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# 1 Elementary Probability

## 1.1 Lecture 1

This lecture I did not have a laptop yet, so I was unable to transcribe anything. Here is what I remember was discussed:

**Definition 1.1 (Conditional Probability)** For two events  $A, B$ , the probability of  $A$  given  $B$  is:

$$\mathbb{P}[A | B] = \frac{\mathbb{P}[A \cap B]}{\mathbb{P}[B]}$$

**Definition 1.2 (MAP)** We say the Most likely A Posteriori (MAP) estimate of a random variable  $X$  given  $Y = y$ , is:

$$\operatorname{argmax}_x \mathbb{P}[X = x | Y = y]$$

**Definition 1.3 (MLE)** We say the Maximum Likelihood Estimate (MLE) of a random variable  $X$  given  $Y$ , is:

$$\operatorname{argmax}_x \mathbb{P}[Y = y | X = x]$$

## 1.2 Lecture 2

### 1.2.1 Probability Fundamentals and Random Variables

We begin probability by defining a set  $\Omega$  called the sample space. Elements of the sample space are termed outcomes. Subsets of  $\Omega$  are termed as events.

For some event  $A$ , we can define the probability of  $A$  as follows:

$$\mathbb{P}[A] = \sum_{\omega \in A} \mathbb{P}[\omega]$$

Probability maps events to  $[0, 1]$  in a consistent manner, satisfying the following axioms:

- $\mathbb{P}[\Omega] = 1$
- $\mathbb{P}[\emptyset] = 0$
- For two disjoint events  $A_1, A_2$ , we have  $\mathbb{P}[A_1 \cup A_2] = \mathbb{P}[A_1] + \mathbb{P}[A_2]$

This is what we term a probability space. Often it is more helpful to work with events than with individual sample points (especially in the case of an uncountably infinite amount of sample points).

**Definition 1.4 (Random Variable)** A random variable  $X : \omega \rightarrow B$  maps each outcome to elements of some other set (often  $\mathbb{R}$ ).  $X = x$  for some  $x$  is an event, with a well-defined probability.

**Definition 1.5 (Independence)** Two random variables  $X$  and  $Y$  are independent if

$$\mathbb{P}[X = x | Y = y] = \mathbb{P}[X = x]$$

i.e.

$$\mathbb{P}[X = x, Y = y] = \mathbb{P}[X = x] \mathbb{P}[Y = y]$$

**Example 1.1** Suppose you flip a coin 10 times. We will show that  $X$ , the amount of heads in the first 4 flips, and  $Y$ , the amount of heads in the last 6 flips, are independent.

Let  $a(x)$  be the amount of ways to get  $x$  heads in 4 flips and  $b(y)$  be the amount of ways to get  $y$  heads in 6 flips. Then,

$$\begin{aligned} \mathbb{P}[X = x] &= \frac{a(x) \cdot 2^6}{2^{10}} = \frac{a(x)}{2^4} \\ \mathbb{P}[Y = y] &= \frac{b(y) \cdot 2^4}{2^{10}} = \frac{b(y)}{2^6} \\ \mathbb{P}[X = x, Y = y] &= \frac{a(x) \cdot b(y)}{2^{10}} = \mathbb{P}[X = x] \cdot \mathbb{P}[Y = y] \end{aligned}$$

Thus, the random variables are independent.

**Definition 1.6 (Expectation)** The expectation of a (discrete) random variable is:

$$\mathbb{E}[X] = \sum_x x \mathbb{P}[X = x]$$

This is often called the mean or the average value.

**Theorem 1.1** Properties of expectation:

- $\mathbb{E}[a] = a$  for  $a \in \mathbb{R}$
- If the space is uniform, then  $\mathbb{E}[X] = \frac{1}{N} \sum_x x$
- $\mathbb{E}[\alpha X + \beta Y] = \alpha \mathbb{E}[X] + \beta \mathbb{E}[Y]$  for  $\alpha, \beta \in \mathbb{R}$
- $X \leq Y \Rightarrow \mathbb{E}[X] \leq \mathbb{E}[Y]$
- If  $X$  and  $Y$  are independent, then  $\mathbb{E}[XY] = \mathbb{E}[X] \mathbb{E}[Y]$
- $\mathbb{E}[XY] = \mathbb{E}[X] \mathbb{E}[Y] \nRightarrow X, Y$  independent

There are two ways of thus computing expectation. You can either sum over sample points, or take a lot of measurements of your random variable, then divide by the amount of measurements. The reason this works is because of property 2 above.

**Definition 1.7 (Variance and Standard Deviation)** The variance of a random variable  $X$  is defined as:

$$\text{Var}(X) = \mathbb{E}[(X - \mathbb{E}[X])^2]$$

The standard deviation of this random variable is:

$$\sigma_X = \sqrt{\text{Var}(X)}$$

The variance measures the spread away from the mean that a random variable may exhibit.

