

# Bedlam

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# 1. Topology

**Definition 1.1** (Topology):

Let  $X$  be a set. A **topology over  $X$**  is a subset  $\Sigma$  of  $2^X$  such that:

1.  $A \subseteq \Sigma \implies \bigcup_{E \in A} E$ . **Infinite or finite unions of sets.**
2.  $A, B \in \Sigma \implies A \cap B \in \Sigma$ . **Finite intersections of sets.**
3.  $X \in \Sigma$

**Definition 1.2** (Topological Space):

$(X, \Sigma)$  is a **topological space** iff.  $\Sigma$  is a *topology* of  $X$ .

**Definition 1.3** (Everywhere dense):

Let  $(X, \Sigma)$  *topological space*, and  $H \subseteq X$ .  $H$  is said **everywhere dense in  $\Sigma$**  iff.  $\forall E \in \Sigma, E \neq \emptyset : H \cap E \neq \emptyset$ . **We can find a bit of  $H$  in every corner of the topology  $\Sigma$ .**

**Definition 1.4** (Separable):

Let  $(X, \Sigma)$  be a *topological space*.  $(X, \Sigma)$  is said **separable** iff  $\exists H \subseteq X, H$  is countable :  $H$  is everywhere dense  $\in \Sigma$ . **There is a sequence of elements  $\{x_n \in X\}_{n=1}^{\infty}$  such that every set in the topology contains at least one element  $x_i$ .**

**Definition 1.5** (Metric Space):

$(X, d)$  is a **metric space** iff.

1.  $X \neq \emptyset$
2.  $d : X \times X \longrightarrow \mathbb{R}_{\geq 0}$  such that ( **$d$  is a distance**):
  1.  $\forall x, y \in X : d(x, y) = 0 \implies x = y$ . **there are no different elements at zero-distance.**
  3.  $\forall x, y \in X : d(x, y) = d(y, x)$ . **symmetry.**
  2.  $\forall x, y, z \in X : d(x, z) \leq d(x, y) + d(y, z)$ . **triangular inequality.**

**Definition 1.6** (open  $\varepsilon$ -ball):

Let  $(X, d)$  be a *metric space*,  $x \in X$ , and  $\varepsilon \in \mathbb{R}_{>0}$ . We call  $B_\varepsilon(x) = \{y \in X \mid d(x, y) < \varepsilon\}$  an **open  $\varepsilon$ -ball**. **A ball of  $\varepsilon$  radius centered at some point.**

**Definition 1.7** (Neighborhood):

Let  $(X, d)$  be a *metric space*,  $S \subseteq X$ ,  $x \in S$ , and  $\varepsilon \in \mathbb{R}_{>0}$  such that the *open  $\varepsilon$ -ball*  $B_\varepsilon(x) \subseteq S$ . Then  $S$  is said a **neighborhood of  $x$** . **A neighborhood of an element is simply a set that contains an open ball containing the element.**

**Definition 1.8** (Open Set):

Let  $(X, d)$  be a *metric space* and  $U \subseteq X$ .  $U$  is an **open set** iff.  $\forall u \in U : \exists \varepsilon \in \mathbb{R}_{>0} : B_\varepsilon(u) \subseteq U$ . **An open set is simply a set which is also neighborhood for all its points.**

**Definition 1.9** (Induced Topology):

Let  $(X, d)$  be a *metric space*.  $\Sigma$  is said an **induced topology** iff.  $\Sigma = \{U \subseteq X \mid U \text{ is an open set in } (X, d)\}$

**Definition 1.10** (Metriizable):

Let  $(X, \Sigma)$  be a *topological space*.  $(X, \Sigma)$  is said **metriizable** iff.  $\exists (X, d)$  *metric space* :  $\Sigma$  is a topology induced by  $(X, d)$ .

