Likelihood

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1 Statistical models

A *statistical model* $\mathcal{P}$ is a family of probability distributions on a measurable space $(\mathcal{X}, \mathbb{E})$ indexed by parameters θ from a parameter space Θ. We can sum this up as:

$$\mathcal{P} = \{\nu_\theta | \theta \in \Theta\} \tag{1.1}$$

1.1 Dominated statistical models

We call such a model *dominated* if there exists a σ-finite measure μ on $(\mathcal{X}, \mathbb{E})$, such that all the distributions in the model has a density function f_θ with respect to μ. Or equivalently, that all the distributions is absolutely continuous with respect to μ:

$$\forall \nu \in \mathcal{P} : \nu \ll \mu \tag{1.2}$$

The Radon-Nikodym derivative $\frac{d\nu}{d\mu}$ is then a density function for ν with respect to μ. We call μ a *dominating measure* for the model.

This may all sound a little hairy, but in practice, the dominating measure will almost always be the Lebesgue measure (for continuous distributions), the counting measure (for discrete distributions), or some combination of the two.

2 The likelihood function

2.1 Definition

Let $\mathcal{P}$ be a dominated statistical model. The *likelihood* function for an outcome $x \in \mathcal{X}$ is a function $L_x : \Theta \to \mathbb{R}$ associates a number to every parameter configuration:
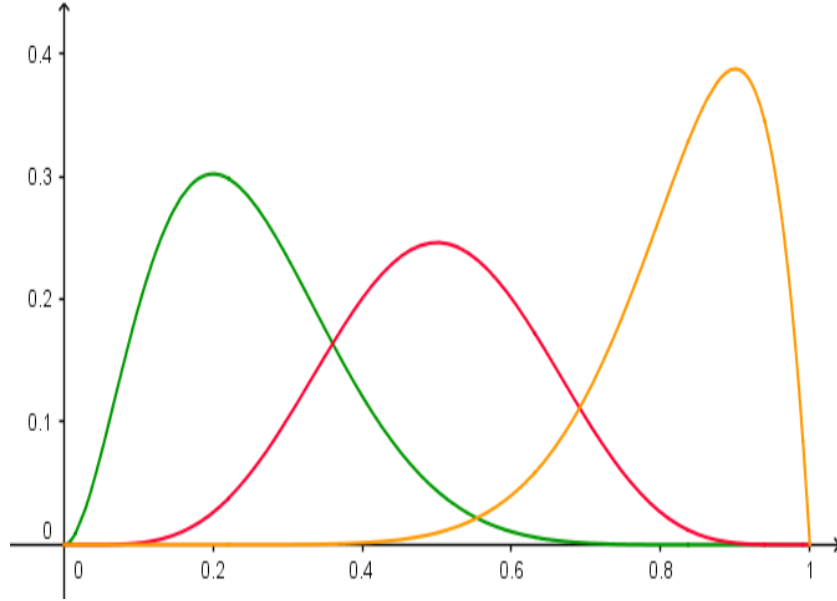
$$L_x(\theta) = f_\theta(x) \tag{2.1}$$

Figure 1: Likelihood function for $n = 10$ and $k = 2, 5, 9$ (green, red, orange) respectively.

The interpretation of the likelihood function is, that the higher its value, the more likely it seems that θ is the true parameters of the model. Hence, we will often seek out the set of parameters which maximize the likelihood function. This process is known as *maximum likelihood estimation* or MLE for short. Note that there's no mathematical justification of this process in itself.

2.1.1 Example: Coin tosses

We consider a repeated coin toss, each i.i.d. Bernoulli processes with parameter p - the probability that the outcome is heads. If the coin is tossed n times, the outcome space is $\mathcal{X} = \{0, 1, 2, \cdots, n\}$ where the number of the outcome heads is counted (the dominating measure is the counting measure). Given a specific outcome $k \in \mathcal{X}$, the likelihood function can be found by the binomial distribution:

$$L_k(p) = \binom{n}{k} p^k (1-p)^{n-k} \tag{2.2}$$

Here $p \in \Theta = [0, 1]$. Figure 1 shows examples of this function.

Now, we can perform MLE by finding the value of the parameter p which

maximizes L_k. We differentiate using the product rule:

$$\frac{\partial L_k}{\partial p} = \binom{n}{k} \left(k(p^{k-1}(1-p)^{n-k} - p^k(n-k)(1-p)^{n-k-1} \right) \qquad (2.3)$$

For this to be zero, the binomial coefficient is irrelevant, so:

$$k(p^{k-1}(1-p)^{n-k} = p^k(n-k)(1-p)^{n-k-1} \Leftrightarrow \qquad (2.4)$$
$$k(1-p) = (n-k)p \Leftrightarrow \qquad (2.5)$$
$$k = np \qquad (2.6)$$

In other words, $p_{\text{MLE}} = \frac{k}{n}$. This will probably not be much of a surprise to anyone.