**Theorem 1.2** Properties of variance:

- $\text{Var}(X) \geq 0$ , with equality only if  $X$  is constant
- $\text{Var}(X) = \mathbb{E}[X^2] - (\mathbb{E}[X])^2$
- $\text{Var}(aX) = a^2 \text{Var}(X)$  for constant  $a$
- If  $X$  and  $Y$  are independent,  $\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y)$
- In general,  $\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y) - 2\text{Cov}(X, Y)$

Often we term  $\mathbb{E}[X^k]$  as the  $k$ th moment of  $X$ , so the variance contains information about the second moment of  $X$ .

## 1.3 Lecture 3

### 1.3.1 Concentration Inequalities

**Definition 1.8 (Indicator Random Variable)**  $\mathbb{1}_A$  is the indicator for event  $A$ , i.e. a random variable with the following values:

$$\mathbb{1}_A = \begin{cases} 1 & \text{if sample point in event } A \\ 0 & \text{otherwise} \end{cases}$$

**Theorem 1.3 (Markov's Inequality)** Consider random variable  $X \geq 0$  and constant  $a > 0$ . Then,

$$\mathbb{P}[X \geq a] \leq \frac{\mathbb{E}[X]}{a}$$

**Proof** Let  $Y = \mathbb{1}_{X \geq a}$ . Then we know:

$$\begin{aligned} \mathbb{E}[Y] &= 0 \cdot \mathbb{P}[X < a] + 1 \cdot \mathbb{P}[X \geq a] = \mathbb{P}[X \geq a] \\ Y &\leq \frac{X}{a} \\ \mathbb{E}[Y] &\leq \mathbb{E}\left[\frac{X}{a}\right] = \frac{\mathbb{E}[X]}{a} \\ \mathbb{P}[X \geq a] &\leq \frac{\mathbb{E}[X]}{a} \end{aligned}$$

Markov's inequality tends to be a coarse bound, and  $X, a$  have to be non-negative.

**Theorem 1.4 (Chebyshev's Inequality)** For random variable  $X$  and  $\epsilon > 0$ :

$$\mathbb{P}[|X - \mathbb{E}[X]| \geq \epsilon] \leq \frac{\text{Var}(X)}{\epsilon^2}$$

Define  $Z = |X - \mathbb{E}[X]|^2$ ,  $a = \epsilon^2$ ,  $\epsilon > 0$ .

**Proof** Apply Markov's inequality:

$$\mathbb{P}[Z \geq \epsilon^2] \leq \frac{\mathbb{E}[Z]}{\epsilon^2}$$

Note that

$$\mathbb{E}[Z] = \mathbb{E}[(X - \mathbb{E}[X])^2] = \text{Var}(X)$$

This means that

$$\mathbb{P}[\sqrt{Z} \geq \epsilon] \leq \frac{\text{Var}(X)}{\epsilon^2}$$

which is exactly the statement of Chebyshev's.

Chebyshev's is generally a tighter bound than Markov's.

**Theorem 1.5 (Weak Law of Large Numbers)** Assume  $X_1, X_2, X_3, \dots$  are independent random variables with the same expectation  $\mu$  and the same variance  $\sigma^2$ , and define  $Y_n = \frac{(X_1 + X_2 + \dots + X_n)}{n}$ . Then, we have that for any

constant  $\epsilon > 0$ .

$$\lim_{n \rightarrow \infty} \mathbb{P}[|Y_n - \mu| \geq \epsilon] \rightarrow 0$$

This can be shown by Chebyshev's inequality, namely note that the expression in the limit is bounded by  $\frac{\text{Var}(Y_n)}{\epsilon^2} = \frac{n\sigma^2}{n^2\epsilon^2} \rightarrow 0$ .

In words, this means the probability of the sample mean being within  $\epsilon$  of the true mean approaches 1.

### 1.3.2 Covariance and Estimation

#### Definition 1.9 (Covariance)

$$\text{Cov}(X, Y) = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y] = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])]$$

If  $X$  and  $Y$  are independent, then  $\text{Cov}(X, Y) = 0$ . If the latter is true, then  $X$  and  $Y$  are uncorrelated. We also define the coefficient of correlation:

$$\rho_{xy} = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

This is handy because  $|\rho_{XY}| \leq 1$ .

Suppose we want to estimate a random variable  $Y$  by  $\hat{Y}$  given a correlated random variable  $X$ .

We want to minimize  $\mathbb{E}[(Y - \hat{Y})^2]$  but have a linear relationship. This yields LLSE:

**Theorem 1.6 (Linear Least Squares Estimate)** The LLSE

$$\hat{Y} = \mathbb{E}[Y] + \frac{\text{Cov}(X, Y)}{\text{Var}(X)}(X - \mathbb{E}[X])$$

is the best linear estimate of  $Y$  given  $X$ .

## 2 Basic Probability

### 2.1 Lecture 3, Continued

#### 2.1.1 Infinite Collections of Events and Borel-Cantelli

There are some important consequences of the axioms of probability.

**Theorem 2.1 (Infinite Sub-Events)** Consider some set  $A$  where  $A = \bigcup_{n=1}^{\infty} A_n$  where:

$$A_1 \subseteq A_2 \subseteq \dots$$

Then,  $\mathbb{P}[A_n] \rightarrow \mathbb{P}[A]$ .