**Definition 1.11** (Cauchy Sequence):

Let  $(X, d)$  be a *metric space*,  $[x_n \in X]$  a sequence.  $[x_n]$  is said a **cauchy sequence** iff.  $\forall \varepsilon \in \mathbb{R}_{>0} : \exists N \in \mathbb{N} : \forall m, n \in \mathbb{N} : d(x_n, x_m) \leq \varepsilon$ . There is a point after which all pairs of elements are close to each other.

**Definition 1.12** (Convergent Sequence):

Let  $(X, d)$  be a *metric space*,  $l \in X$ ,  $[x_n \in X]$  a sequence.  $[x_n]$  is said a **convergent sequence to the limit  $l$**  iff.  $\forall \varepsilon \in \mathbb{R}_{>0} : \exists N \in \mathbb{R}_{>0} : \forall n > N : d(x_n, l) < \varepsilon$ . If such a limit exists the sequence is simply said **convergent**.

**Definition 1.13** (Complete Metric Space):

Let  $(X, d)$  be a *metric space*.  $(X, d)$  is said a **complete metric space** iff. every *cauchy sequence* is *convergent*.

**Definition 1.14** (Polish Space):

Let  $(X, \Sigma)$  be a *topological space*.  $(X, \Sigma)$  is said a **Polish Space** iff.  $(X, \Sigma)$  is *separable*, *metrizable*, and a *complete metric space* for some *metric*.

## 2. Measure Theory

**Definition 2.1** (half open rectangle):

Let  $a_0, b_0, \dots, a_n, b_n \in \mathbb{R}$ . The set  $\times_{i=0}^n [a_i, b_i)$  is called an  $n$ -dimensional **half open rectangle**. The collection of all  $n$ -dimensional **half-open-rectangles** is denoted with  $\mathcal{J}_h^n$ .

**Definition 2.2** (restriction):

Let  $f : X \rightarrow Y$ . Let  $X' \subseteq X$ . Let  $Y'$  such that  $f(X') \subseteq Y' \subseteq Y$ . A **restriction of  $f$  over  $X' \times Y'$** , denoted  $f|_{X' \times Y'}$  is a function  $X' \rightarrow Y'$  such that  $f|_{X \times Y} = \{(x, f(x)) \mid x \in X, f(x) \in Y\}$

**Example 2.1** (restriction):

Let  $f : \mathbb{R} \rightarrow \mathbb{R}$  such that  $f(x) = x^2$  **power operator over the real numbers**. Now, consider  $g : \mathbb{N} \rightarrow \mathbb{N}$  such that  $g(x) = x^2$  **power operator over the natural number only**. Then  $g$  is a *restriction* of  $f$ .

1.  $\mathbb{N} \subseteq \mathbb{R}$ .
2.  $f(\mathbb{N}) \subseteq \mathbb{N} \subseteq \mathbb{R}$ .
3.  $\{(x, g(x)) \mid x \in \mathbb{N}, y \in \mathbb{N}\} \subseteq \{(x, f(x)) \mid x \in \mathbb{R}, y \in \mathbb{R}\}$

**Definition 2.3** (inverse function):

Let  $f : X \rightarrow Y$  be a function. The **inverse function**  $f^{-1} : Y \rightarrow X$  is a function such that  $f^{-1}(y \in Y) = x \in X$  if  $f(x) = y$ .

**Definition 2.4** (preimage):

Let  $f : X \rightarrow Y$  be a function. Let  $E \subseteq Y$ . The **preimage** is the set  $f^{-1}(E) = \{x \in X \mid f(x) \in E\}$ .