However, this estimate might not always be sensible. Specifically, if you've made a very small amount of count throws. If $n = 1$, you will conclude that $p = 0$ or $p = 1$, which meshes badly with our intuition about coin throws. This may be modelled as a *prior distribution* of p, leading to a Bayesian analysis. Contrast with the case where $m \gg 1$: When we have a lot of repetitions, we will be more certain of the value of the parameter p. This idea of probability as a limit for a large number of repetitions is at the heart of the frequentist interpretation.

2.2 The log-likelihood function

When the density functions are nowhere zero, it often makes sense to deal with the logarithm of the likelihood function instead. Since the logarithm is a strictly monotonic function, this makes no difference for the purpose of MLE. Some presentations (this included), introduces a sign change as well:

$$l_x(\theta) = -\log f_\theta(x) \qquad (2.7)$$

So MLE means one of the following, equivalent procedures:

- Maximizing the likelihood function L_x.

- Minimizing the log-likelihood function l_x.

2.2.1 Example: Fish weights

n adult fish of the same species are caught and weighed. The weights can be reasonably modelled by a normal distribution $N(\mu, \sigma^2)$ (and so the dominating measure is the Lebesgue measure). For simplicity, we will assume that the variance is known from historical data. The observations are:

$$x = (w_1, w_2, \cdots, w_n) \qquad (2.8)$$

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Now, the likelihood function is:

$$L_x(\mu) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(w_i - \mu)^2}{2\sigma^2}\right] \tag{2.9}$$

Here we see the practicality of taking the logarithm to get the log-likelihood: It turns a product like this into a much more manageable sum:

$$l_x(\mu) = -\log L_x(\mu) = -n\log\frac{1}{\sqrt{2\pi\sigma^2}} + \sum_{i=1}^{n} \frac{(w_i - \mu)^2}{2\sigma^2} \tag{2.10}$$

Differentiating to find the minimum:

$$\frac{\partial l_x}{\partial \mu} = \frac{1}{2\sigma^2} \sum_{i=1}^{n} 2(w_i - \mu) = \frac{1}{\sigma^2}\left[\sum_{i=1}^{n} w_i - n\mu\right] \tag{2.11}$$

Setting this to zero we find:

$$\mu_{\text{MLE}} = \frac{1}{n} \sum_{i=1}^{n} w_i \tag{2.12}$$

Once again, hardy a surprising result.

3   Score function and observed information

When the parameter space is an open subset of $\mathbb{R}^k$ (usually the case), we define these as follows:

- The *score function* is the gradient of the log-likelihood:

$$V_x(\theta) = \nabla_\theta l_x(\theta) \tag{3.1}$$

- The *observed information function* is the Hessian matrix of the log-likelihood function:

$$\mathcal{J}_x(\theta) = H_\theta[l_x(\theta)] = \nabla_\theta \nabla_\theta^t l_x(\theta) \tag{3.2}$$

The *observed information* is the observed information function evaluated at the MLE estimator: $\mathcal{J}_x(\theta_{\text{MLE}})$.
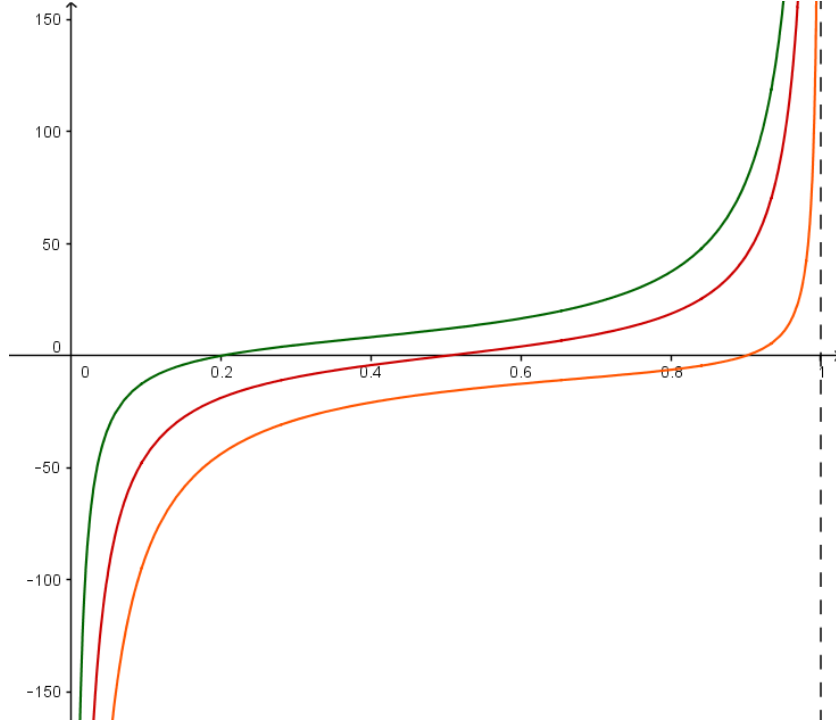
Figure 2: Score function for $n = 10$ and $k = 2, 5, 9$ (green, red, orange) respectively.