Furthermore, consider some set  $B$  where  $B = \bigcap_{n=1}^{\infty} B_n$  where:

$$B_1 \supseteq B_2 \supseteq \dots$$

Then,  $\mathbb{P}[B_n] \rightarrow \mathbb{P}[B]$ .

**Theorem 2.2 (Borel-Cantelli Theorem)** Let  $\{A_n\}_{n=1}^{\infty}$  be a collection of events such that  $\sum_{n=1}^{\infty} \mathbb{P}[A_n] < \infty$ , then  $\mathbb{P}[A_n \text{ infinitely often}] = 0$ .  
 $\{A_n \text{ infinitely often}\}$  is the following event:

$$\{\omega \mid \exists N(\omega) \text{ such that } \forall n > N(\omega), \omega \notin A_n\}$$

In English, the set describes all outcomes where you can assign a number to that outcome such that after  $A_N$ , you have no set membership.

The theorem claims that you CAN assign such a number (max event) to any outcome with nonzero probability.

**Proof** Define

$$B_n = \bigcup_{m \geq n} A_m$$

Note that  $B_1 \supseteq B_2 \supseteq B_3 \dots$

Calling,

$$B = \bigcap_n B_n = B_n$$

Note that  $\omega \in \{A_n \text{ io}\}$  if and only if  $\omega \in B_n$  for all  $n$ . But this means that  $\omega \in B$ . This means that  $\{A_n \text{ io}\} = B$ . So we must calculate  $\mathbb{P}[B]$ . However, note that  $\mathbb{P}[B_n] \rightarrow \mathbb{P}[B]$  as  $n \rightarrow \infty$ . Thus, we must compute:

$$\begin{aligned} \mathbb{P}[B] &= \lim_{n \rightarrow \infty} \mathbb{P}[B_n] \\ \mathbb{P}[B_n] &\leq \sum_{m=n}^{\infty} \mathbb{P}[A_m] \rightarrow 0 \\ \mathbb{P}[B] &= 0 \end{aligned}$$

The second step is justified by the following result from analysis. For non-negative sequence  $a_n$ , if  $\sum_{i=1}^{\infty} a_n < \infty$ , then  $\lim_{n \rightarrow \infty} \sum_{m=n}^{\infty} a_m \rightarrow 0$ .

Our result shows that  $\mathbb{P}[A_n \text{ io}] = 0$  ■

Consider the following example for coin flips:

**Example 2.1 (Infinite Coin Flips)** Consider the experiment of flipping a coin infinitely many times. Let

$$A_n = \{n\text{th flip is heads}\}$$

Then, in this experiment, the event  $\{A_n \text{ infinitely often}\}$  (which we denote as  $\{A_n \text{ io}\}$ )

$$\{A_n \text{ io}\} = \{\omega \mid \text{heads never stop after some } N(\omega)\}$$

Here are some sequences that are in that event:

$$\begin{aligned} \omega &= 0, 0, 1, 1, 1, 1, \dots \\ \omega &= 0, 1, 0, 1, 0, 1, \dots \\ \omega &= 0, 0, \underbrace{\dots}_{1 \text{ million } 0\text{'s}}, 1, 0, 0, \underbrace{\dots}_{1 \text{ million } 0\text{'s}}, 1, \dots \end{aligned}$$

Now consider the assigning the following probabilities to each heads (instead of the normal, uniform probability space):

$$\mathbb{P}[A_n] = \frac{1}{n^2}$$

$\sum_{n=1}^{\infty} \frac{1}{n^2}$  converges, so by Borel-Cantelli,  $\mathbb{P}[A_n \text{ io}] = 0$ , i.e. the heads ALWAYS stop.

Now there is one more question. Does  $\mathbb{P}[A_n \text{ i.o.}] = 0 \implies \{A_n \text{ i.o.}\} = \emptyset$ ? The answer is no. In this case,  $\mathbb{P}[A_n \text{ i.o.}] = 0$ , but consider the outcome  $\omega_n$  where the  $n$ th flip onwards is a heads; these are all in the infinitely often set, so it actually has infinite cardinality!



## 2.2 Lecture 4

### 2.2.1 The Laws of Large Numbers, Revisited

Here is a recap of the two different laws of large numbers.

First, we define two different types of convergence:

**Definition 2.1 (Almost Sure Convergence)** A random variable  $A$  almost surely converges to constant  $b$  if

$$\mathbb{P}[A \rightarrow b] = 1$$

as  $n \rightarrow \infty$ .

**Definition 2.2 (Convergence in Probability)** A random variable  $A$  converges in probability to constant  $b$  if

$$\mathbb{P}[|A - b| < \epsilon \rightarrow 1]$$

for any real number  $\epsilon > 0$ .

**Theorem 2.3 (Strong Law of Large Numbers)** Let  $X_1, X_2, \dots, X_n$  be independent and identically distributed (iid) random variables. Define:

$$Y_n = \frac{X_1 + \dots + X_n}{n}$$

$$Y = \mathbb{E}[X_1]$$

$Y_n$  converges to  $Y$  almost surely.

