## Lecture 02: Summations and Probability

## Overview

In today's lecture, we shall cover two topics.
(1) Technique to approximately sum sequences. We shall see how integration serves as a good approximation of summation of sequences.
(2) Basics of Probability. We shall cover Bayes' Rule, chain rule, expectation and linearity of expectation.

## Estimating Summation of an Increasing Sequence I

- Suppose $f$ is an increasing function.
- We are interested in finding the following summation

$$
S_{n}=f(1)+f(2)+\cdots+f(n)
$$

- For example:
- For $f(x)=x$, we know that $S_{n}=n(n+1) / 2$
- For $f(x)=2 x-1$, we know that $S_{n}=n^{2}$.
- For $f(x)=x^{2}$, we know that $S_{n}=n(n+1 / 2)(n+1) / 3$.
- What if $f(x)=x^{3}$ ?
- What if $f(x)=x \log (x)$ ?
- Do we have general techniques to perform these summations quickly?


## Estimating Summation of an Increasing Sequence II

- We begin with a basic observation


## Observation

For an increasing $f$, we have

$$
f(a) \leqslant \int_{a}^{a+1} f(x) \mathrm{d} x \leqslant f(a+1)
$$

- For a decreasing $f$, the inequalities are reversed


## Estimating Summation of an Increasing Sequence III

## Upper Bound.

- Let us apply the basic observation repeatedly

$$
\begin{aligned}
f(1) & \leqslant \int_{1}^{2} f(x) \mathrm{d} x \\
f(2) & \leqslant \int_{2}^{3} f(x) \mathrm{d} x \\
& \vdots \\
f(n) & \leqslant \int_{n}^{n+1} f(x) \mathrm{d} x
\end{aligned}
$$

- Summing up both the sides, we get

$$
S_{n} \leqslant \int_{1}^{2} f(x) \mathrm{d} x+\cdots+\int_{n}^{n+1} f(x) \mathrm{d} x=\int_{1}^{n+1} f(x) \mathrm{d} x
$$

## Estimating Summation of an Increasing Sequence IV

Lower Bound.

- Let us apply the basic observation repeatedly

$$
\begin{aligned}
& f(1) \geqslant \int_{0}^{1} f(x) \mathrm{d} x \\
& f(2) \geqslant \int_{1}^{2} f(x) \mathrm{d} x \\
& \vdots \\
& f(n) \geqslant \int_{n-1}^{n} f(x) \mathrm{d} x
\end{aligned}
$$

- Summing up both the sides, we get

$$
S_{n} \geqslant \int_{0}^{1} f(x) \mathrm{d} x+\cdots+\int_{n-1}^{n} f(x) \mathrm{d} x=\int_{0}^{n} f(x) \mathrm{d} x
$$

## Estimating Summation of an Increasing Sequence $V$

- We can apply this result directly to several functions $f$ and get the following results
- Suppose $f(x)=x^{c}$, for a positive constant $c$. Then we get

$$
\frac{n^{c+1}}{c+1} \leqslant S_{n} \leqslant \frac{(n+1)^{c+1}-1}{c+1}
$$

- Try applying it to other functions like $f(x)=x \log (x)$, $f(x)=\log (x)$, and $f(x)=\exp (x)$.
- The basic observation for decreasing function changes to

$$
f(a) \geqslant \int_{a}^{a+1} f(x) \mathrm{d} x \geqslant f(a+1)
$$

- This implies that

$$
\int_{0}^{n} f(x) d x \geqslant S_{n} \geqslant \int_{1}^{n+1} f(x) d x
$$

- Apply this observation to estimate $S_{n}$ when $f(x)=1 / x$ and $f(x)=x^{-c}$, where $c$ is a positive constant
- For convex or concave $f$, we can perform a more precise estimation. Think of using trapeziums to estimate the area of the curve $\int_{a}^{a+1} f(x) \mathrm{d} x$.
- Sample Space: $\Omega$ is a set of outcomes (it can either be finite or infinite)
- Random Variable: $\mathbb{X}$ is a random variable that assigns probabilities to outcomes

Example: Let $\Omega=\{$ Heads, Tails $\}$. Let $\mathbb{X}$ be a random variable that outputs Heads with probability $1 / 3$ and outputs Tails with probability $2 / 3$

- The probability that $\mathbb{X}$ assigns to the outcome $x$ is represented by

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

Example: In the ongoing example $\mathbb{P}[\mathbb{X}=$ Heads $]=1 / 3$.