**Definition 2.5** ( $\sigma$ -algebra):

Let  $X$  be a set.  $\Sigma \subseteq 2^X$  is said a **sigma algebra of  $X$**  iff.:

1.  $X \in \Sigma$
2.  $E \in \Sigma \implies X \setminus E \in \Sigma$ . **close under complement.**
3.  $\{A_n \in \Sigma\}_{n=1}^\infty \implies \bigcup_{i=1}^\infty A_i \in \Sigma$ . **close under infinite unions.**

**Definition 2.6** (generate  $\sigma$ -algebra):

Let  $X$  be a set and  $G \subseteq 2^X$ . The  **$\sigma$ -algebra generated by  $G$** , denoted  $\sigma_X(G)$ , is the smallest  $\sigma$ -algebra such that:

1.  $G \subseteq \sigma_X(G)$ .
2.  $\forall \Sigma$   $\sigma$ -algebra :  $G \subseteq \Sigma \implies \sigma_X(G) \subseteq \Sigma$ . **Every other  $\sigma$ -algebra that contains  $G$  contains also the generated one,  $\sigma_X(G)$ .**

**Definition 2.7** (borel  $\sigma$ -algebra):

Let  $(X, G)$  be a topological space. We refer to  $\sigma_X(G) = \mathcal{B}(X, G)$  as a **Borel  $\sigma$ -algebra**.

**Definition 2.8** ( $\sigma$ -algebra product):

Let  $\Sigma_1$  and  $\Sigma_2$  be  $\sigma$ -algebras on  $X_1$  and  $X_2$  respectively. The **product  $\sigma$ -algebra** denoted  $\Sigma_1 \otimes \Sigma_2$  is defined as  $\sigma_{X_1 \times X_2}(\{S_1 \times S_2 \mid S_1 \in \Sigma_1, S_2 \in \Sigma_2\})$

**Definition 2.9** (measurable space):

$(X, \Sigma)$  is said **measurable** iff.  $\Sigma$  is a *sigma-algebra* of  $X$ .

**Definition 2.10** (measure):

Given  $(X, \Sigma)$  measurable space.  $\mu : \Sigma \longrightarrow \mathbb{R} \cup \{+\infty, -\infty\}$  is said a **measure** iff.

1.  $E \in \Sigma \implies \mu(E) \geq 0$ . **positive**.
2.  $\{E_n \in \Sigma\}_{n=1}^{\infty}$  such that  $E_i \cap E_j = \emptyset$  for  $i \neq j \implies \mu\left(\bigcup_{i=1}^{\infty} E_i\right) = \sum_{i=1}^{\infty} \mu(E_i)$ . **The measure of disjoint sets is the sum of the measures of each set.**
3.  $\mu(\emptyset) = 0$ .

**Definition 2.11** (measure space):

$(X, \Sigma, \mu)$  is said a **measure space** iff.  $(X, \Sigma)$  is a sigma algebra and  $\mu$  is a measure of  $(X, \Sigma)$ .

**Definition 2.12** (measurable function):

Let  $(X_1, \Sigma_1)$  and  $(X_2, \Sigma_2)$  be a measurable spaces.  $f : X_1 \longrightarrow X_2$  is said a **measurable function** iff.  $\forall E \in \Sigma_2 : f^{-1}(E) \in \Sigma_1$ . **The preimage of each measurable set is again measurable.**

**Definition 2.13** (pushforward):

Let  $(X_1, \Sigma_1, \mu)$  be a measure space. Let  $(X_2, \Sigma_2)$  be a measurable space. Let  $f : X_1 \longrightarrow X_2$  be a measurable function. The **pushforward of  $\mu$  under  $f$**  is the mapping  $f_{\#}\mu : \Sigma_2 \longrightarrow \mathbb{R}_{\geq 0}$  defined as:

$$\forall E \in \Sigma_2 : f_{\#}\mu(E) = \mu(f^{-1}(E))$$

The **pushforward** is simply a function that generates a measure for a measurable space starting from a different measure space and a measurable function acting as bridge between the two spaces.

**Proposition 2.1** (pushforward of a measure is a measure):

Let  $(X_1, \Sigma_1, \mu)$  be a measure space. Let  $(X_2, \Sigma_2)$  be a measurable space. Let  $f : X_1 \longrightarrow X_2$  be a measurable function. Then  $(X_2, \Sigma_2, f_{\#}\mu)$  is a measure space.

