Figure 2 shows that the mortality rate may not be the same for different risk profiles. For each age x, the mortality table can be built from the regression model result. Table II shows the mortality table for the above-mentioned case. Thus, the company would have a specific mortality table based on its risk profile.

VI. Conclusion

Poisson regression model applied to PT ABC life insurance data is discussed. The statistical testing performed indicates that the death count data from 2012 until 2016 has Poisson distribution. First, the baseline mortality rate is estimated with death count as dependent variable and age as an independent variable. This first step is considered since the mortality rate is usually calculated according to the insured age in life insurance practice. Next, Poisson GLM is modeled with policy duration, underwriting treatment, extra mortality enactment, and sum insured amount as covariates, after the exploratory analysis using SMR is performed. The result shows that the model is fit, no overdispersion occurs, and model parameters are significant. The estimated mortality rate from the regression model is used to construct a mortality table based on the company's risk profile. As an illustration, mortality rate calculation for the insured male whose policy is underwritten with sum insured less than Rp100 million and no extra mortality for both zero-year policy duration and three-year policy duration is discussed. It shows that the mentioned case with three-year policy duration has a higher mortality rate than the same profile with zero-year duration.

In this paper, the mortality rate is calculated only for the unit link product. This is due to the majority policies of PT ABC consist of unit link. The categorical covariates are determined based on the exploratory analysis and the grouping conducted by the company on mortality analysis. For further research, it may be considered to include other product types as well as readjust the categories, if possible.

With the Poisson regression model, a life insurance company can determine its own mortality rate according to its portfolio. By obtaining the specific mortality rate, the company is expected to be more precise in determining premium and reserve amount needed based on its risk profile. To conclude, the Poisson regression model can be used to classify risks and to obtain the mortality rate estimation. In addition to that, the regression result can be implemented to construct a mortality table based on the company's risk profile as illustrated in this paper.

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TABLE II
MORTALITY TABLE

Age	Zero-year duration			Three-year duration		
	Mortality rate	The probability of survival within one year	The probability of death within one year	Mortality rate	The probability of survival within one year	The probability of death within one year
18	0.00004	0.99932	0.00068	0.00006	0.99889	0.00111
19	0.00004	0.99923	0.00077	0.00007	0.99875	0.00125
20	0.00004	0.99914	0.00086	0.00007	0.99860	0.00140
21	0.00005	0.99904	0.00096	0.00007	0.99844	0.00156
22	0.00005	0.99893	0.00107	0.00008	0.99826	0.00174
23	0.00005	0.99881	0.00119	0.00008	0.99807	0.00193
24	0.00006	0.99868	0.00132	0.00009	0.99786	0.00214
25	0.00006	0.99853	0.00147	0.00010	0.99762	0.00238
26	0.00006	0.99838	0.00162	0.00010	0.99737	0.00263
27	0.00007	0.99821	0.00179	0.00011	0.99710	0.00290
28	0.00007	0.99802	0.00198	0.00011	0.99680	0.00320
29	0.00008	0.99782	0.00218	0.00012	0.99647	0.00353
30	0.00008	0.99761	0.00239	0.00013	0.99612	0.00388
31	0.00009	0.99737	0.00263	0.00014	0.99573	0.00427
32	0.00009	0.99711	0.00289	0.00015	0.99532	0.00468
33	0.00010	0.99683	0.00317	0.00016	0.99486	0.00514
34	0.00010	0.99653	0.00347	0.00017	0.99437	0.00563
35	0.00011	0.99620	0.00380	0.00018	0.99384	0.00616
36	0.00012	0.99584	0.00416	0.00019	0.99326	0.00674
37	0.00012	0.99545	0.00455	0.00020	0.99263	0.00737
38	0.00013	0.99503	0.00497	0.00021	0.99195	0.00805
39	0.00014	0.99458	0.00542	0.00023	0.99121	0.00879
40	0.00015	0.99408	0.00592	0.00024	0.99042	0.00958
41	0.00016	0.99355	0.00645	0.00026	0.98956	0.01044
42	0.00017	0.99297	0.00703	0.00027	0.98862	0.01138
43	0.00018	0.99235	0.00765	0.00029	0.98762	0.01238
44	0.00019	0.99167	0.00833	0.00031	0.98653	0.01347
45	0.00020	0.99094	0.00906	0.00033	0.98535	0.01465
46	0.00022	0.99016	0.00984	0.00035	0.98408	0.01592
47	0.00023	0.98930	0.01070	0.00037	0.98271	0.01729
48	0.00024	0.98839	0.01161	0.00039	0.98123	0.01877
49	0.00026	0.98739	0.01261	0.00042	0.97963	0.02037
50	0.00028	0.98632	0.01368	0.00045	0.97790	0.02210
51	0.00029	0.98517	0.01483	0.00048	0.97605	0.02395
52	0.00031	0.98392	0.01608	0.00051	0.97405	0.02595
53	0.00033	0.98258	0.01742	0.00054	0.97189	0.02811
54	0.00035	0.98113	0.01887	0.00057	0.96957	0.03043
55	0.00038	0.97957	0.02043	0.00061	0.96707	0.03293
56	0.00040	0.97789	0.02211	0.00065	0.96438	0.03851
58	0.00045	0.97413	0.02587	0.00073	0.95838	0.04162
59	0.00048	0.97204	0.02796	0.00078	0.95503	0.04497
60	0.00051	0.96978	0.03022	0.00083	0.95145	0.04855
61	0.00054	0.96736	0.03264	0.00088	0.94759	0.05241
62	0.00058	0.96476	0.03524	0.00094	0.94346	0.05654
63	0.00062	0.96196	0.03804	0.00100	0.93902	0.06098
64	0.00065	0.95895	0.04105	0.00106	0.93426	0.06574
65	0.00070	0.95572	0.04428	0.00113	0.92917	0.07083
66	0.00074	0.95226	0.04774	0.00120	0.92371	0.07629
67	0.00079	0.94854	0.05146	0.00128	0.91787	0.08213
68	0.00084	0.94456	0.05544	0.00136	0.91162	0.08838
69	0.00089	0.94029	0.05971	0.00145	0.90494	0.09506
70	0.00095	0.93571	0.06429	0.00154	0.89781	0.10219
71	0.00101	0.93081	0.06919	0.00164	0.89019	0.10981
72	0.00107	0.92556	0.07444	0.00174	0.88207	0.11793
73	0.00114	0.91996	0.08004	0.00185	0.87341	0.12659
74	0.00122	0.91396	0.08604	0.00197	0.86420	0.13580
75	0.00129	0.90755	0.09245	0.00210	0.85439	0.14561
76	0.00138	0.90071	0.09929	0.00223	0.84397	0.15603
77	0.00146	0.89341	0.10659	0.00237	0.83290	0.16710
78	0.00156	0.88563	0.11437	0.00253	0.82116	0.17884
79	0.00166	0.87733	0.12267	0.00269	0.80872	0.19128
80	0.00176	0.86850	0.13150	0.00286	0.79556	0.20444
81	0.00187	0.85911	0.14089	0.00304	0.78165	0.21835
82	0.00199	0.84913	0.16146	0.00344	0.75151	0.24849
84	0.00226	0.82729	0.17271	0.00366	0.73523	0.26477
85	0.00240	0.81539	0.18461	0.00390	0.71814	0.28186

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