- Let $f: \Omega \rightarrow \Omega^{\prime}$ be a function
- Let $\mathbb{X}$ be a random variable over the sample space $\mathbb{X}$
- We define a new random variable $f(\mathbb{X})$ is over $\Omega^{\prime}$ as follows

$$
\mathbb{P}[f(\mathbb{X})=y]=\sum_{x \in \Omega: f(x)=y} \mathbb{P}[\mathbb{X}=x]
$$

## Joint Distribution and Marginal Distributions I

- Suppose ( $\mathbb{X}_{1}, \mathbb{X}_{2}$ ) is a random variable over $\Omega_{1} \times \Omega_{2}$.
- Intuitively, the random variable ( $\mathbb{X}_{1}, \mathbb{X}_{2}$ ) takes values of the form ( $x_{1}, x_{2}$ ), where the first coordinate lies in $\Omega_{1}$, and the second coordinate likes in $\Omega_{2}$

For example, let ( $\mathbb{X}_{1}, \mathbb{X}_{2}$ ) represent the temperatures of West Lafayette and Lafayette. Their sample space is $\mathbb{Z} \times \mathbb{Z}$. Note that these two outcomes can be correlated with each other.

## Joint Distribution and Marginal Distributions II

- Let $P_{1}: \Omega_{1} \times \Omega_{2} \rightarrow \Omega_{1}$ be the function $P_{1}\left(x_{1}, x_{2}\right)=x_{1}$ (the projection operator)
- So, the random variable $P_{1}\left(\mathbb{X}_{1}, \mathbb{X}_{2}\right)$ is a probability distribution over the sample space $\Omega_{1}$
- This is represented simply as $\mathbb{X}_{1}$, the marginal distribution of the first coordinate
- Similarly, we can define $\mathbb{X}_{2}$


## Conditional Distribution

- Let $\left(\mathbb{X}_{1}, \mathbb{X}_{2}\right)$ be a joint distribution over the sample space $\Omega_{1} \times \Omega_{2}$
- We can define the distribution ( $\left.\mathbb{X}_{1} \mid \mathbb{X}_{2}=x_{2}\right)$ as follows
- This random variable is a distribution over the sample space $\Omega_{1}$
- The probability distribution is defined as follows

$$
\mathbb{P}\left[\mathbb{X}_{1}=x_{1} \mid \mathbb{X}_{2}=x_{2}\right]=\frac{\mathbb{P}\left[\mathbb{X}_{1}=x_{1}, \mathbb{X}_{2}=x_{2}\right]}{\sum_{x \in \Omega_{1}} \mathbb{P}\left[\mathbb{X}_{1}=x, \mathbb{X}_{2}=x_{2}\right]}
$$

For example, conditioned on the temperature at Lafayette being 0 , what is the conditional probability distribution of the temperature in West Lafayette?

## Bayes' Rule

## Theorem (Bayes' Rule)

Let $\left(\mathbb{X}_{1}, \mathbb{X}_{2}\right)$ be a joint distribution over the sample space $\left(\Omega_{1}, \Omega_{2}\right)$. Let $x_{1} \in \Omega_{1}$ and $x_{2} \in \Omega_{2}$ be such that $\mathbb{P}\left[\mathbb{X}_{1}=x_{1}, \mathbb{X}_{2}=x_{2}\right]>0$. Then, the following holds.

$$
\mathbb{P}\left[\mathbb{X}_{1}=x_{1} \mid \mathbb{X}_{2}=x_{2}\right]=\frac{\mathbb{P}\left[\mathbb{X}_{1}=x_{1}, \mathbb{X}_{2}=x_{2}\right]}{\mathbb{P}\left[\mathbb{X}_{2}=x_{2}\right]}
$$

The random variables $\mathbb{X}_{1}$ and $\mathbb{X}_{2}$ are independent of each other if the distribution ( $\mathbb{X}_{1} \mid \mathbb{X}_{2}=x_{2}$ ) is identical to the random variable $\mathbb{X}_{1}$, for all $x_{2} \in \Omega_{2}$ such that $\mathbb{P}\left[\mathbb{X}_{2}=x_{2}\right]>0$

## Chain Rule

We can generalize the Bayes' Rule as follows.

## Theorem (Chain Rule)

Let $\left(\mathbb{X}_{1}, \mathbb{X}_{2}, \ldots, \mathbb{X}_{n}\right)$ be a joint distribution over the sample space $\Omega_{1} \times \Omega_{2} \times \cdots \times \Omega_{n}$. For any $\left(x_{1}, \ldots, x_{n}\right) \in \Omega_{1} \times \cdots \times \Omega_{n}$ we have
$\mathbb{P}\left[\mathbb{X}_{1}=x_{1}, \ldots, \mathbb{X}_{n}=x_{n}\right]=\prod_{i=1}^{n} \mathbb{P}\left[\mathbb{X}_{i}=x_{i} \mid \mathbb{X}_{i-1}=x_{i-1} \ldots, \mathbb{X}_{1}=x_{1}\right]$

