ACTSC432 — Loss Models II

Classnotes for Spring 2019

by

Johnson Ng

BMath (Hons), Pure Mathematics major, Actuarial Science Minor University of Waterloo

Table of Contents

Ta	ble of Contents	2
Li	st of Definitions	4
Li	st of Theorems	5
Li	st of Procedures	6
Pı	eface	7
1	Introduction and Review of Probability	9
	1.1 Introduction to Credibility Theory	9
	1.2 Review of Probability	11
2	Review of Statistics	13
	2.1 Unbiased Estimation	13
	2.2 Mean Squared Error	18
	2.3 Maximum Likelihood Estimation	19
	2.4 Bayesian Estimation	21
	2.4.1 Conjugate Prior Distributions and the Linear Exponential Family	23
3	Limited Fluctuation Credibility Theory	27
	3.1 Limited Fluctuation Credibility	27
	3.2 Full Credibility	28
	3.3 Partial Credibility	33
	3.4 Problems with Limited Fluctuation Credibility	36
4	Greatest Accuracy Credibility	37

4.1	The Bayesian Methodology	38
4.2	The Credibility Premium	41
4.3	The Bühlmann Model	46
Bibliog	raphy	53
Index		54

List of Definitions

1	■ Definition (Estimate)	13
2	■ Definition (Estimator)	13
3	■ Definition (Biased and Unbiased Estimator)	14
4	■ Definition (Sample Variance)	16
5	■ Definition (Mean Squared Error)	18
6	■ Definition (Likelihood Function)	19
7	■ Definition (Maximum Likelihood Estimation)	19
8	■ Definition (Log-likelihood Function)	19
9	■ Definition (Prior Distribution)	21
10	■ Definition (Joint Distribution)	22
11	■ Definition (Marginal Distribution)	22
12	■ Definition (Posterior Distribution)	22
13	■ Definition (Posterior Mean)	23
14	■ Definition (Bayes Estimator)	23
15	■ Definition (Conjugate Prior Distribution)	2 4
16	■ Definition (Linear Exponential Family)	2 4
17	■ Definition (Predictive Distribution)	38
18	E Definition (Individual Premium)	39
19	■ Definition (Pure Premium)	39
20	■ Definition (Bayesian Premium)	39
21	■ Definition (Estimator for the Credibility Premium)	43
22	■ Definition (The Bühlmann Model)	46

List of Theorems

1	♦ Proposition (Sample Mean as the Unbiased Estimator of the Mean)	16
2	♦ Proposition (Sample Variance as the Unbiased Estimator of the Variance)	16
3	♦ Proposition (Formula for the Posterior Distribution)	23
4	■ Theorem (Conjugate Prior Distributions of Linear Exponential Distributions)	25
5	♦ Proposition (Formula for Predictive Distribution)	38
6	■Theorem (General Model for Credibility Premium)	41
7	$ ightharpoonup$ Corollary (\hat{P} as Best Linear Estimator)	43
8	■Theorem (Theorem 1)	44
9	■Theorem (Bühlmann Credibility Premium)	48

List of Procedures

Į,	(Condition for Full Credibility)	29
وإ	(Finding the Bayesian Premium)	39
وإ	(Finding Bühlmann Credibility Premium)	48



For this set of notes, I shall follow the format of which the course is presented, by breaking contents into modules instead of lectures. Also, I will be relying on the standard textbook for this topic, namely Klugman et al. 2012.

1 Introduction and Review of Probability

We shall first take an overview of what this course is about, and we will review on some of the relevant notions from earlier courses.

1.1 Introduction to Credibility Theory

Credibility Theory is a form of statistical inference that

- uses newly observed past events; to
- more accurately re-forecasts uncertain future events.

From Klugman et al. 2012,

It 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 (also called a pure premium), then the policyholder may demand a rate reduction.

That's all fancy mumbo-jumbo so let's go through an example that will hopefully enlighten us.

Example 1.1.1 (Enlightening Example to Credibility Theory)

Suppose automobile insurance policies are classified according to the following factors:

• number of drivers;

- gender of each driver;
- number of vehicles; and
- brand, model, production year, and approximate mileage driver per year.

Policies with identical characteristics are assumed to belong to the same **rating class**, which represents a group of individuals with similar risks.

Suppose there are 2 policies in the same rating class. Both policies are charged with a so-called **manual premium** of \$1,500 per year. This is the premium specified in the insurance manual for a policy with similar characteristics.

Let's say that after 3 years, we obtain the following data: We want

	Policy 1	Policy 2
Year 1	0	500
Year 2	200	4000
Year 3	0	2500

to find out what's a good premium to charge to each policy for Year 4.

Table 1.1: Newly acquired past history for finding 'credibility'

Remark 1.1.1

The shall leave the following as remarks.

- How is the policyholder's own experience account for? This is a key question that will be addressed in this course.
- Risks in a given rating class are not perfectly identical (i.e., no rating system is perfect)
- One may refine the rating system by incorporating more factors but it is time-consuming (and no system is perfect).

Thus, credibility theory is designed such that it

- accounts for heterogeneity within a given rating lass; and
- provides a theoretical justification to charge a premium that reflects to the policyholder's own experience.

1.2 Review of Probability

You are expected to be familiar with the following concepts:

- Joint and Marginal Distribution
- Conditional Distribution
- Mixture Distributions (see also ACTSC₄₃₁)
 - *n*-point Mixture
- Conditional Expectation

Some examples or more detailed review will be added for each topic if I come to work through them in detail.

Review of Statistics

In this chapter, we will review the following notions:

- Unbiased estimation
- Maximum likelihood estimation
- Bayesian estimation 🖈

2.1 Unbiased Estimation

Suppose we are given a **parametric model** ¹ of X, i.e. the distribution of $X \mid \Theta = \theta$ is known but θ is unknown. Furthermore, we have a **random sample** of X, i.e. we have $\{X_i\}_{i=1}^n$ is an independent and identically distributed (iid) sequence of random variables (rv) such that $X_i \sim X$.

¹ See ACTSC431.

■ Definition 1 (Estimate)

An estimate is a specific value that is obtained when applying an estimation procedure to a set of numbers, and in our case, rvs. We usually denote an estimate by a hat \cdot.

■ Definition 2 (Estimator)

An estimator is a rule or formula that produces an estimate. We usually denote an estimator by ~.

66 Note 2.1.1

An estimate is a number or a function, while an estimator is an rv or a random function.

Remark 2.1.1

In this course, we will not make a difference between the estimator and the estimate, and will use only .

■ Definition 3 (Biased and Unbiased Estimator)

We say that an estimator, $\hat{\theta}$, is unbiased if

$$E[\hat{\theta} \mid \theta] = \theta$$

for all θ . We say that an estimator is biased if it is not unbiased, and we define the bias as

$$bias_{\hat{\theta}}(\theta) = E[\hat{\theta} \mid \theta] - \theta.$$

Let's have ourselves a silly example.

Example 2.1.1

Let $(X_1, ..., X_n)$ be a random sample of $\text{Exp}(\beta)$. The sample mean

$$\overline{X} = \frac{1}{n} \sum_{i=1}^{n} X_i,$$

is an unbiased estimator for the mean β ; observe that by the **linearity** of the expectation, we have

$$E[\overline{X}] = E\left[\frac{1}{n}\sum_{i=1}^{n}X_{i}\right] = \frac{1}{n}\sum_{i=1}^{n}E[X_{i}] = \frac{1}{n}(n\beta) = \beta.$$

Example 2.1.2

Let $\{X_i\}_{i=1}^n$ be a random sample of $X \sim \text{Unif}(0, \theta)$. Let us construct two unbiased estimators for θ using

- 1. the sample mean \overline{X} ; and
- 2. order statistics $X_{(n)} \coloneqq \max_{1 \le i \le n} \{X_i\}$.



Solution

1. Observe that

$$E[\overline{X}] = E\left[\frac{1}{n}\sum_{i=1}^{n}X_i\right] = \frac{1}{n}\sum_{i=1}^{n}E[X_i] = \frac{1}{n}\cdot n\left(\frac{\theta}{2}\right) = \frac{\theta}{2}.$$

This tells us that if we picked $\hat{\theta} = 2\overline{X}$, then we would end up with

$$E[2\overline{X}] = \theta.$$

Thus $2\overline{X}$ is an unbiased estimator of θ .

2. Using the Darth Vader rule 2 , since the X_i 's form a random sample of X, and the bounds for each X_i is 0 and θ , we have that

$$\begin{split} E[X_{(n)}] &= \int_0^\infty \overline{F}_{X_{(n)}}(x) \, dx \\ &= \int_0^\infty \left(1 - P(\max\{X_1, X_2, \dots, X_n\}) \le x \right) dx \\ &= \int_0^\infty \left(1 - P(X_1 \le x) P(X_2 \le x) \dots P(X_n \le x) \right) dx \\ &= \int_0^\theta \left(1 - \left(\frac{x}{\theta} \right)^n \right) dx \\ &= \theta - \frac{1}{n+1} \left(\frac{x^{n+1}}{\theta^n} \right) \Big|_{x=0}^{x=\theta} = \frac{n}{n+1} \theta, \end{split}$$

where we note that we can change the bounds as such since $X \sim$ Unif $(0, \theta)$ implies that

$$P(X \le \theta) = \begin{cases} \frac{x}{\theta} & 0 \le x \le \theta \\ 1 & x > \theta \end{cases}.$$

Thus, to get an unbiased estimator for θ , we simply need to consider

$$\hat{\theta} = \frac{n+1}{n} X_{(n)},$$

which then

$$E\left[\frac{n+1}{n}X_{(n)}\right]=\theta.$$

² The **Darth Vader rule** is given as: if *X* is a non-negative rv, then

$$E[X] = \int_0^\infty \overline{F}_X(x) \, dx,$$

where \overline{F}_X is the survival function of X.

