Throughout this section we denote by $(\Omega, \mu, \mathcal{A})$ a probability space with measure μ and σ -algebra \mathcal{A} .

Recall, a **probability density** is a non-negative, measure-able function $f: \Omega \to R_+$ such that

$$\int_{\Omega} f d\mu = 1$$

A special case is given by a **histogram** in which case \mathcal{A} is just a finite disjoint separation of Ω :

$$\Omega = \bigcup_{i=1}^{n} A_{i}$$

A 'bar' of this histogram is then associated with an element $A \in \mathcal{A}$, and its height h_i can be interpreted as a probability density:

$$f: A_i \mapsto h_i$$

Moreover, we can define μ by

$$\mu(A_i) = 1/\sum_i h_i$$

This step usually is denoted 'normalization'.

Then we have:

$$\int_{\Omega} f d\mu = \sum_{i} f(A_i)\mu(A_i) = \sum_{i} h_i\mu(A_i) = 1$$

Next, we define a way to measure the distance between two probability densities.

Definition. Histogram distance

Let f and g denote two probability densities defined on (Ω, μ, A) . We define its distance by

$$d(f,g) = 1 - \int_{\Omega} \min\{f, g\} d\mu$$

Note, that since min is a continuous and hence measure-able function, the above integral is well-defined.

For the case of two histograms the distance is given by

$$d(f,g) = 1 - \sum_{i} \min\{h_i, k_i\} \mu(A_i)$$

where h_i, k_i denote the *i*'th bar's height for the first resp. second histogram. To visualize the above definition, note that $\min\{h_i, k_i\}$ just is the amount the two bars do intersect. If h_i, k_i are equal, then this is equivalent to full intersection, and if $\min\{h_i, k_i\} = 0$ then this means no intersection at all.

A satisfactory definition of a distance must fulfill the axiom of a metric. These are:

Definition. Metrix axioms

- (1) d(f,g) = d(g,f)
- (2) d(f, f) = 0
- (3) $d(f,g) = 0 \leftrightarrow f = g$
- (4) $d(f,g) \leq d(f,h) + d(h,g)$ for any h
- (4) is the so called 'triangle inequality' and can be interpreted as moving directly from f to g has shorter or the same distance as by forcing the move to pass via h.

Let us verify that all this is fulfilled by the histogram distance.

Theorem. The histogram distance is a metric defined on the space of probability densities on (Ω, μ, A) .

Proof. (1) and (2) are trivial by the definition.

For (3) assume d(f, g) = 0. Then,

$$\int \min\{f, g\} d\mu = 1 = \int f d\mu$$

Therefore

$$\int f - \min\{f, g\} d\mu = 0$$

Since $f - \min\{f, g\} \ge 0$ this implies

$$f = \min\{f, g\} \ a.e$$

a.e stands for 'almost everywhere' and expresses equality up to a set of measure zero. Since in probability theory functions are identified that are equal except on a set of measure zero, we have shown (3) to hold. To show (4) assume h is another probability density. We have to show

$$1 - \int \min\{f, g\} d\mu \le 1 - \int \min\{f, h\} d\mu + 1 - \int \min\{h, g\} d\mu$$

what is equivalent to

$$\int \min\{f, h\} d\mu + \int \min\{h, g\} d\mu \le 1 + \int \min\{f, g\} d\mu \qquad (1)$$

For any point ω assume w.l.o.g $f(\omega) \leq g(\omega)$ We split Ω into two disjoint sets

$$A_1 := \{ \omega \in \Omega : f(\omega) < g(\omega) \}$$
$$A_2 := \{ \omega \in \Omega : f(\omega) \ge g(\omega) \}$$

Both sets are measure-able since the subtraction is a continuous function. With this we can write

$$\int \min\{f, g\} d\mu = \int_{A_1} \min\{f, g\} d\mu + \int_{A_2} \min\{f, g\} d\mu$$

$$= \int_{A_1} f d\mu + \int_{A_2} g d\mu$$

$$\geq \int_{A_1} \min\{f, h\} d\mu + \int_{A_2} \min\{h, g\} d\mu$$

So according to (1) is remains to show

$$\int_{A_2} \min\{f, h\} d\mu + \int_{A_1} \min\{h, g\} d\mu \le 1$$

But this is straightforward by noting

$$\int_{A_2} \min\{f, h\} d\mu + \int_{A_1} \min\{h, g\} d\mu \le \int_{A_2} h d\mu + \int_{A_1} h d\mu$$
$$= \int h d\mu = 1$$