Note the contrast with the weak law of natural numbers. The weak law had only convergence in probability. A key thing to note is that the strong law **implies** the weak law.

### 2.2.2 Independence

Let us now refine the notion of Independence.

**Definition 2.3 (Pairwise Independence)** Consider events  $A_j$  with  $j \in J$ . The events are pairwise independent if for any  $j, k \in J$ ,

$$\mathbb{P}[A_j \cap A_k] = \mathbb{P}[A_j] \mathbb{P}[A_k]$$

**Definition 2.4 (Mutual Independence)** Consider events  $A_j$  with  $j \in J$ . The events are mutually independent if

$$\mathbb{P}\left[\bigcap_{j \in K} A_j\right] = \prod_{j \in K} \mathbb{P}[A_j], \forall K \subseteq J$$

Note that pairwise independence does not imply mutual independence. Here is an example of that edge case:

**Example 2.2** Take probability space  $\Omega = \{1, 2, 3, 4\}$ , all equally likely. Consider the events:  $A = \{1, 2\}$ ,  $B = \{1, 3\}$ ,  $C = \{1, 4\}$ .

Note that  $\mathbb{P}[A \cap B] = \frac{1}{4} = \mathbb{P}[A] \mathbb{P}[B]$ ,

but  $\mathbb{P}[A \cap B \cap C] = \frac{1}{4} \neq \frac{1}{8} = \mathbb{P}[A] \mathbb{P}[B] \mathbb{P}[C]$ .

Now with independence, we can find that the converse of Borel-Cantelli is often true:

**Theorem 2.4 (Converse of Borel-Cantelli Theorem)** Let  $A_n$  be a collection of mutually independent events such that  $\sum_{n=1}^{\infty} \mathbb{P}[A_n] = \infty$ . Then,  $\mathbb{P}[A_n \text{ infinitely often}] = 1$ .

Let us use another example to understand this:

**Example 2.3** Let  $A_n$  be the same event as the other example (the  $n$ th flip is heads) and assign:

$$\mathbb{P}[A_n] = \frac{1}{n}$$

where all the  $A_n$  are mutually independent.

Since  $\sum_{n=1}^{\infty} \frac{1}{n} = \infty$  and thus by the converse of Borel-Cantelli:  $\mathbb{P}[A_n \text{ io}] = 1$ .

**Example 2.4 (Glued Coins)** Suppose you have  $n$  coins that are all glued together, i.e. the only two outcomes are  $HHH \dots$  or  $TTT \dots$ . Then let  $A_n$  be the  $n$ th coin is heads. Note that

$$\mathbb{P}[A_n] = \frac{1}{2}$$

which means  $\sum \mathbb{P}[A_n] = \infty$ . Thus the probability of getting a sequence which has heads infinitely often is 1.

**Theorem 2.5 (Kolmogorov's 0-1 theorem)** If you have a set of events  $\{A_n\}_{n=1}^{\infty}$  that all independent, then

$$\mathbb{P}[A_n \text{ infinitely often}] = 0 \text{ or } 1$$

### 2.2.3 Conditional Probability

Now we refine conditional probability for many events.

**Definition 2.5 (Conditional Probability)** Let  $A$  and  $B$  be two events, and assume  $\mathbb{P}[B] > 0$ . Then the conditional probability of  $A$  given  $B$  is:

$$\mathbb{P}[A | B] = \frac{\mathbb{P}[A \cap B]}{\mathbb{P}[B]}$$

**Theorem 2.6 (Chain Rule)** For two events we had  $\mathbb{P}[A \cap B] = \mathbb{P}[A | B] \mathbb{P}[B]$ . For  $n$  events  $A_i$ , we have:

$$\mathbb{P}[A_1 \cap A_2 \cap \dots \cap A_n] = \mathbb{P}[A_1] \mathbb{P}[A_2 | A_1] \mathbb{P}[A_3 | A_1 \cap A_2] \dots \mathbb{P}[A_n | A_1 \cap A_2 \cap \dots \cap A_{n-1}]$$

if  $\mathbb{P}[A_1 \cap A_2 \cap \dots \cap A_{n-1}] > 0$ .

The generalized result above can be shown by induction, taking the case of two events as the base case and then inducting on  $n$ . Now we will bring in some of the most powerful tools.