♦ Proposition 1 (Sample Mean as the Unbiased Estimator of the Mean)

Let $\{X_i\}_{i=1}^n$ be a random sample of X which has mean μ . Then \overline{X} is an unbiased estimator of μ .

Proof

We have that

$$E[\overline{X}] = \frac{1}{n} \sum_{i=1}^{n} E[X_i] = \frac{1}{n} (n\mu) = \mu.$$

■ Definition 4 (Sample Variance)

Let $\{X_i\}_{i=1}^n$ be a random sample of X which has mean μ and variance σ^2 . We define the sample variance as

$$\hat{\sigma}^2 := \frac{1}{n-1} \sum_{i=1}^n (X_i - \overline{X})^2.$$

♦ Proposition 2 (Sample Variance as the Unbiased Estimator of the Variance)

Let $\{X_i\}_{i=1}^n$ be a random sample of X which has mean μ and variance σ^2 . Then the sample variance $\hat{\sigma}^2$ is an unbiased estimator of σ^2 .

Proof

First, note that

$$Var(\overline{X}) = Var\left(\frac{1}{n}\sum_{i=1}^{n}X_{i}\right)$$
$$= \frac{1}{n^{2}}n Var(X_{i})$$
$$= \frac{1}{n}\sigma^{2}.$$

Thus

$$E\left[\sum_{i=1}^{n} (X_{i} - \overline{X})^{2}\right] = E\left[\sum_{i=1}^{n} (X_{i} - \mu + \mu - \overline{X})^{2}\right]$$

$$= \sum_{i=1}^{n} E\left[(X_{i} - \mu)^{2}\right] + \sum_{i=1}^{n} E\left[(\mu - \overline{X})^{2}\right]$$

$$+ 2E\left[\sum_{i=1}^{n} (X_{i} - \mu)(\mu - \overline{X})\right]$$

$$= n\sigma^{2} + n \operatorname{Var}(\overline{X})^{-3} + 2nE\left[(\overline{X} - \mu)(\mu - \overline{X})\right]^{-4}$$

$$= n\sigma^{2} - n \operatorname{Var}(\overline{X})$$

$$= n\sigma^{2} - n \left(\frac{1}{n}\sigma^{2}\right)$$

$$= (n-1)\sigma^{2}.$$

It follows that

$$E\left[\frac{1}{n-1}\sum_{i=1}^{n}(X_i-\overline{X})^2\right]=\sigma^2.$$

Remark 2.1.2

In general, unbiasedness is not preserved under parameter transformations. *E.g.*, $\frac{1}{\overline{X}}$ is generally not unbiased for μ , where μ is the mean of \overline{X} .

Some unbiased estimators can also be unreasonable.

Example 2.1.3

Consider $X \sim \text{Poi}(\lambda)$, where $\lambda > 0$. Note that

$$E[(-1)^X] = e^{\lambda(-1-1)} = e^{-2\lambda}$$

by the probability generating function method, and we see that $(-1)^X$ is an unbiased estimator of $e^{-2\lambda}$. However, we see that $(-1)^X$ only takes on values ± 1 , which is nowhere close to $e^{-2\lambda}$.

Intuitively, $e^{-2\overline{X}}$ would be a "better" estimator despite the fact that it is biased.

- ⁴ This relies on the fact that \overline{X} is the unbiased estimator for μ (cf.
- ♦ Proposition 1). We then use the definition of the variance to achieve
- ⁴ We used the fact that

$$\sum_{i=1}^{n} (X_i - \mu) = \sum_{i=1}^{n} X_i - n\mu = n\overline{X} - n\mu.$$

Also, note that

$$Var(\overline{X}) = E[(\overline{X} - \mu)^2].$$

Despite shortcomings like the above, unbiasedness is generally a good property for an estimator to have.

2.2 Mean Squared Error

■ Definition 5 (Mean Squared Error)

Suppose $\hat{\theta}$ is an estimator for the parameter θ . The mean squared error (MSE) of $\hat{\theta}$ is defined as

$$\mathrm{MSE}_{\hat{\theta}}(\theta) \coloneqq E\left\lceil (\hat{\theta} - \theta)^2 \right\rceil = \mathrm{Var}(\hat{\theta}) + \mathrm{bias}_{\hat{\theta}}(\theta)^2.$$

Proof

It is not immediately clear how the two expressions are the same. We shall prove it here. First, note that $\operatorname{bias}_{\hat{\theta}}(\theta) = E[\hat{\theta}] - \theta$ is a real value. Using a similar idea as in \bullet Proposition 2, we see that

$$E\left[\left(\hat{\theta} - \theta\right)^{2}\right] = E\left[\left(\hat{\theta} - E[\hat{\theta}] + E[\hat{\theta}] - \theta\right)^{2}\right]$$

$$= E\left[\left(\hat{\theta} - E[\hat{\theta}]\right)^{2}\right] + E\left[\left(E[\hat{\theta}] - \theta\right)^{2}\right]$$

$$+ 2E\left[\left(\hat{\theta} - E[\hat{\theta}]\right)\left(E[\hat{\theta}] - \theta\right)\right]$$

$$= Var(\hat{\theta}) + bias_{\hat{\theta}}(\theta)^{2}$$

$$+ 2bias_{\hat{\theta}}(\theta) E[\hat{\theta} - E[\hat{\theta}]]$$

$$= Var(\hat{\theta}) + bias_{\hat{\theta}}(\theta)^{2}.$$

66 Note 2.2.1

The MSE is a measure to evaluate the quality of estimators. The smaller the MSE, the better the estimator.

2.3 Maximum Likelihood Estimation

■ Definition 6 (Likelihood Function)

Let $\{X_i\}_{i=1}^n$ be a random sample of X with density $f(x;\underline{\theta})$, where $\underline{\theta}$ is possibly a vector of parameters. The likelihood function for $\underline{\theta}$ is defined as

 $L(\underline{\theta}) = \prod_{i=1}^{n} f(X_i; \underline{\theta}).$

■ Definition 7 (Maximum Likelihood Estimation)

The maximum likelihood estimation (MLE) of $\hat{\underline{\theta}}$ of $\underline{\theta}$ is an approach that maximizes $L(\hat{\theta})$.

66 Note 2.3.1

Heuristically, under the MLE, $\hat{ heta}$ is the most likely parameter for the sample (X_1, \ldots, X_n) to be realized.

Sometimes, the likelihood function is difficult to work with. Fortunately, since ln x is a increasing bijective function that preserves monotonicity, we can make us of this property to ensure maximality.

■ Definition 8 (Log-likelihood Function)

The log-likelihood function is defined as

$$l(\underline{\theta}) = \sum_{i=1}^{n} \ln(f(X_i; \underline{\theta})).$$

Example 2.3.1

Let $\{X_i\}_{i=1}^n$ be a random sample for $N(\mu, v)$. Find the MLE for $\mu, v.$

Solution

First, we shall work on getting an MLE for μ . The likelihood function here is

$$L(\mu) = \prod_{i=1}^{n} f(X_i; \mu)$$

$$= \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(X_i - \mu)^2}{2\sigma^2}}$$

$$\propto \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^{n} (X_i - \mu)^2\right\}.$$

Evaluating the derivative and equating it to 0 would be fruitless, since this is an exponentiation. Thus we appeal to the log-likelihood, which is

$$l(\mu) \propto \sum_{i=1}^{n} (X_i - \mu)^2.$$

The derivative log-likelihood is thus

$$\frac{dl}{d\mu} \propto -2\sum_{i=1}^{n} (X_i - \mu).$$

Equating the above to 0, we get

$$\hat{\mu} = \overline{X}$$
.

Now for an MLE of σ^2 . For sanity, let us denote $\tau = \sigma^2$. Then the likelihood function, focusing on τ , is

$$L(\tau) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\tau}} e^{-\frac{(X_i - \mu)^2}{2\tau}}$$
$$\propto \tau^{-\frac{n}{2}} e^{-\frac{1}{2\tau} \sum_{i=1}^{n} (X_i - \mu)^2}.$$

Again, the likelihood involves an exponentiation, so we appeal to the log-likelihood, which is

$$l(\tau) \propto -\frac{n}{2} \ln \tau - \frac{1}{2\tau} \sum_{i=1}^{n} (X_i - \mu)^2.$$

The derivative of the log-likelihood is

$$\frac{dl}{d\tau} = -\frac{n}{2\tau} + \frac{1}{2\tau^2} \sum_{i=1}^{n} (X_i - \mu)^2.$$

Equating the above to 0, we get

$$n = \frac{1}{\hat{\tau}} \sum_{i=1}^{n} (X_i - \hat{\mu})^2,$$

and so

$$\hat{\sigma}^2 = \hat{\tau} = \frac{1}{n} \sum_{i=1}^n (X_i - \overline{X})^2$$

Bayesian Estimation

From Klugman et al. 2012,

The Bayesian approach assumes that only the data actually observed are relevant and it is the population distribution that is variable.

■ Definition 9 (Prior Distribution)

The prior distribution is a probability distribution over the space of possible parameter values. It is denoted $\pi(\theta)$ and represents our opinion concerning the relative chances that various values of θ are the true value of the parameter.