**Proof 2.1** (of Proposition 2.1):

To prove that statement, we need to prove only the axioms of a measure.

1. Let  $E \in \Sigma_2$ , we need to show that  $f_{\#}\mu(E) \geq 0$ . This is trivial by definition of pushforward and measure.
2. Let  $[E_n \in \Sigma_2]_{n=1}^{\infty}$  be a sequence of pairwise disjoint sets. We need to show that:  $f_{\#}\mu\left(\bigcup_{n=1}^{\infty} E_n\right) = \sum_{n=1}^{\infty} f_{\#}\mu(E_n)$ .

$$\begin{aligned} f_{\#}\mu\left(\bigcup_{n=1}^{\infty} E_n\right) &= \mu\left(f^{-1}\left(\bigcup_{n=1}^{\infty} E_n\right)\right) \text{ definition of pushforward} \\ &= \mu\left(\bigcup_{n=1}^{\infty} f^{-1}(E_n)\right) \\ &= \sum_{n=1}^{\infty} \mu(f^{-1}(E_n)) \text{ definition of measure} \\ &= \sum_{n=1}^{\infty} f_{\#}\mu(E_n) \text{ definition of pushforward} \end{aligned}$$

3. We need to show that  $\exists E \in \Sigma_1$  such that  $f_{\#}\mu(E) \geq 0$ . Let  $E' \in \Sigma_1$  such that  $\mu(E') \geq 0$  (such  $E'$  exists by definition of measure). Then,  $f(E')$  is a set that meets the requirements, that is

$$f_{\#}(f(E')) = \mu(f^{-1}(f(E'))) = \mu(E') \geq 0$$

■

**Example 2.2** (pushforward example):

Consider the measure space  $(\mathbb{N}, 2^{\mathbb{N}}, \mu(E) = |E|)$ . Consider the measurable space  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ . Consider the measurable function  $f : \mathbb{N} \longrightarrow \mathbb{R}$  such that  $f(x) = x$ . Consider pushforward  $f_{\#}\mu : \mathbb{R} \longrightarrow \mathbb{R}_{\geq 0}$ . Then  $f_{\#}\mu$  is a measure for the measurable space  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  since:



1.  $f_{\#}\mu(E \in \mathcal{B}(\mathbb{R})) = |\{n \in \mathbb{N} \mid n \in E\}| \geq 0$ .
2. Let  $\{E_n\}_{n=1}^{\infty}$  pairwise disjoint, then  $f_{\#}\mu(\bigcup_{n=1}^{\infty} E_n) = \mu(f^{-1}(\bigcup_{n=1}^{\infty} E_n)) = \mu(\bigcup_{n=1}^{\infty} f^{-1}(E_n)) = \sum_{n=1}^{\infty} \mu(f^{-1}(E_n)) = \sum_{n=1}^{\infty} f_{\#}\mu(E_n)$ .
3.  $f_{\#}\mu(\emptyset) = \mu(f^{-1}(\emptyset)) = \mu(\emptyset) = 0$

## 2.1. Lebesgue Measure

**Definition 2.1.1** (pre-measure):

Let  $(X, \Sigma)$  such that  $\emptyset \in \Sigma$ . Let  $\mu : \Sigma \rightarrow \mathbb{R}_{\geq 0} + \{+\infty\}$ .  $\mu$  is said a **pre-measure** iff.

1.  $\mu(\emptyset) = 0$ .
2. Given a collection of pairwise disjoint sets  $\{A_n \in \Sigma\}_{n \in \mathbb{N}}$  such that  $\bigcup_{n \in \mathbb{N}} A_n \in \Sigma \Rightarrow \mu(\bigcup_{n \in \mathbb{N}} A_n) = \sum_{n \in \mathbb{N}} \mu(A_n)$ .
3.  $\forall A \in \Sigma : \mu(A) \geq 0$ .

