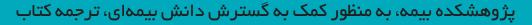
STUART A. KLUGMAN · HARRY H. PANJER GORDON E. WILLMOT

LOSS
MODELS
FROM DATA TO DECISIONS

FIFTH EDITION

SOCIETY OF ACTUARIES

فراخوان ترجمه کتاب



LOSS MODELS FROM DATA TO DECISIONS

را در دستور کار خود قرار داده است. لذا از کلیه اساتید، پژوهشگران، صاحبنظران و کارشناسان دعوت میشود که در صورت تمایل به ترجمه کتاب مذکور، کاربرگ درخواست ترجمه پیوست را به همراه سوابق علمی و اجرایی خود و ترجمه صفحات ذکر شده با ذکر عنوان کتاب، حداکثر تا تاریخ ۱۴۰۳/۰۲/۳۱ به آدرس ایمیل nashr@irc.ac.ir ارسال فرمایند.

ضريب	امتيازات	معیارهای ارزیابی
١	میانگین امتیاز ۲ داور (حداکثر ۱۰)	كيفيت ترجمه
۲.٠	سوابق علمی مرتبط با موضوع کتاب: دکترا ۱۰ – ارشد ۸ – کارشناسی ۲ سوابق علمی غیرمرتبط: دکترا ٤ – ارشد ۳ – کارشناسی ۲	سوابق علمى
٤.٠	سوابق مرتبط با موضوع کتاب: حداکثر ۱۰ امتیاز براساس نرمالسازی سوابق غیرمرتبط : ۲۰ درصد امتیاز فوق	سوابق تاليف/ترجمه كتاب
٤.٠	حداکثر ۱۰ امتیاز براساس نرمالسازی	سابقه فعالیت تخصصی در حوزه بیمه





کاربرگ درخواست ترجمه کتاب

LOSS MODELS: FROM DATA TO DECISIONS	كتاب:	عنوان
-------------------------------------	-------	-------

ناشر: WILEY سال نشر: ۲۰۱۹

الف- اطلاعات عمومي

نام و نام خانوادگی
شغل و سمت فعلى
مرتبه علمي (ویژه اعضای هیاتعلمي)
آخرین مدرک تحصیلی و رشته
آدرس
شماره تماس ثابت
شماره تماس همراه
پست الكترونيك

ب- سابقه تأليف/ترجمه (حداقل ٣ عنوان از آثار خود را اعلام بفرمائيد)

ناشر	سال انتشار	عنوان كتاب/ترجمه	ردیف

ج- سابقه اجرایی

مدت زمان خدمت	محل خدمت	ردیف

5.3 Selected Distributions and Their Relationships

5.3.1 Introduction

There are many ways to organize distributions into groups. Families such as Pearson (12 types), Burr (12 types), Stoppa (5 types), and Dagum (11 types) are discussed in Chapter 2 of [69]. The same distribution can appear in more than one system, indicating that there are many relations among the distributions beyond those presented here. The systems presented in Section 5.3.2 are particularly useful for actuarial modeling because all the members have support on the positive real line and all tend to be skewed to the right. For a comprehensive set of continuous distributions, the two volumes by Johnson, Kotz, and Balakrishnan [63, 64] are a valuable reference. In addition, there are entire books devoted to single distributions (such as Arnold [6] for the Pareto distribution). Leemis and McQueston [78] present 76 distributions on one page, with arrows showing all the various relationships.

5.3.2 Two Parametric Families

As noted when defining parametric families, many of the distributions presented in this section and in Appendix A are special cases of others. For example, a Weibull distribution with $\tau=1$ and θ arbitrary is an exponential distribution. Through this process, many of our distributions can be organized into groupings, as illustrated in Figures 5.2 and 5.3. The transformed beta family includes two special cases of a different nature. The paralogistic and inverse paralogistic distributions are created by setting the two nonscale parameters of the Burr and inverse Burr distributions equal to each other rather than to a specified value.

5.3.3 Limiting Distributions

The classification in Section 5.3.2 involved distributions that are special cases of other distributions. Another way to relate distributions is to see what happens as parameters go to their limiting values of zero or infinity.

■ EXAMPLE 5.10

Show that the transformed gamma distribution is a limiting case of the transformed beta distribution as $\theta \to \infty$, $\alpha \to \infty$, and $\theta/\alpha^{1/\gamma} \to \xi$, a constant.