66 Note 2.4.1

- The parameter θ may be scalar or vector valued.
- Determining the prior distribution has always been one of the barriers to the widespread acceptance of the Bayesian methods, since it is almost certainly the case that your experience has provided you with some insight about possible parameter values before the first data point has been observed.

We shall use the following concepts from multivariate statistics to obtain the following definitions.

■ Definition 10 (Joint Distribution)

Let $\{X_i\}_{i=1}^n$ be a random sample of the $rv\ X$, and Θ another $rv\ that$ is independent of the X_i 's 5 , with pdf π . Let $\vec{X}=(X_1,X_2,\ldots,X_n)$. Then the joint distribution of \vec{X} and Θ is defined as

$$f_{\vec{X},\Theta}(\vec{x},\theta) = f_{\vec{X}\mid\Theta}(\vec{x}\mid\theta)\pi(\theta).$$

⁵ Note that Θ does not necessarily have a similar distribution to X.

■ Definition 11 (Marginal Distribution)

Let $\{X_i\}_{i=1}^n$ be a random sample of the $rv\ X$, and Θ another $rv\ that$ is independent of the X_i 's 6 , with pdf π . Let $\vec{X}=(X_1,X_2,\ldots,X_n)$. Then the marginal distribution of \vec{X} is defined as

$$f_{\vec{X}}(\vec{x}) = \int f_{\vec{X}|\Theta}(\vec{x} \mid \theta) \pi(\theta) d\theta.$$

 6 Note that Θ does not necessarily have a similar distribution to X.

Once we have obtained data, we can look back at our prior distribution and "update" it to...

■ Definition 12 (Posterior Distribution)

Let $\{X_i\}_{i=1}^n$ be a random sample of the rv X, and Θ another rv that is independent of the X_i 's 7 , with pdf π . The posterior distribution, denoted by $\pi_{\Theta \mid \vec{X}}(\theta \mid \vec{x})$, is the conditional probability distribution of the parameters given the observed data.

 7 Note that Θ does not necessarily have a similar distribution to X.

It is easy to find out what the general formula of the posterior distribution is. One simply needs to make use of E Definition 10 and Definition 11. The proof of the following proposition is left as an easy brain exercise for the reader.

Exercise 2.4.1

Prove Proposition 3.

• Proposition 3 (Formula for the Posterior Distribution)

With the assumptions in 🗏 Definition 12, we have that the posterior distribution can be computed as

$$\begin{split} \pi_{\Theta \mid \vec{X}}(\theta \mid \vec{x}) &= \frac{f_{\vec{X},\Theta}(\vec{x},\theta)}{f_{\vec{X}}(\vec{x})} \\ &= \frac{\left(\prod_{i=1}^{n} f_{X_{i}\mid\Theta}(x_{i}\mid\theta)\right)\pi(\theta)}{\int_{\forall \theta} \left(\prod_{i=1}^{n} f_{X_{i}\mid\Theta}(x_{i}\mid\theta)\right)\pi(\theta)\,d\theta}. \end{split}$$

■ Definition 13 (Posterior Mean)

The posterior mean is defined as the expected value of the posterior distribution.

■ Definition 14 (Bayes Estimator)

The Bayes estimator of Θ is the posterior mean of Θ , defined as

$$\hat{\theta}_{B} := E[\Theta \mid \vec{X} = \vec{x}] = \int_{\forall \theta} \theta \cdot \pi_{\Theta \mid \vec{X}}(\theta \mid \vec{x}).$$

66 Note 2.4.2

It can be shown that $\hat{\theta}_B$ minimizes the mean square error

$$\min_{\hat{\theta}} E\left[\left(\hat{\theta} - \Theta\right)^2 \mid \vec{X} = \vec{x}\right].$$

2.4.1 Conjugate Prior Distributions and the Linear Exponential Family

■ Definition 15 (Conjugate Prior Distribution)

A prior distribution is said to be a conjugate prior distribution for a given model if the resulting posterior distribution is from the same family as the prior, although possibly with different parameters.

8

⁸ More examples should be added here.

Example 2.4.1

The following are some important/prominent examples of conjugate prior distributions:

$\pi(\theta)$	$f(x \mid \theta)$	$\pi(\theta \mid \vec{x})$
Gamma	Poisson	Gamma
Normal	Normal	Normal
Beta	Binomial	Beta
Beta	Geometric	Beta

Table 2.1: Important/Prominent Conjugate Prior Distributions

■ Definition 16 (Linear Exponential Family)

An rv X is said to belong to the linear exponential family if its pdf is of the form

$$f(x,\theta) = \frac{p(x)e^{xr(\theta)}}{q(\theta)},$$

where p(x) is some function of x, and $r(\theta)$, $q(\theta)$ are some functions of θ , and the support of f does not depend on θ .

Example 2.4.2

Some members of the linear exponential family include

- $\operatorname{Exp}(\theta): f(x, \theta) = \frac{1}{\theta} e^{-\frac{x}{\theta}}$, where p(x) = 1, $r(\theta) = -\frac{1}{\theta}$ and $q(\theta) = \theta$.
- $Gam(\alpha, \theta)$: $f(x, \alpha, \theta) = \frac{1}{\Gamma(\alpha)\theta^{\alpha}} x^{\alpha 1} e^{-\frac{x}{\theta}}$.
- $\operatorname{Poi}(\theta) : f(x, \theta) = \frac{\theta^x e^{-\theta}}{x!} = \frac{\frac{1}{x!} e^{x \ln \theta}}{e^{\theta}}$
- $N(\theta, v) : f(x, \theta, v) = \frac{1}{\sqrt{2\pi v}} e^{-\frac{(x-\theta)^2}{2v}} = \frac{(2\pi v)^{-\frac{1}{2}} e^{-\frac{x^2}{2v}} e^{x\frac{\theta}{v}}}{e^{\theta^2/2v}}$

66 Note 2.4.3

Basically, functions the belong to a linear exponential family is a linear-like function with an exponent.

Theorem 4 (Conjugate Prior Distributions of Linear Exponential Distributions)

Suppose that given $\Theta= heta$ the rvs $ec{X}$ are iid with pf

$$f_{X_j \mid \Theta}(x_j \mid \theta) = \frac{p(x_j)e^{r(\theta)x_j}}{q(\theta)},$$

where Θ has the pdf

$$\pi(\theta) = \frac{[q(\theta)]^{-k} e^{\mu k r(\theta)} r'(\theta)}{c(\mu, k)},$$

where μ and k are parameters of the distribution and $c(\mu, k)$ is the nor*malizing constant* ⁹. Then the posterior pf $\pi_{\Theta \mid \vec{X}}(\theta \mid \vec{x})$ is of the same form as $\pi(\theta)$, i.e. $\pi(\theta)$ is a conjugate prior distribution function.

⁹ The normalizing constant is used to reduce any probability function to a probability density function with a total probability of 1. (Source: Wikipedia)

Proof

Notice that the posterior distribution is

$$\pi(\theta \mid \vec{x}) = \frac{\left(\prod_{i=1}^{n} f_{X_{i}\mid\Theta}(x_{i}\mid\theta)\right)\pi(\theta)}{\int_{\forall\theta} \left(\prod_{i=1}^{n} f_{X_{i}\mid\Theta}(x_{i}\mid\theta)\right)\pi(\theta)d\theta}$$

$$\propto \left(\prod_{i=1}^{n} f_{X_{i}\mid\Theta}(x_{i}\mid\theta)\pi(\theta)\right)$$

$$= \left(\prod_{i=1}^{n} \frac{p(x_{j})e^{r(\theta)x_{j}}}{q(\theta)}\right) \left(\frac{[q(\theta)]^{-k}e^{\mu k r(\theta)}r'(\theta)}{c(\mu,k)}\right)$$

$$\propto q(\theta)^{-(n+k)}e^{\mu k + n\bar{x}r(\theta)}r'(\theta)$$

$$= q(\theta)^{-k^{*}}e^{\mu^{*}k^{*}r(\theta)}r'(\theta),$$

where

$$k^* = k + n$$
, and $\mu^* = \frac{\mu k + \sum x_j}{k + n} = \frac{k}{k + n} \mu + \frac{n}{k + n} \overline{x}$,

and we see that the posterior distribution has the same form as $\pi(\theta)$.

Example 2.4.3

One non-example is mentioned in Example 2.4.1: the distribution of X_i is not from the linear exponential family, but we still obtain that the posterior distribution has a similar distribution to the posterior distribution.

Limited Fluctuation Credibility The-

ory

The Limited Fluctuation Credibility Theory provides a mechanism for assigning **full** or **partial credibility** to a policyholder's experience. The difficulty with this approach is its lack of a sound underlying mathematical theory that justifies the use of these methods. Despite that fact, it is still widely used today, especially in the United States.

3.1 Limited Fluctuation Credibility

From Klugman et al. 2012,

This branch of credibility theory represents the first attempt to quantify the credibility problem.

This approach is also known as the "American credibility". It was first proposed by Mowbray in 1914 ¹.

The problem can be formulated as follows. Suppose that $\{X_i\}_{i=1}^n$ represents a policyholder's claim amounts in the past n years. Furthermore, we assume that the X_i 's have

- the same expected value, i.e. $E[X_i] = \mu$ for some μ ; and
- variance, i.e. $Var(X_i) = \sigma^2$ for some σ .

From our revision in the last section, we know that \overline{X} is an unbiased estimator for μ , and if the X_i 's are independent, then $Var(\overline{X}) = \frac{\sigma^2}{n}$.