**Theorem 2.7 (Law of Total Probability)** Let  $A, B_1, \dots, B_n$  be events where  $B_i$ 's are disjoint and  $\bigcup_{i=1}^n B_i = \Omega$ . Then,

$$\mathbb{P}[A] = \sum_{i=1}^n \mathbb{P}[A \cap B_i]$$

**Theorem 2.8 (Bayes' Rule)** Let  $A, B_1, \dots, B_n$  be events where  $B_i$ 's are disjoint and  $\bigcup_{i=1}^n B_i = \Omega$ .

$$\mathbb{P}[B_i | A] = \frac{\mathbb{P}[A | B_i] \mathbb{P}[B_i]}{\sum_{j=1}^n \mathbb{P}[A | B_j] \mathbb{P}[B_j]}$$

**Proof** Note that we can use the initial definition to expand the left side:

$$\begin{aligned} \mathbb{P}[B_i | A] &= \frac{\mathbb{P}[A \cap B_i]}{\mathbb{P}[A]} \\ &= \frac{\mathbb{P}[A | B_i] \mathbb{P}[B_i]}{\sum_{j=1}^n \mathbb{P}[A \cap B_j]} \\ &= \frac{\mathbb{P}[A | B_i] \mathbb{P}[B_i]}{\sum_{j=1}^n \mathbb{P}[A | B_j] \mathbb{P}[B_j]} \end{aligned}$$

where the summation in the denominator comes from the law of total probability.

Often the  $B_j$ 's are termed the prior probabilities, and  $A$  is considered the posterior probability.

For an event  $B \subseteq R$ ,  $\mathbb{P}[X \in B] = \mathbb{P}[(X^{-1}(B))]$  where

$$X^{-1}(B) = \{\omega \in \Omega \mid X(\omega) \in B\}$$

.

We can define the following for a random variable to the reals.

**Definition 2.6 (Cumulative Distribution Function (CDF))** The Cumulative Distribution Function  $F_X(x)$  of random variable  $X$  is defined by:

$$F_X(x) = \mathbb{P}[X \in (-\infty, x]] = \mathbb{P}[X \leq x]$$

Here are some properties of the CDF:

- $F_X$  is non-decreasing.
- $F_X$  is right-continuous.
- $F_X \rightarrow 0$  as  $x \rightarrow -\infty$  and  $F_X \rightarrow 1$  as  $x \rightarrow \infty$ .

**Example 2.5 (CDF of an Indicator)** Consider the following random variable:

$$I = \begin{cases} 0 & \text{with probability } 1 - p \\ 1 & \text{with probability } p \end{cases}$$

Then the  $F_I(i)$  is a step function: TODO Add figure

## 2.3 Lecture 5

**Definition 2.7 (Discrete Random Variable)** A discrete random variable  $X$  can be described fully by:

$$\{(x_n, p_n), n = 1, \dots, N\}$$

where  $p_n = \mathbb{P}[X = x_n]$ . This is called the probability mass function (PMF) of  $X$ .

We can write the expectation as follows:

$$\mathbb{E}[X] = \sum_{n=1}^N x_n p_n$$

With  $N = \infty$ , the expectation may not be defined.

**Definition 2.8 (Function of a Random Variable)** Calling  $h(X)$  means changing to another random variable with the following PMF:

$$(h(x_n), p_n), n = 1, \dots, N$$

The expectation of this is as follows:

$$\mathbb{E}[h(X)] = \sum_{n=1}^N h(x_n) p_n$$

**Definition 2.9 (Coefficient of Variation)** The coefficient of variation  $c$  of  $X$  is defined:

$$c = \sigma_X / \mathbb{E}[X]$$

### 2.3.1 Common Discrete Distributions

Bernoulli random variables model situations like individual coin flips.

**Definition 2.10 (Bernoulli Random Variables)** If  $X =_D B(p)$  with  $p \in [0, 1]$ , then the PMF of  $X$  is:

$$\{(0, 1 - p), (1, p)\}$$

Furthermore,  $\mathbb{E}[X] = p$  and  $\text{Var}(X) = p(1 - p)$ .

Geometric random variables model the situation where you count the number of coin flips until you get "heads".

**Definition 2.11 (Geometric Random Variable)** If  $X =_D G(p)$  with  $p \in [0, 1]$ , then the PMF of  $X$  is:

$$\mathbb{P}[X = n] = (1 - p)^{n-1} p$$

Furthermore,  $\mathbb{E}[X] = \frac{1}{p}$  and  $\text{Var}(X) = \frac{1-p}{p^2}$ .

The CDF can also be derived as  $\mathbb{P}[X \leq n] = 1 - (1 - p)^n$ , since it's the complement of failing  $n$  times. The CCDF (Complementary CDF) is thus  $\mathbb{P}[X > n] = (1 - p)^n$ .

**Note 2.1 (Memoryless Property)** The geometric distribution is memoryless, i.e. if  $X =_D G(p)$ , then

$$\mathbb{P}[X > m + n \mid X > m] = \mathbb{P}[X > n]$$

Binomial random variables model the situation of doing  $n$  coin flips and counting the heads, or the sum of  $n$  i.i.d. Bernoulli random variables.

**Definition 2.12 (Binomial Random Variable)** If  $X \stackrel{D}{=} B(N, p)$  with  $p \in [0, 1]$  and  $N \geq 1$ , then the PMF of  $X$  is:

$$\mathbb{P}[X = n] = \binom{N}{n} p^n (1 - p)^{N-n}$$

Furthermore,  $\mathbb{E}[X] = Np$  and  $\text{Var}(X) = Np(1 - p)$

The mode of the binomial distribution (the maximum probability) is at  $n = \lfloor p(N + 1) \rfloor$ .