A *pre-measure* is a precursor of a full-fledged *measure*. The main difference is that a *measure* is defined on sigma algebras, meanwhile the *pre-measure* is defined on a simple collection of subsets. Further, given that this collection is not necessarily closed under unions as a sigma algebra does, we also need to check that, in the second requirement, the union of  $A_n$  is indeed contained in the collection.

**Definition 2.1.2** (Lebesgue pre-measure):

The **Lebesgue pre-measure** is a mapping  $\lambda^n : \mathcal{J}_h^n \rightarrow \mathbb{R}_{\geq 0} \cup \{+\infty\}$  ( $\mathcal{J}_h^n$  denotes the set *half open rectangle*) such that  $\lambda^n(\times_{i=1}^n [a_i, b_i)) = \prod_{i=1}^n (b_i - a_i)$  for  $a_i, b_i \in \mathbb{R}$  and  $a_i \leq b_i$ .

**Proposition 2.1.1:**

The Lebesgue pre-measure is a pre-measure.

**Proof 2.1.1** (of Proposition Proposition 2.1.1):

1.  $\lambda^n(\emptyset) = \lambda^n(\times_{i=1}^n [a_i, a_i)) = \prod_{i=1}^n (a_i - a_i) = 0$
2. Let  $I = \times_{i=1}^n [a_i, b_i)$  and  $I' = \times_{i=1}^n [a'_i, b'_i)$  be disjoint *half open rectangles*. The  $I \cup I'$  belongs to  $\mathcal{J}_h^n$  if we can stitch one to the other. This can only happen if there is an  $i$  such that:
  1.  $j = i \Rightarrow b_j = a'_j$ .
  2.  $j \neq i \Rightarrow b_j = b'_j$ .
  3.  $j \neq i \Rightarrow a_j = a'_j$ .

This can be intuitively visualized in Figure 1 where two 2-dimensional *half open rectangles* met at one side. The only difference between the rectangles is that one is shifted along a single dimension, in such a way that they met at the open and close edges.

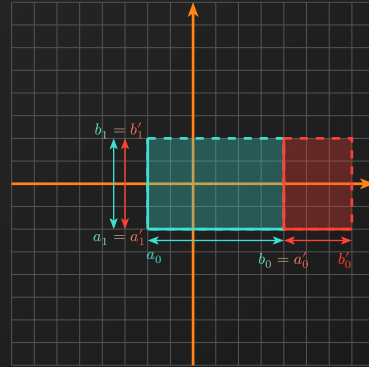


Figure 1: Two *half open rectangles* that can be stitched together.

In this situation we have that:

$$\begin{aligned}
 \lambda^n(I) + \lambda^n(I') &= \prod_{j=1}^n (b_j - a_j) + \prod_{j=1}^n (b'_j - a'_j) \quad \text{Lebesgue pre-measure definition} \\
 &= ((b_i - a_i) + (b'_i - a'_i)) \prod_{\substack{j=1 \\ j \neq i}}^n (b_j - a_j) \quad \text{factoring out } \prod_{\substack{j=1 \\ j \neq i}}^n (b_j - a_j) \\
 &= ((b_i - a'_i)) \prod_{\substack{j=1 \\ j \neq i}}^n (b_j - a_j) \quad \text{stitching half open rectangles together} \\
 &= \lambda^n(I \cup I')
 \end{aligned}$$

Thus it is verified that  $\lambda^n$  is finitely additive.

3. The  $\forall E \in \mathcal{J}_h^n : \lambda^n(E) \geq 0$  since the product of positive terms is positive.

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# 3. Probability Theory

**Definition 3.1** (Probability Space):

$(\Omega, \Sigma, p)$  is said a **probability space** iff.

1.  $(\Omega, \Sigma, p)$  is a *measure space*.
2.  $p(\Omega) = 1$ .