3.1 Example: Coin toss

As we saw above, here the likelihood is given by the binomial distribution:

$$L_k(p) = \binom{n}{k} p^k (1-p)^{n-k} \Rightarrow l_k(p) = -\log \binom{n}{k} - k \log p - (n-k) \log(1-p)$$

(3.3)

Now to get the score function, we differentiate with respect to p:

$$V_k(p) = \frac{\partial l_x}{\partial p} = -\frac{k}{p} + \frac{n-k}{1-p} = \frac{(n-k)p - k(1-p)}{p(1-p)} = \frac{n-k}{p(1-p)}$$

(3.4)

Three examples of the score function are shown in figure 2.

The observed information function, like the score function, is simply a scalar in this case:

$$\mathcal{J}_k(p) = \frac{\partial V_k}{\partial p} = \frac{k}{p^2} + \frac{n-k}{(1-p)^2}$$

(3.5)

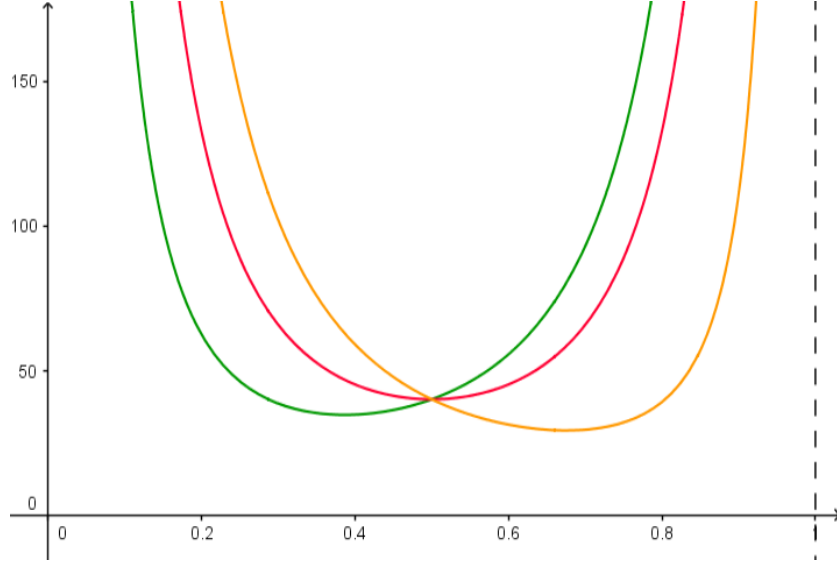Examples of these functions are shown in figure 3.

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Figure 3: Observed information function for $n = 10$ and $k = 2, 5, 9$ (green, red, orange) respectively.

The observed information is found by setting $p = p_{\text{MLE}} = \frac{k}{n}$ in 3.5:

$$\frac{kn^2}{k^2} + \frac{n-k}{\frac{(n-k)^2}{n^2}} = \frac{n^2}{k} + \frac{n^2}{n-k} = \frac{n^2(n-k+k)}{k(n-k)} = \frac{n}{\frac{k}{n} \cdot \left(1 - \frac{k}{n}\right)} \tag{3.6}$$

Reinstating p_{MLE}, this means that the observed information is:

$$\frac{n}{p_{\text{MLE}}(1 - p_{\text{MLE}})} \tag{3.7}$$

4 Fisher information

The *Fisher information* (somtimes simply called the information) is the expected value of the observed information function:

$$\mathcal{I}(\theta) = E[\mathcal{J}_x(\theta)] \tag{4.1}$$

Note that this is not a function of the actual outcome - The Fisher information is a property of the model, not the realized observations.

4.1 Example: Bernoulli distribution

The (log)likelihood for a random Bernoulli variable X is:

$$L_x(p) = p^x(1-p)^{1-x} \Rightarrow l_x(p) = -x \log p - (1-x) \log(1-p) \tag{4.2}$$

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The score function is:
$$V_x(p) = -\frac{x}{p} + \frac{1-x}{1-p} \tag{4.3}$$

The observed information function is:
$$\mathcal{J}_x(p) = \frac{x}{p^2} + \frac{1-x}{(1-p)^2} \tag{4.4}$$

Now, to get the Fisher information we find the expectation value by summing over the two possible values of x:
$$\mathcal{I}(p) = E[\mathcal{J}_x(p)] = \sum_x P(X = x)\mathcal{J}_x(p) = p\frac{1}{p^2} + (1-p)\frac{1}{(1-p)^2} = \tag{4.5}$$

$$\frac{1}{p} + \frac{1}{1-p} = \frac{1-p+p}{p(1-p)} = \frac{1}{p(1-p)} \tag{4.6}$$

This is simply the reciprocal of the variance of X.