Poisson random variables are the limit of the binomials as the rate of coin flips goes to infinity. This represents the number of successes in an interval during a continuous process.

**Definition 2.13 (Poisson Random Variable)** If  $X \stackrel{D}{=} P(\lambda)$  with  $\lambda > 0$ , then the PMF of  $X$  is:

$$\mathbb{P}[X = n] = \frac{e^{-\lambda} \lambda^n}{n!}$$

Furthermore,  $\mathbb{E}[X] = \lambda$  and  $\text{Var}(X) = \lambda$ .

In fact, we can make this limit more precise.

**Theorem 2.9 (Binomial Converges to Poisson)** We have, setting  $Np = \lambda$ , where  $\lambda$  is fixed,

$$B(N, \lambda/N) \rightarrow P(\lambda)$$

### 2.3.2 Multiple Discrete Random Variables

Consider a pair of random variables  $(X, Y)$ .

**Definition 2.14 (Joint PMF)** The joint distribution is given by:

$$p_{i,j} = \mathbb{P}[X = x_i, Y = y_j]$$

To find the PMF of one of the variables from the joint distribution, we can

**Note 2.2 (Marginal PMF from JPMF)**

$$\mathbb{P}[X = x_i] = \sum_j \mathbb{P}[X = x_i, Y = y_j]$$

Furthermore,

**Theorem 2.10 (Independence for Random Variables)**  $X$  and  $Y$  are independent if and only if

$$\mathbb{P}[X = x, Y = y] = \mathbb{P}[X = x] \mathbb{P}[Y = y]$$

If you have a function of multiple random variables, you can apply it similarly to the one variable case.

$$\mathbb{E}[h(X, Y)] = \sum_i \sum_j h(x_i, y_j) \mathbb{P}[X = x_i, Y = y_j]$$

First we extend the idea of conditioning to random variables.

**Definition 2.15 (Conditional PMF)** We call the conditional distribution of  $Y$  given  $X$  as:

$$\mathbb{P}[Y = y_j | X = x_i] = \frac{\mathbb{P}[X = x_i, Y = y_j]}{\mathbb{P}[X = x_i]}$$

**Definition 2.16 (Conditional Expectation)** The expectation of  $Y$  given  $X$  (i.e. the best guess of  $Y$  given  $X$ ) is denoted  $\mathbb{E}[Y | X]$  and is a function of  $X$

Furthermore, if we want to use a function, we can compute it as follows:

$$\mathbb{E}[h(Y) | X = x_i] = \sum_j h(y_j) \mathbb{P}[Y = y_j | X = x_i]$$

**Theorem 2.11 (Properties of Conditional Expectation)** For two random variables  $X, Y$ ,

$$\begin{aligned}\mathbb{E}[\mathbb{E}[Y | X]] &= \mathbb{E}[Y] \\ \mathbb{E}[h(X)Y | X] &= h(X)\mathbb{E}[Y | X] \\ \mathbb{E}[Y | X] &= \mathbb{E}[Y] \text{ if } X \text{ and } Y \text{ are independent} \\ \mathbb{E}[h_1(Y) + h_2(Y) | X] &= \mathbb{E}[h_1(Y) | X] + \mathbb{E}[h_2(Y) | X]\end{aligned}$$

## 2.4 Lecture 6

Unfortunately, I didn't transcribe this lecture, as I was very tired. Here is one of the more important results.

In general  $X_n \rightarrow X \not\Rightarrow \mathbb{E}[X_n] \rightarrow \mathbb{E}[X]$ . However, Dominated Convergence Theorem (DCT) and Monotone Convergence Theorem (MCT) provide sufficient conditions in the following form.

**Theorem 2.12 (Continuous Tail Sum Formula)** Let  $X \geq 0$  be a non-negative random variable with  $\mathbb{E}[X] < \infty$ . Then,

$$\mathbb{E}[X] = \int_0^\infty \mathbb{P}[X > x] \, dx$$



## 2.5 Lecture 7

### 2.5.1 Multiple Continuous Random Variables

**Definition 2.17 (JCDF)** For random variables  $X$  and  $Y$ , the joint CDF (JCDF) is given by:

$$F_{X,Y}(x, y) = \mathbb{P}[X \leq x, Y \leq y]$$

For continuous random variables, this is:

$$F_{X,Y}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{X,Y}(x', y') dy' dx'$$

Then, note that to find  $F_{\max X, Y}(k) = \mathbb{P}[\max X, Y \leq k] = \mathbb{P}[X \leq k, Y \leq k]$ , we can invoke the JCDF (and make simplifications if  $X$  and  $Y$  are independent). Furthermore, to find the probability density, we can simply differentiate with respect to  $k$ .

Similarly,  $\mathbb{P}[\min X, Y > k] = \mathbb{P}[X > k, Y > k]$ , which would be the JCCDF (which is the product of the CCDFs if  $X$  and  $Y$  are independent).

The sum of independent random variables is given by the convolution,  $*$ .