8.4.1 Exercises

8.14 Determine the effect of 10% inflation on a policy limit of 150,000 on the following distribution. This is the same distribution as used in Exercises 8.1 and 8.6.

$$F_4(x) = \begin{cases} 0, & x < 0, \\ 1 - 0.3e^{-0.00001x}, & x \ge 0. \end{cases}$$

8.15 (*) Let X have a Pareto distribution with $\alpha = 2$ and $\theta = 100$. Determine the range of the mean excess loss function e(d) as d ranges over all positive numbers. Then, let Y = 1.1X. Determine the range of the ratio $e_Y(d)/e_X(d)$ as d ranges over all positive numbers. Finally, let Z be X right censored at 500 (i.e. a limit of 500 is applied to X). Determine the range of $e_Z(d)$ as d ranges over the interval 0 to 500.

8.5 Coinsurance, Deductibles, and Limits

The final common coverage modification is coinsurance. In this case, the insurance company pays a proportion, α , of the loss and the policyholder pays the remaining fraction. If coinsurance is the only modification, this changes the loss variable X to the payment variable, $Y = \alpha X$. The effect of multiplication has already been covered. When all four items covered in this chapter are present (ordinary deductible, limit, coinsurance, and inflation), we create the following per-loss random variable:

$$Y^{L} = \begin{cases} 0, & X < \frac{d}{1+r}, \\ \alpha[(1+r)X - d], & \frac{d}{1+r} \le X < \frac{u}{1+r}, \\ \alpha(u-d), & X \ge \frac{u}{1+r}. \end{cases}$$

For this definition, the quantities are applied in a particular order. In particular, the coinsurance is applied last. For the illustrated contract, the policy limit is $\alpha(u-d)$, the

maximum amount payable. In this definition, u is the loss above which no additional benefits are paid and is called the **maximum covered loss**. For the per-payment variable, Y^P is undefined for X < d/(1+r).

Previous results can be combined to produce the following theorem, presented without proof.

Theorem 8.7 For the per-loss variable,

$$\mathrm{E}(Y^L) = \alpha(1+r) \left[\mathrm{E}\left(X \wedge \frac{u}{1+r}\right) - \mathrm{E}\left(X \wedge \frac{d}{1+r}\right) \right].$$

The expected value of the per-payment variable is obtained as

$$E(Y^P) = \frac{E(Y^L)}{1 - F_X\left(\frac{d}{1+r}\right)}.$$

Higher moments are more difficult. Theorem 8.8 gives the formula for the second moment. The variance can then be obtained by subtracting the square of the mean.

Theorem 8.8 For the per-loss variable,

$$E[(Y^L)^2] = \alpha^2 (1+r)^2 \{ E[(X \wedge u^*)^2] - E[(X \wedge d^*)^2] - 2d^* E(X \wedge u^*) + 2d^* E(X \wedge d^*) \},$$

where $u^* = u/(1+r)$ and $d^* = d/(1+r)$. For the second moment of the per-payment variable, divide this expression by $1 - F_X(d^*)$.

Proof: From the definition of Y^L ,

$$Y^{L} = \alpha(1+r)[(X \wedge u^{*}) - (X \wedge d^{*})]$$

and, therefore,

$$\frac{(Y^L)^2}{[\alpha(1+r)]^2} = [(X \wedge u^*) - (X \wedge d^*)]^2$$

$$= (X \wedge u^*)^2 + (X \wedge d^*)^2 - 2(X \wedge u^*)(X \wedge d^*)$$

$$= (X \wedge u^*)^2 - (X \wedge d^*)^2 - 2(X \wedge d^*)[(X \wedge u^*) - (X \wedge d^*)].$$

The final term on the right-hand side can be written as

$$2(X \wedge d^*)[(X \wedge u^*) - (X \wedge d^*)] = 2d^*[(X \wedge u^*) - (X \wedge d^*)].$$

To see this, note that when $X < d^*$, both sides equal zero; when $d^* \le X < u^*$, both sides equal $2d^*(X - d^*)$; and when $X \ge u^*$, both sides equal $2d^*(u^* - d^*)$. Make this substitution and take expectations on each side to complete the proof.²

²Thanks to Ken Burton for providing this improved proof.

9.3.2 Stop-Loss Insurance

It is common for insurance to be offered in which a deductible is applied to the aggregate losses for the period. When the losses occur to a policyholder, it is called **insurance coverage**, and when the losses occur to an insurance company, it is called **reinsurance coverage**. The latter version is a common method for an insurance company to protect itself against an adverse year (as opposed to protecting against a single, very large claim). More formally, we present the following definition.