The goal here is to figure our how much to charge for the next

¹ Mowbray, A. H. (1914). How extensive a payroll exposure is necessary to give a dependable pure premium? *Proceedings* of the Casualty Actuarial Society, I:24–30 premium, i.e. determining $E[X_{n+1}]$. We have at least the following 3 possibilities:

- ignore past data (no credibility) and charge M, a value, called the manual premium ², obtained from experience on other similar but non-identical policyholders;
- ignore M and charge \overline{X} (full credibility); and a third possibility is to
- choose some combination of M and \overline{X} (partial credibility).

From the POV of an insurer, it seems sensible to favor \overline{X} if the experience is "stable", i.e. there is little fluctuation, represented by a small σ^2 . Stable values imply that \overline{X} is more reliable as a predictor. Conversely, if \overline{X} is volatile, then M would be a safer choice.

² This name is obtained from the fact that it usually comes from a book (manual) of premiums.

3.2 Full Credibility

In full credibility theory, there are only 2 outcomes: either we

- assign full credibility, that is to charge \overline{X} ; or
- no credibility, where we charge *M*.

One method to 'quantify the stability' of \overline{X} 3 is to infer that \overline{X} is stable if the difference between \overline{X} and μ is small relative to μ with high probability, i.e.

$$P(\left|\overline{X} - \mu\right| \le \varepsilon \mu) \ge p \tag{3.1}$$

for some $\varepsilon > 0$ and 0 . We may rewrite Equation (3.1) as

$$P\left(\frac{\left|\overline{X}-\mu\right|}{\sigma/\sqrt{n}} \le \frac{\varepsilon\mu}{\sigma/\sqrt{n}}\right) \ge p.$$

Now let y_p be defined as by

$$y_p = \operatorname{VaR}_p\left(\frac{\left|\overline{X} - \mu\right|}{\sigma/\sqrt{n}}\right) = \inf\left\{y \in \mathbb{R} : P\left(\frac{\left|\overline{X} - \mu\right|}{\sigma/\sqrt{n}} \le y\right) \ge p\right\}.$$

If \overline{X} is continuous, then the \geq sign above can be replaced with an "=" sign ⁴, and y_p satisfies

⁴ See ACTSC431.

³ This has become the standard method for 'quantifying stability' for \overline{X} .

$$P\left(\frac{\left|\overline{X}-\mu\right|}{\sigma/\sqrt{n}} \le y_p\right) = p. \tag{3.2}$$

Then the condition for full credibility is

$$y_p \leq \frac{\varepsilon \mu}{\sigma/\sqrt{n}}$$
.

Making n the subject, we have that the number of exposure required for full credibility is thus

$$n \ge \left(\frac{y_p}{\varepsilon}\right)^2 \frac{\sigma^2}{\mu^2} = \lambda_0 \frac{\sigma^2}{\mu^2},\tag{3.3}$$

where we let $\lambda_0 = \left(\frac{y_p}{\varepsilon}\right)^2$ for notational succinctness since it is a constant that depends only p and ε .

It is often difficult to identify a distribution for \overline{X} , of which y_p depends on. Recall the normal approximation, which is applicable if *n* is large ⁵:

$$\frac{\overline{X} - \mu}{\sigma / \sqrt{n}} \approx Z_{0,1} \sim N(0,1)$$

Then Equation (3.2) becomes

$$p = P(|Z| \le y_p) = \Phi(y_p) - \Phi(-y_p)$$

= $\Phi(y_p) - 1 + \Phi(y_p) = 2\Phi(y_p) - 1$.

Thus

$$y_p pprox \Phi^{-1}\left(\frac{1+p}{2}\right).$$

Example 3.2.1

Suppose that one has data $\{X_i\}_{i=1}^{10}$ on the claim amounts in the last 10 periods, where

$$X_i = 0 \text{ for } i = 1, \dots, 6,$$

and

$$X_7 = 253$$
, $X_8 = 398$, $X_9 = 439$, $X_{10} = 756$.

Determine the condition for full credibility with $\varepsilon = 0.05$ and p =0.9.

Solution

P (Condition for Full Credibility)

- 1. Use the central limit theorem argument
- 2. Calculate RHS of Equation (3.3).

5 Is this not circular!?

We need to first determine the sample mean and sample variance, and we shall use the unbiased estimators of μ and σ^2 respectively: they are

$$\overline{X} = \frac{1}{10} \sum_{i=1}^{10} X_i = \frac{0 + 253 + 398 + 439 + 756}{10} = 184.6,$$

and

$$\hat{\sigma}^2 = \frac{1}{10-1} \sum_{i=1}^{10} (X_i - \overline{X})^2 = 267.89^2.$$

We also need

$$y_p = \Phi^{-1}\left(\frac{1+p}{2}\right) = \Phi^{-1}(.95) = 1.645.$$

Then we require that

$$n \ge \left(\frac{1.645}{0.05}\right)^2 \left(\frac{267.89^2}{184.6^2}\right) = 2279.5.$$

We see that the 10 observations definitely do not deserve full credibility.

Full credibility is sometimes given on a number of claims basis (instead of on the claims amount).

Example 3.2.2

Suppose that one has iid data $\{N_i\}_{i=1}^n$ on the number of claims in the past n periods, with $N_i \sim \operatorname{Poi}(\lambda)$. Determine the condition for full credibility in terms of the **expected total number of claims** given that p = 0.9 and $\varepsilon = 0.05$.

Solution

Since $N_i \sim \text{Poi}(\lambda)$, we have $E[N_i] = \lambda = \text{Var}(N_i)$. Furthermore,

$$y_p = \Phi^{-1}(0.95) = 1.645.$$

Now since the condition is

$$n \ge \lambda_0 \frac{\sigma^2}{u^2} = \frac{\lambda_0}{\lambda},$$

and we want the expected total number of claims, we focus on look-

ing at

$$n\mu = n\lambda \ge \lambda_0$$
.

Observe that

$$\lambda_0 = \left(\frac{1.645}{0.05}\right)^2 = 1082.41,$$

we have that the required expected total number of claims should fulfill

$$n\lambda \ge 1082.41$$
.

Example 3.2.3 (Compound Poisson for Full Credibility)

Let $\{X_i\}_{i=1}^n$ be a sequence of iid compound Poisson rvs, given by

$$X_i = \sum_{j=1}^{N_i} Y_{i,j} = \begin{cases} \sum_{j=1}^{N_i} Y_{i,j}, & N_i \ge 0 \\ 0 & N_i = 0 \end{cases}$$

where

- $\{N_i\}_{i=1}^n$ are iid with $N_i \sim \text{Poi}(\lambda)$ for each i; and
- $\{Y_{i,j}\}$ are also iid with mean μ_Y and variance σ_Y^2 .

Determine the condition for full credibility.

Solution

We require the unconditional sample mean and sample variance of X_i ; they are

$$E[X_i] = E[E[X_i \mid N_i]] = E[N_i]E[Y_{i,j}] = \lambda \mu_Y,$$

and

$$Var(X_i) = Var(E[X_i \mid N_i]) + E[Var(X_i \mid N_i)]$$

$$= Var(N_i\mu_Y) + E[N_i\sigma_Y^2]$$

$$= \mu_Y^2\lambda + \sigma_Y^2\lambda$$

$$= \lambda(\mu_Y^2 + \sigma_Y^2).$$

Thus, the condition for full credibility is

$$n \geq \lambda_0 rac{\lambda(\mu_Y^2 + \sigma_Y^2)}{\lambda^2 \mu_Y^2} = rac{\lambda_0}{\lambda} \left(1 + rac{\sigma_Y^2}{\mu_Y^2}
ight).$$

To further illustrate that we can use the concept of full credibility for different things, the following example is provided.

Example 3.2.4

Suppose that the average claim size for a group of insureds is 1500 with a standard deviation of 7500. Furthermore, assume that claim counts have a Poisson distribution. For $\varepsilon=0.06$ and p=0.9, determine the standard for full credibility based on the

- 1. total claim amount; and
- 2. total number of claims,

in terms of the expected total number of claims.



1. Using the last example and letting

$$E[X_i] = \mu$$
 and $Var(X_i) = Var(X_i) = \sigma^2$,

the standard for full credibility is

$$n \ge \frac{\lambda_0}{\lambda} \left(1 + \frac{\sigma_Y^2}{\mu_Y^2} \right).$$

We are given that

$$\mu_Y = 1500$$
 and $\sigma_Y^2 = 7500^2$.

Thus

$$n \ge \frac{1.645^2}{0.06^2 \lambda} \left(1 + \frac{7500^2}{1500^2} \right) = \frac{19543.51}{\lambda}.$$

In terms of the expected total number of claims, we have

$$n\lambda > 19543.51$$
.

Thus the observed total number of claims of past claims must be at least 19544 to assign full credibility.

2. Using Example 3.2.2, we have

$$n \ge \frac{\lambda_0}{\lambda} = \frac{751.67}{\lambda}.$$

Thus, in terms of the expected total number of claims, we have

$$n\lambda \ge 751.67$$
.

Therefore, the observed total number of past claims must be at least 752 to assign full credibility.

3.3 Partial Credibility

If full credibility is inappropriate, then we may want to assign partial **credibility** to the past experience \overline{X} in the net premium. Without much mathematical support, it was suggested that we let the net premium be defined as a weighted average of \overline{X} and the manual premium M, i.e.

$$P = Z\overline{X} + (1 - Z)M,$$

where $Z \in [0,1]$ is known as the credibility factor ⁶ ⁷, which is a value that needs to be chosen.