Intuitively,  $\Omega$  represents the set of all possible outcomes, it is also known as **sample space**.  $\Sigma$  represents the set of all possible events. These are nothing more than set of outcomes. It is also known as **event space**.  $p$  is a measure on the event space, it is also known as **probability function**. It maps events to their likelihood.

**Example 3.1** (Fair Die):

Consider the *probability space*  $(\Omega, \Sigma, p)$ , where:

1.  $\Omega = \{1, 2, 3, 4, 5, 6\}$  is the sample space, representing the possible outcomes of rolling a standard six-sided die.
2.  $\Sigma = 2^\Omega$  is the event space.
3.  $p : \Sigma \rightarrow [0, 1]$  is the probability measure function, defined as  $P(E) = \frac{|E|}{6}$  for any event  $E \in \Sigma$ .

For example, consider the event  $A = \{1, 2, 3\}$ , which represents rolling a 1, 2, or 3. This event is an element of  $\Sigma$ . The probability of event  $A$  occurring is  $p(A) = \frac{|A|}{6} = \frac{3}{6} = \frac{1}{2}$ .

**Definition 3.2** (Coupling):

Let  $(\Omega_1, \Sigma_1, \mu_1)$  and  $(\Omega_2, \Sigma_2, \mu_2)$  be *probability spaces*. A **coupling** is a *probability space*  $(\Omega_1 \times \Omega_2, \Sigma_1 \otimes \Sigma_2, \gamma)$  such that:

1.  $\forall E \in \Sigma_1 : \gamma(E \times \Omega_2) = \mu_1(E)$ . The **left marginal** of  $\gamma$  is  $\mu_1$ .
2.  $\forall E \in \Sigma_2 : \gamma(\Omega_1 \times E) = \mu_2(E)$ . The **right marginal** of  $\gamma$  is  $\mu_2$ .

**Example 3.2** (Coupling a Dice and a Coin):

Consider a *probability space*  $\mathcal{F}_1 = (\Omega_1 = \{1, 2, 3, 4\}, \Sigma_1 = 2^{\Omega_1}, p_1 = A \mapsto \frac{|A|}{4})$  (The *probability space* corresponding to a 4 sided die). Further, consider a *probability space*  $\mathcal{F}_2 = (\Omega_2 = \{1, 2\}, \Sigma_2 = 2^{\Omega_2}, p_2 = A \mapsto \frac{|A|}{2})$  (The *probability space* corresponding to a coin). We can define a *probability space*  $\mathcal{F} = (\Omega_1 \times \Omega_2, \Sigma_1 \otimes \Sigma_2, p)$  by *coupling*  $\mathcal{F}_1$  and  $\mathcal{F}_2$ . Here, sample space and event space are already decided, we need to provide only a proper measure  $p$ . Such a measure can be built by providing a *coupling* table:

$$\begin{pmatrix} p & \{1\} & \{2\} & \{3\} & \{4\} & p_1 \\ \{1\} & \frac{1}{4} & 0 & \frac{1}{4} & 0 & \frac{1}{2} \\ \{2\} & 0 & \frac{1}{4} & 0 & \frac{1}{4} & \frac{1}{2} \\ p_2 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & 1 \end{pmatrix}$$

On the top row, we have the possible singleton events from  $\mathcal{F}_1$ . On the left column, we have the possible singleton event from  $\mathcal{F}_2$ . The last row and column corresponds to marginal distributions. These marginals match  $p_2$  and  $p_1$  as required by the definition of *coupling*. The central body of this matrix represents join probabilities of the die and coin. For example,  $p(\{1\} \times \{3\}) = \frac{1}{4}$ .

Note that we could fill this matrix in such a way that we have a *probability space* but not a *coupling* by breaking the marginal axioms.

Retrieving event probabilities from singleton events is only matter of applying traditional probability rules.

## 4. Optimal Transport

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