Definition 9.3 Insurance on the aggregate losses, subject to a deductible, is called **stop-loss insurance**. The expected cost of this insurance is called the **net stop-loss premium** and can be computed as $E[(S-d)_+]$, where d is the deductible and the notation $(\cdot)_+$ means to use the value in parentheses if it is positive and to use zero otherwise.

For any aggregate distribution,

$$E[(S - d)_{+}] = \int_{d}^{\infty} [1 - F_{S}(x)] dx.$$

If the distribution is continuous for x > d, the net stop-loss premium can be computed directly from the definition as

$$E[(S-d)_+] = \int_d^\infty (x-d) f_S(x) \, dx.$$

Similarly, for discrete random variables,

$$E[(S - d)_{+}] = \sum_{x > d} (x - d) f_{S}(x).$$

Any time there is an interval with no aggregate probability, the following result may simplify calculations.

Theorem 9.4 Suppose that Pr(a < S < b) = 0. Then, for $a \le d \le b$,

$$E[(S-d)_{+}] = \frac{b-d}{b-a}E[(S-a)_{+}] + \frac{d-a}{b-a}E[(S-b)_{+}].$$

INTRODUCTION TO LIMITED FLUCTUATION CREDIBILITY

16.1 Introduction

Credibility theory is a set of quantitative tools that allows an insurer to perform prospective experience rating (adjust future premiums based on past experience) on a risk or group of risks. If the experience of a policyholder is consistently better than that assumed in the underlying manual rate (sometimes called the **pure premium**), then the policyholder may demand a rate reduction.

The policyholder's argument is as follows. The manual rate is designed to reflect the expected experience (past and future) of the entire rating class and implicitly assumes that the risks are homogeneous. However, no rating system is perfect, and there always remains some heterogeneity in the risk levels after all the underwriting criteria are accounted for. Consequently, some policyholders will be better risks than that assumed in the underlying manual rate. Of course, the same logic dictates that a rate increase should be applied to a poor risk, but in this situation the policyholder is certainly not going to ask for a rate increase! Nevertheless, an increase may be necessary, due to considerations of equity and the economics of the situation.

The insurer is then forced to answer the following question: How much of the difference in experience of a given policyholder is due to random variation in the underlying claims experience and how much is due to the fact that the policyholder really is a better or worse risk than average? In other words, how credible is the policyholder's own experience? Two facts must be considered in this regard:

- 1. The more past information the insurer has on a given policyholder, the more **credible** is the policyholder's own experience, all else being equal. In the same manner, in group insurance the experience of larger groups is more credible than that of smaller groups.
- 2. Competitive considerations may force the insurer to give full (using the past experience of the policyholder only and not the manual rate) or nearly full credibility to a given policyholder in order to retain the business.

Another use for credibility is in the setting of rates for classification systems. For example, in workers compensation insurance, there may be hundreds of occupational classes, some of which may provide very little data. To accurately estimate the expected cost for insuring these classes, it may be appropriate to combine the limited actual experience with some other information, such as past rates, or the experience of occupations that are closely related.

From a statistical perspective, credibility theory leads to a result that would appear to be counterintuitive. If experience from an insured or group of insureds is available, our statistical training may convince us to use the sample mean or some other unbiased estimator. But credibility theory tells us that it is optimal to give only partial weight to this experience and give the remaining weight to an estimator produced from other information. We will discover that what we sacrifice in terms of bias, we gain in terms of reducing the average (squared) error.

Credibility theory allows an insurer to quantitatively formulate the problem of combining data with other information, and this part provides an introduction to this theory. This chapter deals with **limited fluctuation credibility theory**, a subject developed in the early part of the twentieth century. This theory provides a mechanism for assigning full (Section 16.3) or partial (Section 16.4) credibility to a policyholder's experience. The difficulty with this approach is the lack of a sound underlying mathematical theory to justify the use of these methods. Nevertheless, this approach provided the original treatment of the subject and is still in use today.

A classic paper by Bühlmann in 1967 [19] provides a statistical framework within which credibility theory has developed and flourished. While this approach, termed **greatest accuracy credibility theory**, was formalized by Bühlmann, the basic ideas had been around for some time. This approach is introduced in Chapter 17. The simplest model, that of Bühlmann [19], is discussed in Section 17.5. Practical improvements were made by Bühlmann and Straub in 1970 [21]. Their model is discussed in Section 17.6. The concept of exact credibility is presented in Section 17.7.

¹The terms *limited fluctuation* and *greatest accuracy* go back at least as far as a 1943 paper by Arthur Bailey [8].