In the actuarial literature ⁸, there are various suggestions for determining Z. However, they are usually justified on intuition rather than theoretically sound grounds. We shall discuss one of the choices here, which is flawed, but is at least simple.

Recall that the goal of the full-credibility standard is to ensure that the difference between \overline{X} and μ is small with high probability (cf. beginning of Section 3.2). Since \overline{X} is unbiased, to achieve this standard is basically ⁹ equivalent to controlling the variance of \overline{X} . Note that full credibility fails when

$$n < \lambda_0 \left(\frac{\sigma^2}{\mu^2} \right), \tag{3.4}$$

and since the sample variance (which is unbiased for the variance) is

$$\operatorname{Var}(\overline{X}) = \frac{\sigma^2}{n},$$

rearranging Equation (3.4), we have that

$$\operatorname{Var}(\overline{X}) = \frac{\sigma^2}{n} > \frac{\mu^2}{\lambda_0}.$$

⁶ It is important to note there that *Z* is not an rv. It is simply a pretentious choice of notation for what is to come. 7 It is interesting to remark that Mowbray 1914 considered full but not partial credibility.

⁸ Klugman, S. A., Panjer, H. H., and Willmot, G. E. (2012). Loss Models: From Data to Decisions. John Wiley & Sons Inc., Hoboken, New Jersey, 4th edition

⁹ This is exactly the case if \overline{X} is normal.

Thus, we choose *Z* such that it controls the variance of the credibility premium as such:

$$\frac{\mu^2}{\lambda_0} = \text{Var}(P) = \text{Var}(Z\overline{X} + (1 - Z)M)$$
$$= Z^2 \text{Var}(\overline{X}) = Z^2 \cdot \frac{\sigma^2}{n}.$$

Thus, since we want Z as a weighted average, we let

$$Z = \min \left\{ \frac{\mu}{\sigma} \sqrt{\frac{n}{\lambda_0}}, 1 \right\}.$$

10 Note that

$$\frac{\mu}{\sigma}\sqrt{\frac{n}{\lambda_0}} = \sqrt{\frac{n}{\lambda_0(\frac{\sigma^2}{\mu^2})}},$$

which is the square root of the actual number of exposures divided by the number of exposures needed for full credibility. This is also referred to as the Square-root rule for partial credibility.

Example 3.3.1

Suppose that past observations of the number of claims $\{N_i\}_{i=1}^n$ are iid and $N_i \sim \text{Poi}(\lambda)$. Determine the credibility factor Z based on the number of claims.

Solution

Note that

$$\mu = E[N_i] = \lambda$$
 and $\sigma^2 = Var(N_i) = \lambda$.

We have that

$$Z = \min \left\{ \frac{\mu}{\sigma} \sqrt{\frac{n}{\lambda_0}}, 1 \right\} = \min \left\{ \sqrt{\frac{n\lambda}{\lambda_0}}, 1 \right\}.$$

Example 3.3.2

Consider the setup in Example 3.2.3. Determine the credibility factor Z based on the amount of claims.

Solution

¹⁰ Note that this choice of *Z* has some consistency with full credibility, since Z=1 iff $n \geq \lambda_0 \frac{\sigma^2}{\sigma^2}$.

We have that

$$\mu = E[X_i] = \lambda \mu_Y$$
 and $\sigma^2 = Var(X_i) = \lambda(\mu_Y^2 + \sigma_Y^2)$.

Then since

$$rac{\mu}{\sigma}\sqrt{rac{n}{\lambda_0}}=\sqrt{rac{n\lambda}{\lambda_0}\cdotrac{\mu_Y^2}{\mu_Y^2+\sigma_Y^2}},$$

we have that

$$Z = \min \left\{ \sqrt{rac{n\lambda}{\lambda_0} \cdot rac{\mu_Y^2}{\mu_Y^2 + \sigma_Y^2}}, 1
ight\}$$

DIFFERENT CREDIBILITY FACTORS may arise depending on the basis of which the credibility is founded upon.

Example 3.3.3

Consider the setup in Example 3.2.4. Further suppose that

- in thelast year, this group of insureds had 600 claims and a total loss of 15600; and
- the prior estimate of the total loss was 16500 (this is *M*).

Estimate the credibility premium for the group based on the

- 1. total claim amount; and
- 2. total number of claims.

Solution

1. We are given that $\mu_Y = 1500$, $\sigma_Y = 7500$ and $n\lambda = 600$. Thus

$$Z = \min \left\{ \sqrt{\frac{n\lambda}{\lambda_0} \cdot \frac{\mu_Y^2}{\mu_Y^2 + \sigma_Y^2}}, 1 \right\}$$
$$= \min \left\{ \sqrt{\frac{600}{\left(\frac{1.645}{0.06}\right)^2} \cdot \frac{1500^2}{1500^2 + 7500^2}}, 1 \right\}$$
$$= 0.17522$$

Thus the credibility premium for the group is

$$P = 0.17522\overline{X} + (1 - 0.17522)M$$

$$= 0.17522(15600) + (1 - 0.17522)(16500)$$
$$= 16342.302$$

11

2. Based on the total number of claims, the credibility factor is

$$Z = \min\left\{\sqrt{\frac{n\lambda}{\lambda_0}}, 1\right\} = \min\left\{\sqrt{\frac{600}{\left(\frac{1.645}{0.06}\right)^2}}, 1\right\} = 0.89343.$$

Thus the credibility premium for the group is

$$P = 0.89343\overline{X} + (1 - 0.89343)M = 15696.$$

3.4 Problems with Limited Fluctuation Credibility

 There is no theoretical model for the distribution of X_i's, and so there is no reason why

$$P = Z\overline{X} + (1 - Z)M$$

is a reasonable and more preferable to *M*.

- The choice of *Z* is rather arbitrary.
- There is no guidance to the choices of ε and p.
- The limited fluctuation approach does not examine the difference between μ and M. Furthermore, it is usually the case that M is also an estimate, and hence unreliable in itself.

 $\overline{X}=15600$ in this case, since this is the total loss over '1' period of time, in particular it is the total amount up to the latest time.

Greatest Accuracy Credibility

The **Greatest Accuary Credibility** approach is a model-based approach to the solution of the credibility problem, which is an outgrowth of Bühlmann's classic paper in 1967 ¹. The greater accuracy credibility is also called the **European credibility**.

In greatest accuracy credibility, we assume that all risk units in a given rating class have an **unknown risk parameter** θ that is associated with their risk level. Since different insureds have different θ values, risk units within a rating class are **not completely homogeneous**. This assumption allows us to quantify the differences between policyholders wrt to the risk characteristics.

¹ Bühmann, H. (1967). Experience rating and credibility. *ASTIN Bulletin*, 4:199–207

66 Note 4.0.1 (Assumptions)

We shall also always assume that θ exists, but we shall assume that it is not observable, and that we can never know its true value.

Since θ varies by policyholder, there is a probability distribution Θ across the rating class. We denote

- $\pi_{\Theta}(\theta)$ as the probability distribution of Θ ; and
- $\Pi_{\Theta}(\theta)$ as the cdf of Θ .

If θ is a scalar parameter ², then we may interpret

$$\Pi(\theta) = P(\Theta \le \theta)$$

as the percentage of policyholders in the rating class with risk parameter Θ less than or equal to θ .

² Refer to STAT330.

Furthermore, if we let $\{X_i\}_{i=1}^n$ be the past exposure units 3 , we will suppose that

³ which is not necessarily iid

$$\{X_i \mid \Theta = \theta\}_{i=1}^n$$

are iid, with common density function $f_{X|\Theta}(x \mid \theta)$.

We want to use these assumptions to derive a rate to cover for X_{n+1} .

4.1 The Bayesian Methodology

■ Definition 17 (Predictive Distribution)

The predictive distribution is the conditional probability distribution of a new observation y given the data \vec{x} . It is denoted as $f_{Y|\vec{X}}(y \mid \vec{x})$.

♦ Proposition 5 (Formula for Predictive Distribution)

Given exposure units $\{X_i\}_{i=1}^n$, the predictive distribution of a new observation, Y, can be computed as

$$f_{Y\mid \vec{X}}(y\mid \vec{x}) = \int_{\forall \theta} f_{Y\mid \Theta}(y\mid \theta) \pi_{\Theta\mid \vec{X}}(\theta\mid \vec{x}).$$

Proof

By the formula for the posterior distribution, we have that

$$\begin{split} \pi_{\Theta \mid \vec{X}}(\theta \mid \vec{x}) &= \frac{f_{\Theta, \vec{X}}(\theta, \vec{x})}{f_{\vec{X}}(\vec{x})} \\ &= \frac{f_{\vec{X} \mid \Theta}(\vec{x} \mid \theta) \pi(\theta)}{\int_{\forall \theta} f_{\vec{X} \mid \Theta}(\vec{x} \mid \theta) \pi(\theta) \, d\theta}. \end{split}$$

Also, observe that

$$f_{Y,\vec{X}}(y,\vec{x}) = \int_{\forall \theta} f_{(Y,\vec{X})|\Theta}(y,\vec{x} \mid \theta) \pi(\theta) d\theta$$

$$= \int_{\forall \theta} f_{Y \mid \Theta}(y \mid \theta) f_{\vec{X} \mid \Theta}(\vec{x} \mid \theta) \pi(\theta) d\theta,$$

where the second equality follows from our assumption that the conditional observations are independent. Then

$$\begin{split} f_{Y\mid\vec{X}}(y\mid\vec{x}) &= \frac{f_{Y,\vec{X}}(y,\vec{x})}{f_{\vec{X}}(\vec{x})} \\ &= \frac{\int_{\forall\theta} f_{Y\mid\Theta}(y\mid\theta) f_{\vec{X}\mid\Theta}(\vec{x}\mid\theta) \pi(\theta) \, d\theta}{\int_{\forall\theta} f_{\vec{X}\mid\Theta}(\vec{x}\mid\theta) \pi(\theta) \, d\theta} \\ &= \int_{\forall\theta} f_{Y\mid\Theta}(y\mid\theta) \pi_{\Theta\mid\vec{X}}(\theta\mid\vec{x}). \end{split}$$

■ Definition 18 (Individual Premium)

Given the X_{n+1} exposure unit and risk Θ , we define the individual premium (or hypothetical mean) of X_{n+1} as

$$\mu_{n+1}(\theta) = E[X_{n+1} \mid \Theta = \theta].$$

■ Definition 19 (Pure Premium)

We define the pure premium (or collective premium) of X_{n+1} as

$$\mu_{n+1} = E[X_{n+1}].$$

■ Definition 20 (Bayesian Premium)

The Bayesian premium of X_{n+1} is defined as

$$E[X_{n+1} \mid \vec{X}] = \int_{\Theta} \mu_{n+1}(\theta) \pi_{\Theta \mid \vec{X}}(\theta \mid \vec{x}) d\theta.$$

Example 4.1.1

The number of claims for a policyholder in year i is X_i for i = 1, 2.