**Theorem 2.13 (Convolution)** Let  $Z = X + Y$  where  $X$  and  $Y$  are independent. Then,

$$f_Z(z) = f_X * f_Y = \int_{-\infty}^{\infty} f_X(x) f_Y(z - x) dx$$

In addition, we have conditioning for continuous random variables as well.

**Definition 2.18 (Conditional PDF)** Consider two random variables,  $X$  and  $Y$  such that  $f_X(x) \neq 0$  at the point we are considering. Then:

$$f_{X|Y}(x | y) = f_{XY}(x, y) / f_Y(y)$$

**Definition 2.19 (Conditional Variance)** Let  $X$  and  $Y$  be random variables. Then we define conditional variance as:

$$\text{Var}(Y | X) = \mathbb{E}[Y^2 | X] - (\mathbb{E}[Y | X])^2$$

Similar to the law of iterated expectation, there is a similar formula for variance:

**Theorem 2.14 (Law of Iterated Variance)** Let  $X$  and  $Y$  be random variables. Then,

$$\text{Var}(Y) = \mathbb{E}[\text{Var}(Y | X)] + \text{Var}(\mathbb{E}[Y | X])$$

**Proof**

$$\begin{aligned} \text{Var}(Y | X) &= \mathbb{E}[Y^2 | X] - (\mathbb{E}[Y | X])^2 \\ \mathbb{E}[\text{Var}(Y | X)] &= \mathbb{E}[Y^2] - \mathbb{E}[(\mathbb{E}[Y | X])^2] \\ &= \text{Var}(Y) + (\mathbb{E}[Y])^2 - \mathbb{E}[(\mathbb{E}[Y | X])^2] \\ &= \text{Var}(Y) + (\mathbb{E}[\mathbb{E}[Y | X]])^2 - \mathbb{E}[(\mathbb{E}[Y | X])^2] \\ &= \text{Var}(Y) - \text{Var}(\mathbb{E}[Y | X]) \\ \text{Var}(Y) &= \mathbb{E}[\text{Var}(Y | X)] + \text{Var}(\mathbb{E}[Y | X]) \end{aligned}$$

An interpretation of this is to think about dividing  $\Omega$  into disjoint sets where  $S_i$  where  $X = x_i$ . The conditional expectation, The first term is saying that taking the variance of replacing each set with the average over the set, is the first-order approximation. Then, to correct, we average the variances across each and add those in.

### 3 Page Rank

#### 3.1 Lecture 7, Continued

Page rank is an algorithm originally used by Google for ranking the pages from a keyword search.

It tries to look at the problem as a Markov chain; the weight of each page  $p$  is sum over all pages linking to  $p$ , times the probability of visiting  $p$  from that other page. Symbolically, this is:

$$\pi(i) = \sum_{j \in \mathcal{X}} \pi(j)P(j, i), \forall i \in \mathcal{X}$$

where  $\pi$  is a (row) vector of the weights, and  $P$  is a matrix whose  $(j, i)$  entry corresponds to the probability of transitioning from  $j$  to  $i$ . So, we can rewrite the above equations as

$$\pi = \pi P$$

We also add the normalization constraint

$$\sum_{i \in \mathcal{X}} \pi(i) = 1$$

So,  $\pi$  is a probability distribution.

##### 3.1.1 Discrete-Time Markov Chains

**Definition 3.1 (Discrete Time Markov Chain (DTMC))** The DTMC  $\{X(n), n \geq 0\}$  over state space  $\mathcal{X}$  with  $P = [P(i, j)]$  as the transition matrix with  $P(i, j) = \mathbb{P}[X(n+1) = j \mid X(n) = i]$ . Markov chains have the memoryless property:

$$\mathbb{P}[X(n+1) = j \mid X(n) = i, X(m), m < n] = P(i, j) \forall i, j$$

Generally, we have  $P$  constant with respect to time, i.e. it's time-homogenous. Note that we have not shown that defining probabilities like this is consistent with the axioms of probability; let us assume such a choice exists for now.

Then, let  $\pi_n(i)$  be the probability that the Markov chain is in state  $i$  at time  $n$ . Then, for every time step, using vector notation, we get the recurrence:

$$\pi_{n+1} = \pi_n P \implies \pi_n = \pi_0 P^n$$

**Definition 3.2 (Stationary Distribution)** Let  $P$  be the transition matrix of a markov chain. We call  $\pi$  a stationary distribution of the Markov chain if:

$$\pi = \pi P \text{ and } \sum_{i=1}^n \pi(i) = 1$$

We call these equations the balance equations.

One thing to note is that we can rewrite the equations as  $(P - I)\pi = 0$ . However, since every row sums to 0, this is not a full rank matrix, so we need the extra constraint about the sum of all the elements of  $\pi$ .

Next, we have some ways to classify Markov chains.

**Definition 3.3 (Irreducible)** A Markov Chain is irreducible if it can reach any state from any other state (possibly in multiple steps).

**Definition 3.4 (Aperiodic)** Let  $d(i) = \gcd\{n \geq 1 \mid P^n(i, i) > 0\}$ . An irreducible DTMC is aperiodic if  $d(i) = 1$  for all  $i$  (in fact in an irreducible DTMC,  $d(i)$  is the same as  $i$ ).