4.2   Example: Binomial distribution

From equation 3.5 we know that:
$$\mathcal{J}_k(p) = \frac{k}{p^2} + \frac{n-k}{(1-p)^2} = \frac{(1-p)^2 k + p^2(n-k)}{p^2(1-p)^2} \tag{4.7}$$

The numerator is:
$$(1 - 2p + p^2)k + p(n - k) = k - 2pk + p^2 k + pn - pk = k - 2pk + np^2 \tag{4.8}$$

So:
$$\mathcal{J}_k(p) = \frac{(1-2p)k + np^2}{p^2(1-p)^2} \tag{4.9}$$

Now, the Fisher information is found by taking the expectation value of this, again by summing over outcomes (here $n+1$ possibilities). This means that everything that does not involve k can be taken outside of the expectation:
$$\mathcal{I}(p) = E[\mathcal{J}_x(p)] = \frac{1}{p^2(1-p)^2}((1-2p)\ E[k] + np^2) \tag{4.10}$$

The expected value of k is np, so the parenthesis is equal to:
$$(1-2p)np + np^2 = np - 2np^2 + np^2 = np - np^2 = n(p - p^2) = np(1-p) \tag{4.11}$$

All in all, we get:
$$\mathcal{I}(p) = \frac{n}{p(1-p)} \tag{4.12}$$

5   Bartlett's identities

These identities holds when the log-likelihood is sufficiently nice that integration and differentiation with respect to θ are interchangeable. In that case, the following two theorems are true:

Theorem 5.1. *The expectation value of the score function is zero:*

$$E[V_x(\theta)] = 0 \tag{5.1}$$

Proof. To prove the identity, note that because $L_x(\theta)$ regarded as a function of x is a probability density function we have:

$$\int L_x(\theta) \, d\mu(x) = 1 \tag{5.2}$$

Differentiating with respect to θ on each side of the equation and using the regularity assumption above we get:

$$\frac{\partial}{\partial \theta} \int L_x(\theta) \, d\mu(x) = \int \frac{\partial}{\partial \theta} L_x(\theta) \, d\mu(x) = 0 \tag{5.3}$$

Now rewrite the integrand by multiplying by 1 in the form $\frac{L_x(\theta)}{L_x(\theta)}$ (we assume that the likelihood is positive everywhere):

$$\int \underbrace{\frac{\frac{\partial L_x}{\partial \theta}}{L_x(\theta)}} L_x(\theta) \, d\mu(x) = 0 \tag{5.4}$$

Now, the underbraced part is actually the score function except for a sign change, since:

$$V_x(\theta) = \frac{\partial l_x}{\partial \theta} = -\frac{\partial}{\partial \theta} \log L_x(\theta) = -\frac{1}{L_x(\theta)} \frac{\partial L_x}{\partial \theta} \tag{5.5}$$

Which means:

$$\int V_x(\theta) L_x(\theta) \, d\mu(x) = 0 \tag{5.6}$$

But this is just the expected value. $\qquad\square$

Theorem 5.2. *The variance of the score function is equal to the Fisher information:*

$$Var(V_x(\theta)) = \mathcal{I}(\theta) \tag{5.7}$$

Proof. The proof uses the same basic idea as above, except that a second derivative is used:

$$\frac{\partial^2}{\partial\theta^2}\int L_x(\theta)\; d\mu(x) = \int \frac{\partial^2}{\partial\theta^2} L_x(\theta)\; d\mu(x) = 0 \qquad (5.8)$$

Following the same steps as above, the integrand can be written as:

$$\frac{\partial}{\partial\theta}\left[V_x(\theta)L_x(\theta)\right] = \frac{\partial V_x}{\partial\theta}L_x(\theta) + V_x(\theta)\frac{\partial L_x}{\partial\theta} \qquad (5.9)$$

$$\mathcal{J}_x(\theta)L_x(\theta) - \left(V_x(\theta)\right)^2 L_x(\theta) \qquad (5.10)$$

Here, the second term has been rewritten in the same way we did above. Now, when integrating this yields:

$$\mathcal{I}(\theta) - \mathrm{Var}(V_x(\theta)) = 0 \qquad (5.11)$$

Here we've used that the expectation value of the score is zero. The desired result immediately follows. $\qquad\square$

These are known as Bartlett's first and second identity, respectively. In principle, one could continue this pattern to higher order derivatives for more identities.