? (Finding the Bayesian Premium)

- 1. Identify $X_i \mid \Theta = \theta$.
- 2. Identify the prior distribution Θ .
- 3. Identify the posterior distribution $\Theta \mid \vec{X}$.
- 4. Calculate

$$P = \int_{\Theta} E[X_{n+1} \mid \Theta = \theta] \pi_{\Theta \mid \vec{X}}(\theta \mid \vec{x}) d\theta.$$

Suppose that $X_1 \mid \Theta = \theta$ and $X_2 \mid \Theta = \theta$ are iid with pmf

$$P(X = 1 \mid \Theta = \theta) = 1 - \theta$$

and

$$P(X = 2 \mid \Theta = \theta) = \theta.$$

The prior distribution is given as $\Theta \sim \text{Beta}(2,3)$. Determine the Bayesian premium $E[X_2 \mid X_1 = 2]$.

Solution

Method 1: Using predictive distribution Observe that

$$P(X_2 = 2 \mid X_1 = 2) = \int_{\forall \theta} P(X_2 = 2 \mid \Theta = \theta) \pi_{\Theta|X_1}(\theta \mid x_1) d\theta$$

$$= \int_{\forall \theta} \theta \cdot \frac{f_{X_1|\Theta}(2 \mid \theta) \pi(\theta)}{\int_{\forall \theta} f_{X_1|\Theta}(x_1 \mid \theta) \pi(\theta) d\theta} d\theta$$

$$= \int_{\forall \theta} \frac{\theta^2 \pi(\theta)}{E[\Theta]} d\theta$$

$$= \frac{E[\Theta^2]}{E[\Theta]} = \frac{\frac{1}{5}}{\frac{5}{5}} = \frac{1}{2}.$$

Thus

$$P(X_2 = 1 \mid X_1 = 2) = 1 - \frac{1}{2} = \frac{1}{2}.$$

Hence

$$E[X_2 \mid X_1 = 2] = 1 \cdot \frac{1}{2} + 2 \cdot \frac{1}{2} = \frac{3}{2}.$$

Method 2: Using Bayesian premium formula We have that

$$\begin{split} E[X_2 \mid X_1 = 2] &= \int_{\forall \theta} E[X_2 \mid \Theta = \theta] \pi_{\Theta \mid X_1}(\theta \mid 2) \, d\theta \\ &= \int_{\forall \theta} [1(1-\theta) + 2\theta] \cdot \frac{P(X_1 = 2 \mid \Theta = \theta) \pi(\theta)}{\int_{\forall \theta} P(X1 = 2 \mid \Theta = \theta) \pi(\theta) \, d\theta} \, d\theta \\ &= \int_{\forall \theta} \frac{(1+\theta) \theta \pi(\theta)}{E[\Theta]} \, d\theta \\ &= \frac{E[\Theta] + E[\Theta^2]}{E[\Theta]} \\ &= \frac{\frac{2}{5} + \frac{1}{5}}{\frac{2}{5}} = \frac{3}{2}. \end{split}$$

4.2 The Credibility Premium

The Bayesian premium strongly depends on the assumed distribution of $X_i \mid \Theta = \theta$ and Θ . Furthermore, the Bayesian premium may be difficult to evaluate.

Another method to estimate X_{n+1} which we shall study is to make use of linear combinations of past observations, in particular

$$\alpha_0 + \sum_{i=1}^n \alpha_i X_i.$$

The estimates $\hat{\alpha}_0, \dots \hat{\alpha}_n$ are chosen to minimize the mean square error

$$Q(\alpha_0,\ldots,\alpha_n) = E\left[\left(X_{n+1} - \left[\alpha_0 + \sum_{i=1}^n \alpha_i X_i\right]\right)^2\right].$$

Let us now develop the general model in calculating the credibility premium.

Theorem 6 (General Model for Credibility Premium)

Let $\{X_i\}_{i=1}^n$ be a sequence of past observations (rvs), and X_{n+1} the predictive rv. Then, the solution $(\hat{\alpha}_0, \dots, \hat{\alpha}_n)$ to the system of linear equations, called the normal equations,

$$E[X_{n+1}] = \hat{\alpha}_0 + \sum_{i=1}^n \hat{\alpha}_i E[X_i]$$

$$Cov(X_j, X_{n+1}) = \sum_{i=1}^n \hat{\alpha}_i Cov(X_i, X_j), \quad \forall j \in \{1, \dots, n\},$$

minimizes the mean square error

$$Q(\alpha_0,\ldots,\alpha_n)=E\left[\left(X_{n+1}-\left[\alpha_0+\sum_{i=1}^n\alpha_iX_i\right]\right)^2\right].$$

Proof

First, we take partial derivative wrt α_0 , and set the derivative to 0,

i.e.

$$\frac{\partial \mathcal{Q}}{\partial \alpha_0} = E \left[-2 \left(X_{n+1} - \hat{\alpha}_0 - \sum_{i=1}^n \hat{\alpha}_i X_i \right) \right] = 0.$$

This gives us

$$E[X_{n+1}] = \hat{\alpha}_0 + \sum_{i=1}^n \hat{\alpha}_i E[X_i]. \tag{4.1}$$

Now, we take partial derivatives wrt each α_j , $j \in \{1, ..., n\}$, and equate the derivatives to 0, i.e.

$$\frac{\partial \mathcal{Q}}{\partial \alpha_j} = E\left[-2X_j\left(X_{n+1} - \hat{\alpha}_0 - \sum_{i=1}^n \hat{\alpha}_i X_i\right)\right] = 0.$$

Then we have

$$E[X_j X_{n+1}] = \hat{\alpha}_0 E[X_j] + \sum_{i=1}^n \hat{\alpha}_i E[X_i X_j]. \tag{4.2}$$

Multiplying Equation (4.1) by $E[X_j]$, for each $j \in \{1, ..., n\}$, we get that

$$E[X_{n+1}]E[X_j] = \hat{\alpha}_0 E[X_j] + \sum_{i=1}^n \hat{\alpha}_i E[X_i]E[X_j].$$

Subtracting the above from Equation (4.2), we get

$$Cov(X_i, X_{n+1}) = \hat{\alpha}_0 E[X_j] + \sum_{i=1}^n \hat{\alpha}_i Cov(X_i, X_j),$$

for $j \in \{1, ..., n\}$.

It is then clear that $\hat{\alpha}_0, \dots, \hat{\alpha}_n$ satisfies the normal equations

$$E[X_{n+1}] = \hat{\alpha}_0 + \sum_{i=1}^n \hat{\alpha}_i E[X_i]$$

$$Cov(X_j, X_{n+1}) = \sum_{i=1}^n \hat{\alpha}_i Cov(X_i, X_j), \quad \forall j \in \{1, \dots, n\}.$$

66 Note 4.2.1

The equation

$$E[X_{n+1}] = \hat{\alpha}_0 + \sum_{i=1}^{n} \hat{\alpha}_i E[X_i]$$

is also called the unbiased equation because it requires that the estimate

 $\hat{\alpha}_0 + \sum_{i=1}^n \hat{\alpha}_i X_i$ be unbiased for $E[X_{n+1}]$.

■ Definition 21 (Estimator for the Credibility Premium)

We define the estimator for the credibility premium as

$$\hat{P} := \hat{\alpha}_0 + \sum_{i=1}^n \hat{\alpha}_i X_i.$$

Corollary 7 (P as Best Linear Estimator)

The α_i 's, for $j \in \{0, ..., n\}$, also minimizes

$$Q_1(\alpha_0,\ldots,\alpha_n) = E\left[\left(E[X_{n+1}\mid \vec{X}] - \left[\alpha_0 + \sum_{i=1}^n \alpha_i X_i\right]\right)^2\right];$$

and

$$Q_2(\alpha_0,\ldots,\alpha_n) = E\left[\left(E[X_{n+1}\mid\Theta] - \left[\alpha_0 + \sum_{i=1}^n \alpha_i X_i\right]\right)^2\right].$$

We say that P is the Best Linear Estimator for

- X_{n+1} ;
- the Bayesian premium $E[X_{n+1} \mid \vec{X}]$; and
- the hypothetical mean $E[X_{n+1} \mid \Theta] = \mu_{n+1}(\Theta)$.