Note that if a Markov chain has a self loop, it is aperiodic because we can get from  $i$  to  $i$  in a single step, so  $d(i) = 1$  always.

**Example 3.1** Consider the following Markov chain, which is irreducible and aperiodic. (DIAGRAM NEEDED)

$$P = \begin{bmatrix} 0 & 1 & 0 \\ 0.6 & 0 & 0.4 \\ 0 & 0.9 & 0.1 \end{bmatrix}$$

Note that  $P(i, j)$  is the probability of going from  $i$  to  $j$ . Note that all the rows sum to 1 (by the total probability rule). Now let us solve the balance equations:

$$\pi = \pi P$$

$$\begin{bmatrix} \pi_0 & \pi_1 & \pi_2 \end{bmatrix} = \begin{bmatrix} \pi_0 & \pi_1 & \pi_2 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 \\ 0.6 & 0 & 0.4 \\ 0 & 0.9 & 0.1 \end{bmatrix}$$

This yields the equations:

$$\begin{cases} 0.6\pi_1 = \pi_0 \\ \pi_0 + 0.9\pi_2 = \pi_1 \\ 0.4\pi_1 + 0.1\pi_2 = \pi_2 \\ \pi_0 + \pi_1 + \pi_2 = 0 \end{cases}$$

Note that some of these equations are dependent, so we needed the extra constraint. This can then be solved to get:

$$\pi = \begin{bmatrix} 0.294 & 0.489 & 0.217 \end{bmatrix}$$

With these notions, we have the following results.

**Theorem 3.1 (Big Theorem for Finite DTMC)** Consider an irreducible DTMC over a finite state space. Then,

- There is a unique invariant distribution  $\pi$
- The long-term fraction of time spent in state  $n$  is given by

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{n=0}^{N-1} \mathbb{1}_{\{X(n)=i\}} = \pi(i)$$

- If the DTMC is aperiodic,  $\pi_n \rightarrow \pi$  as  $n \rightarrow \infty$ , independent of  $\pi_0$

Another way to state the last result is that each row in  $P^n$  converges to  $\pi$  as  $n \rightarrow \infty$ . Why? Consider  $\pi_0 = \begin{bmatrix} 1 & 0 & \dots & 0 \end{bmatrix}$ . Then  $\pi_n = \pi_0 P^n = p_1 \rightarrow \pi$ , so the first row approaches  $\pi$ . The argument is similar for any row.

## 3.2 Lecture 8

### 3.2.1 Hitting Times

**Note 3.1** Consider a Markov Chain  $X_i$ . Suppose we wanted to find the time it takes to hit any state in some set  $A$ , starting at some other state  $i$ . Formally, we are asking,

$$\beta(i) := \mathbb{E} [T_A \mid X_0 = i], i \in \mathcal{X}, A \subseteq \mathcal{X}$$

Since Markov chains are memoryless, we only need to consider the ways to step from edges out of us, i.e. one step. We call these equations first-step equations (FSEs). The FSEs for this problem are:

$$\begin{cases} 1 + \sum_j P(i, j)\beta(j) & i \notin A \\ 0 & i \in A \end{cases}$$

The reasoning for this is as follows. If we are already in set  $A$ , it takes us 0 steps to get into it. Otherwise, we take one step to another state  $j$ , which has probability  $P(i, j)$  of happening, and then the value of  $\beta(i)$  will just be  $1 + \beta(j)$ .

This way of solving for hitting times produces  $n^2$  linear equations to solve.

Here are some other problems we can solve with FSEs/Hitting times.

**Note 3.2** Suppose you want to find the probability of hitting a state in one set  $A$  before another  $B$ ,

$$\alpha(i) := \mathbb{P} [T_A < T_B \mid X_0 = i], i \in \mathcal{X}, A, B \subseteq \mathcal{X}, A \cap B = \emptyset$$

Then, the FSEs are the following:

$$\begin{cases} \sum_j P(i, j)\alpha(j) & i \notin A \cup B \\ 1 & i \in A \\ 0 & i \in B \end{cases}$$

The reasoning is similar: once you hit a bad state, your probability drops to 0 and if you hit a good state, your probability is 1. Otherwise, it is the sum of the probabilities of moving to an adjacent state and that state ending up as something good (the sum is due to total probability rule).

**Note 3.3** Consider a discounted reward for visiting states earlier. Define  $h(i)$  as the reward for being in state  $i$ . Then we define

$$Z = \sum_{n=0}^{T_A} \beta^n h(X(n)), A \subseteq \mathcal{X}, 0 < \beta \leq 1$$

as the discounted reward (from a gambling run, perhaps). You accrue wealth until you hit  $A$ , but take too long and your reward is reduced. We want to find:

$$\mathbb{E} [Z \mid X_0 = i], i \in \mathcal{X}$$

The FSEs then become:

$$\begin{cases} h(i) + \beta \sum_j P(i, j)\delta(j) & i \in A \\ h(i) & i \in A \end{cases}$$