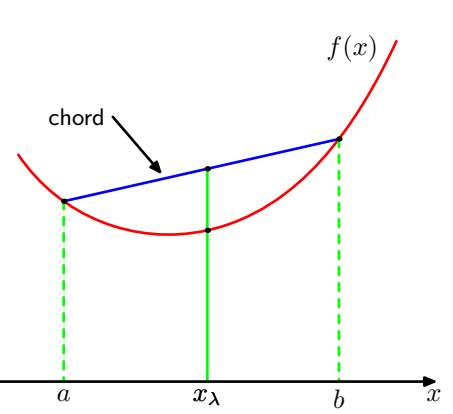


Figure 2.15 A convex function $f(x)$ is one for which every chord (shown in blue) lies on or above the function (shown in red).



is given by $\lambda f(a) + (1 - \lambda)f(b)$, and the corresponding value of the function is $f(\lambda a + (1 - \lambda)b)$. Convexity then implies

$$f(\lambda a + (1 - \lambda)b) \leq \lambda f(a) + (1 - \lambda)f(b). \quad (2.101)$$

Exercise 2.32

This is equivalent to the requirement that the second derivative of the function be everywhere positive. Examples of convex functions are $x \ln x$ (for $x > 0$) and x^2 . A function is called *strictly convex* if the equality is satisfied only for $\lambda = 0$ and $\lambda = 1$. If a function has the opposite property, namely that every chord lies on or below the function, it is called *concave*, with a corresponding definition for *strictly concave*. If a function $f(x)$ is convex, then $-f(x)$ will be concave.

Exercise 2.33

Using the technique of proof by induction, we can show from (2.101) that a convex function $f(x)$ satisfies

$$f\left(\sum_{i=1}^M \lambda_i x_i\right) \leq \sum_{i=1}^M \lambda_i f(x_i) \quad (2.102)$$

where $\lambda_i \geq 0$ and $\sum_i \lambda_i = 1$, for any set of points $\{x_i\}$. The result (2.102) is known as *Jensen's inequality*. If we interpret the λ_i as the probability distribution over a discrete variable x taking the values $\{x_i\}$, then (2.102) can be written

$$f(\mathbb{E}[x]) \leq \mathbb{E}[f(x)] \quad (2.103)$$

where $\mathbb{E}[\cdot]$ denotes the expectation. For continuous variables, Jensen's inequality takes the form

$$f\left(\int \mathbf{x} p(\mathbf{x}) d\mathbf{x}\right) \leq \int f(\mathbf{x}) p(\mathbf{x}) d\mathbf{x}. \quad (2.104)$$

We can apply Jensen's inequality in the form (2.104) to the Kullback–Leibler divergence (2.100) to give

$$\text{KL}(p\|q) = - \int p(\mathbf{x}) \ln \left\{ \frac{q(\mathbf{x})}{p(\mathbf{x})} \right\} d\mathbf{x} \geq - \ln \int q(\mathbf{x}) d\mathbf{x} = 0 \quad (2.105)$$