Exercise 4.2.1

Prove Prove Corollary 7 by showing that the derivative of the above equations wrt $\alpha_0, \alpha_1, ..., \alpha_n$ still satisfy the normal equations.

The name for **P**Theorem 8 is unfortunate, but I can't think of a good name for it, and it is what is used in lectures.

■Theorem 8 (Theorem 1)

Suppose $\{X_i\}_{i=1}^n$ is a sequence of past observations, X_{n+1} is the predictive RV, with

- $E[X_i] = \mu$;
- $Var(X_i) = \sigma^2$; and
- $Cov(X_i, X_i) = \rho \sigma^2$,

for $i \neq j, i, j \in \{1, ..., n+1\}$, and $\rho \in (-1, 1)$. Then the credibility premium for X_{n+1} is

$$P = Z\overline{X} + (1 - Z)\mu,$$

where

$$Z = \frac{n\rho}{1 - \rho + n\rho'}$$

and

$$\overline{X} = \frac{1}{n} \sum_{i=1}^{n} X_i.$$

Proof

By Prheorem 6, we have that

$$P = \hat{\alpha}_0 + \sum_{i=1}^n \hat{\alpha}_i X_i.$$

We shall use the normal equations to attain this, and we know that we can do quite a number of things with the given assumptions. First,

$$\mu = E[X_{n+1}] = \hat{\alpha}_0 + \sum_{i=1}^n \hat{\alpha}_i E[X_i] = \hat{\alpha}_0 + \sum_{i=1}^n \hat{\alpha}_i \mu$$
$$= \hat{\alpha}_0 + \mu \sum_{i=1}^n \hat{\alpha}_i.$$

Making $\sum_{i=1}^{n} \hat{\alpha}_i$ the subject, we get

$$\sum_{i=1}^{n} \hat{\alpha}_i = 1 - \frac{\hat{\alpha}_0}{\mu}.$$
 (4.3)

Next, for each $j \in \{1, ..., n\}$, the equations with covariances

become

$$\rho\sigma^{2} = \operatorname{Cov}(X_{j}, X_{n+1}) = \sum_{i=1}^{n} \hat{\alpha}_{i} \operatorname{Cov}(X_{i}, X_{j})$$
$$= \sum_{\substack{i=1\\i\neq j}}^{n} \hat{\alpha}_{i} \rho\sigma^{2} + \hat{\alpha}_{j} \sigma^{2},$$

and so dividing both sides by σ^2 and then trying to patch that summation, we get

$$ho = \sum_{i=1}^n \hat{lpha}_i
ho + \hat{lpha}_j (1 -
ho).$$

Substituting in Equation (4.3), we get

$$ho = \left(1 - rac{\hat{lpha}_0}{\mu}
ight)
ho + \hat{lpha}_j(1-
ho)$$
 ,

and making $\hat{\alpha}_i$ the subject,

$$\hat{\alpha}_j = \frac{\hat{\alpha}_0 \rho}{\mu (1 - \rho)}.$$

We want to have a more explicit formula for $\hat{\alpha}_0$ and $\hat{\alpha}_j$. Looking at Equation (4.3), we first take the sum of the \hat{a}_i 's (save when i =0):

$$\sum_{i=1}^{n} \hat{\alpha}_i = \frac{n\hat{\alpha}_0 \rho}{\mu(1-\rho)}.$$

So

$$1 - \frac{\hat{\alpha}_0}{\mu} = \frac{n\hat{\alpha}_0 \rho}{\mu (1 - \rho)},$$

and after rearrangement, we get

$$\hat{\alpha}_0 = \frac{(1-\rho)\mu}{n\rho + 1 - \rho}.$$

Going for $\hat{\alpha}_i$, we get

$$\hat{\alpha}_j = \frac{\hat{\alpha}_0 \rho}{\mu(1-\rho)} = \frac{\rho}{n\rho+1-\rho}.$$

Thus

$$P = \frac{(1-\rho)\mu}{n\rho + 1 - \rho} + \sum_{i=1}^{n} \frac{\rho X_i}{n\rho + 1 - \rho}$$

$$=\frac{n\rho}{n\rho+1-\rho}\cdot\frac{1}{n}\sum_{i=1}^{n}X_{i}+\frac{1-\rho}{n\rho+1-\rho}\mu,$$

where we note that

$$1 - \frac{n\rho}{n\rho + 1 - \rho} = \frac{1 - \rho}{n\rho + 1 - \rho}.$$

Thus if we let

$$Z = \frac{n\rho}{n\rho + 1 - \rho}$$
 and $\overline{X} = \frac{1}{n} \sum_{i=1}^{n} X_i$,

we have that

$$P = Z\overline{X} + (1 - Z)\mu,$$

as desired.

4.3 The Bühlmann Model

An example of Theorem 8 is the Bühlmann model, which is one of the (if not the) simplest credibility model.

■ Definition 22 (The Bühlmann Model)

Under the Bühlmann model, conditional on Θ (the risk distribution), for each policyholder, past losses X_1, \ldots, X_n have the same mean and variance, and are iid conditional on Θ . In particular, in this model, we define the **hypothetical mean** as

$$\mu(\theta) := E[X_i \mid \Theta = \theta],$$

and the process variance as

$$v(\theta) = \text{Var}(X_i \mid \Theta = \theta).$$

Furthermore, we also define the structural parameters: the expected hypothetical mean

$$\mu = E[\mu(\Theta)],$$

the mean of the process variance

$$v = E[v(\Theta)],$$

and the variance of the hypothetical mean

$$a = Var(\mu(\Theta)).$$

66 Note 4.3.1

 μ is the estimate to use if we have no information about θ (thus no info about $\mu(\theta)$). In this case, we call μ the collective premium.

It is not difficult to obtain the mean, variance, and covariance of X_j 's for each j. We see that the mean of X_j is

$$E[X_j] = E[E[X_j \mid \Theta]] = E[\mu(\Theta)] = \mu.$$

The variance of X_i is

$$Var(X_j) = Var(E[X_j \mid \Theta]) + E[Var(X_j \mid \Theta)]$$
$$= Var(\mu(\Theta)) + E[v(\Theta)]$$
$$= a + v.$$

The covariance of X_i with X_i is

$$Cov(X_i, X_j) = E[X_i X_j] - E[X_i] E[X_j]$$

$$= E[E[X_i X_j \mid \Theta]] - \mu^2$$

$$= E[E[X_i \mid \Theta] E[X_j \mid \Theta]] - \mu^2$$

$$= E[\mu(\Theta)^2] - [\mu(\Theta)]^2$$

$$= Var(\mu(\Theta)) = a.$$

This is exactly what the Bühlmann model assumes. In fact, if we apply **P**Theorem 8, noting that

$$Var(X_i) = \sigma^2 \text{ and } Cov(X_i, X_j) = \rho \sigma^2 \implies \rho = \frac{Cov(X_i, X_j)}{Var(X_i)},$$

we observe that

$$\mu = \mu$$
, $\sigma^2 = v + a$, $\rho = \frac{a}{v + a}$,

and so

$$Z = \frac{n\frac{a}{v+a}}{n\frac{a}{v+a} + 1 - \frac{a}{v+a}} = \frac{na}{na+v} = \frac{n}{n+\frac{v}{a}}.$$

The following result follows exactly from our discussion above.

Theorem 9 (Bühlmann Credibility Premium)

The Bühlmann credibility premium is

$$P = Z\overline{X} + (1 - Z)\mu$$

where

$$Z = \frac{n}{n + \frac{v}{a}}$$

is called the Bühlmann credibility factor.

66 Note 4.3.2

- The Bühlmann credibility premium is a weighted average of the sample mean \overline{X} and the collective premium μ .
- As n increases, $Z \to 1$, giving more credit to \overline{X} , which is reasonable by intuition since our past data is more robust with more exposure.
- If the population is fairly homogeneous wrt the risk parameter Θ , then (relatively speaking) the hypothetical means $\mu(\Theta)$ to not vary greatly with Θ , which then gives small variability. In other words, a is small relative to v, and thus Z is nudged closer to 0. This agrees with our intuition, since for a homogeneous population, the overall mean μ is more of value in helping the prediction of next year's claims for a particular policyholder.
- If the population is heterogeneous, μ(Θ) is more variable, so a is large, and in turn Z is closer to 1. This agrees with intuition, since experience of other policyholders is of less value in predicting future experience of a particular policyholder as compared to past experience.

P (Finding Bühlmann Credibility Premium)

- 1. Find hypothetical mean $\mu(\theta)$ and process variance $v(\theta)$.
- 2. Find structural parameters μ , v, a.
- 3. Calculate the Bühlmann credibility factor Z (and mean loss \overline{X} if necessary).
- 4. Calculate the Bühlmann credibility premium $P = Z\overline{X} + (1 Z)\mu$.

Example 4.3.1 (A Poisson-Gamma Example for Bühlmann Credibility)

Let $\{X_i \mid \Theta = \theta\}_{i=1}^n$ with $X_i \mid \Theta = \theta \sim \text{Poi}(\theta)$ for $i \in \{1, ..., n\}$, and the prior distribution $\Theta \sim \text{Gam}(\alpha, \beta)$. Find both the Bühlmann credibility premium and the Bayesian premium.

Solution

Bühlmann Credibility Premium We observe that

$$\mu(\theta) = E[X_i \mid \Theta = \theta] = \theta,$$

and

$$v(\theta) = \text{Var}(X_i \mid \Theta = \theta) = \theta.$$

The structural parameters are

$$\mu = E[\mu(\Theta)] = E[\Theta] = \alpha \beta, \quad v = E(v(\Theta)) = E(\Theta) = \alpha \beta,$$

and

$$a = Var(\mu(\Theta)) = Var(\Theta) = \alpha \beta^2.$$

Thus the Bühlmann credibility factor is

$$Z = \frac{n}{n + \frac{v}{a}} = \frac{n}{n + \beta^{-1}}.$$

Hence the Bühlmann credibility premium is

$$\begin{split} P &= Z\overline{X} + (1 - Z)\mu \\ &= \frac{n}{n + \beta^{-1}}\overline{X} + \frac{\beta^{-1}}{n + \beta^{-1}}\alpha\beta \\ &= \frac{\alpha + n\overline{X}}{n + \beta^{-1}}. \end{split}$$

Bayesian Premium We are given that $X_i \mid \Theta = \theta \sim Poi(\theta)$ and $\Theta \sim \text{Gam}(\alpha, \beta)$. The posterior distribution $\Theta \mid \vec{X}$ is

$$\pi_{\theta \mid \vec{X}}(\theta \mid \vec{x}) \propto \left(\prod_{i=1}^{n} f_{X_{i} \mid \Theta}(x_{i} \mid \theta)\right) \pi(\theta)$$

$$\propto \theta^{\alpha - 1} e^{-\frac{\theta}{\beta}} \prod_{i=1}^{n} e^{-\theta} \theta^{x_i}$$
$$= e^{-(n + \frac{1}{\theta})\theta} \theta^{n\overline{x} + \alpha - 1}$$

It follows that $\Theta \mid \vec{X} = \vec{x} \sim \text{Gam}\left(n\overline{x} + \alpha, \frac{1}{n + \frac{1}{\beta}}\right)$. Thus the Bayesian premium is

$$\begin{split} E[X_{n+1} \mid \vec{X} &= \vec{x}] \\ &= \int_{\forall \theta} E[X_{n+1} \mid \Theta = \theta] \pi_{\Theta \mid \vec{X}}(\theta \mid \vec{x}) \, d\theta \\ &= \int_{\forall \theta} \theta \frac{1}{\theta \Gamma(n \overline{x} + \alpha)} \left(\frac{\theta}{\frac{1}{n + \frac{1}{\beta}}} \right)^{n \overline{x} + \alpha} e^{-\frac{\theta}{\frac{1}{n + \frac{1}{\beta}}}} \, d\theta \\ &= (n \overline{x} + \alpha) \frac{1}{n + \frac{1}{\beta}} \int_{\forall \theta} \frac{1}{\theta \Gamma(n \overline{x} + \alpha + 1)} \left(\frac{\theta}{\frac{1}{n + \frac{1}{\beta}}} \right)^{n \overline{x} + \alpha + 1} e^{-\frac{\theta}{\frac{1}{n + \frac{1}{\beta}}}} \, d\theta \\ &= (n \overline{x} + \alpha) \frac{1}{n + \frac{1}{\beta}} \\ &= \frac{n}{n + \beta^{-1}} \overline{x} + \frac{\beta^{-1}}{n + \beta^{-1}} \alpha \beta \\ &= \frac{\alpha + n \overline{x}}{n + \beta^{-1}}. \end{split}$$

66 Note 4.3.3

We notice that the Bühlmann credibility premium and the Bayesian premium coincides. This is no accidental coincidence, and we shall see why this is the case later on in exact credibility.

Example 4.3.2 (Disagreement of Bühlmann Credibility Premium and Bayesian Premium)

Consider 2 urns with different proportions of balls marked with 0 or 1.

- Urn 1 has 60% of its balls marked as 0 and 40% marked as 1.
- Urn 2 has 80% of its balls marked as 0 and 20% marked as 1.

An urn is randomly picked with equal probability and a total of 2 balls out of 3 is marked 1 (with replacement).

Calculate the Bühlmann credibility premium and the Bayesian premium for the number on the next ball drawn from the urn.

Solution

In any of the cases, we need to find out what Θ and $X_i \mid \Theta$ are. Let X_i be the number drawn on the *i*th ball, and Θ the number of the chosen urn. Then the prior distribution is

$$\Theta = \begin{cases} \theta_1 & \text{urn 1 is selected wp } \frac{1}{2} \\ \theta_2 & \text{urn 2 is selected wp } \frac{1}{2} \end{cases}.$$

The conditional probabilities are

$$P(X_i = x \mid \Theta = \theta_1) = \begin{cases} 0.6 & x = 0 \\ 0.4 & x = 1 \end{cases}$$

and

$$P(X_i = x \mid \Theta = \theta_2) = \begin{cases} 0.8 & x = 0 \\ 0.2 & x = 1 \end{cases}.$$

Bühlmann credibility premium The hypothetical means are

$$\mu(\theta_1) = E[X_i \mid \Theta = \theta_1] = 0(0.6) + 1(0.4) = 0.4$$

and

$$\mu(\theta_2) = E[X_i \mid \Theta = \theta_2] = 0(0.8) + 1(0.2) = 0.2.$$

The process variances are

$$v(\theta_1) = \text{Var}(X_i \mid \Theta = \theta_1) = 0.4 - 0.4^2 = 0.24$$

and

$$v(\theta_2) = \text{Var}(X_i \mid \Theta = \theta_2) = 0.2 - 0.2^2 = 0.16.$$

It follows that the structural parameters are

$$\mu = E[\mu(\Theta)] = \frac{1}{2}(0.4) + \frac{1}{2}(0.2) = 0.3,$$

$$v = E[v(\Theta)] = \frac{1}{2}(0.24) + \frac{1}{2}(0.16) = 0.2,$$

and

$$a = \text{Var}(\mu(\Theta)) = (0.4 - 0.3)^2 \frac{1}{2} + (0.2 - 0.3)^2 \frac{1}{2} = 0.01$$

Thus the Bühlmann credibility factor is

$$Z = \frac{n}{n + \frac{v}{a}} = \frac{n}{n + \frac{0.2}{0.01}} = \frac{n}{n + 20}.$$

Hence the Bühlmann credibility premium is

$$P = \frac{n}{n+20} \frac{2}{3} + \frac{20}{n+20} 0.3 = 0.34783.$$

Bayesian premium Let $\vec{X} = X_1 + X_2 + X_3$. Our observation is that $X_1 + X_2 + X_3 = 2$. Thus

$$\begin{split} &\pi_{\Theta \mid \vec{X}}(\theta_1 \mid 2) \\ &= \frac{P(X_1 + X_2 + X_3 = 2 \mid \Theta = \theta_1)\pi(\theta_1)}{P(X_1 + X_2 + X_3 = 2 \mid \Theta = \theta_1)\pi(\theta_1) + P(X_1 + X_2 + X_3 \mid \Theta = \theta_2)\pi(\theta_2)} \\ &= \frac{\binom{3}{2}(0.4)^2(0.6)\frac{1}{2}}{\binom{3}{2}(0.4)^2(0.6)\frac{1}{2} + \binom{3}{2}(0.2)^2(0.8)\frac{1}{2})} \\ &= 0.75, \end{split}$$

and so

$$\pi_{\Theta\mid\vec{X}}(\theta_2\mid 2) = 0.25.$$

Hence, to the Bayesian premium is

$$E[X_4 \mid X_1 + X_2 + X_3 = 2] = E[X_4 \mid \Theta = \theta_1]0.75 + E[X_4 \mid \Theta = \theta_2]0.25$$
$$= 0.4(0.75) + 0.2(0.25)$$
$$= 0.3 + 0.05 = 0.35.$$

Bibliography

Bühmann, H. (1967). Experience rating and credibility. *ASTIN Bulletin*, 4:199–207.

Klugman, S. A., Panjer, H. H., and Willmot, G. E. (2012). *Loss Models: From Data to Decisions*. John Wiley & Sons Inc., Hoboken, New Jersey, 4th edition.

Mowbray, A. H. (1914). How extensive a payroll exposure is necessary to give a dependable pure premium? *Proceedings of the Casualty Actuarial Society*, I:24–30.

Index

American credibility, 27 Individual Premium, 39

Bühlmann Credibility Premium,

Credibility Theory, 9

Bühlmann credibility factor, 48 Joint D	Distribution, 22
---	------------------

48	Likelihood Function, 19
Bayes Estimator, 23	Linear Exponential Family, 24

Bayesian Premium, 39 Log-likelihood Function, 19 Best Linear Estimator, 43

Bias, 14 manual premium, 10, 28
Biased Estimator, 14 Marginal Distribution, 22

Maximum Likelihood Estimation,

collective premium, 39, 47 19
Conjugate Prior Distribution, 24 mean of the process variance, 47

credibility factor, 33 Mean Squared Error, 18

Darth Vader rule, 15 normal equations, 41 normalizing constant, 25

Estimate, 13 partial credibility, 33
Estimator, 13 Posterior Distribution, 22

European credibility, 37 Posterior Mean, 23 expected hypothetical mean, 46 Predictive Distribution, 38

expected hypothetical mean, 46 Predictive Distribution, 38
Prior Distribution, 21

full credibility, 28 process variance, 46
Pure Premium, 39
Greatest Accuary Credibility, 37 pure premium, 9

hypothetical mean, 39, 46 rating class, 10

Sample Variance, 16 Square-root rule for partial credibility, 34 structural parameters, 46

The Bühlmann Model, 46 Theorem 1, 44

unbiased equation, 42 Unbiased Estimator, 14

variance of the hypothetical mean, 47