

Lecture_8

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L8_S1_A - PDF Example Lecture Scribe - PDF Task Instructions: Using the same...

1. Topic Title Lecture 8: Gaussian, Uniform, Exponential, and Gamma Random...



L8_S1_A - PDF

Example Lecture Scribe - PDF

Task Instructions: Using the same structure as the example provided above, generate a comprehensive lecture scribe based on the attached context for Lecture 4 (L4.pdf). This scribe is authored by Vansh Lilani (ID: AU2320146). It is intended to serve as a primary exam-oriented reference material for a reading-based/closed-notes exam.

Requirements:

Faithfulness & Detail: Include all definitions, notation, and assumptions exactly as presented. Every formula, theorem statement, and worked example from the lecture must be included in full.

Step-by-Step Explanations: For all proofs and derivations, provide the complete step-by-step logic shown in the slides. Do not summarize; ensure the explanation covers the transition between each mathematical step to ensure exam readiness.

Scope: Stick strictly to the provided PDF. Do not invent new content or add external "intuition" not present in the lecture materials.

Correctness & Tone: Maintain a formal academic tone. Prioritize mathematical precision and clarity in the layout of formulas.

Structure: Adhere strictly to the organizational pattern (headings, lists, and layout) demonstrated in the "Example Lecture Scribe" provided above.





1. Topic Title

**Lecture 8: Gaussian, Uniform, Exponential, and Gamma Random Variables CSE
400: Fundamentals of Probability in Computing Vansh Lilani - AU2320146**

+2

2. Definitions and Notation

- **Continuous Random Variable (CRV):** Defined by its Probability Density Function (PDF) and Cumulative Distribution Function (CDF).
- **Gaussian Random Variable:** A random variable X is Gaussian if its PDF is given by:
$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-m)^2}{2\sigma^2}\right)$$
- **Notation:** $X \sim N(m, \sigma^2)$, where m is the mean (μ_X) and σ^2 is the variance. +1
- **Standard Normal Distribution:** A Gaussian distribution where $m = 0$ and $\sigma^2 = 1$.
- ** n^{th} order Central Moment**: Defined as $E[(X - \mu_X)^n]$. +1
- **Skewness (C_s):** A measure of the symmetry of the PDF, defined as $C_s = \frac{E[(X - \mu_X)^3]}{\sigma_{X3}}$
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- **Kurtosis (C_k):** A measure of the "peakiness" of the PDF, defined as $C_k = E[(X - \mu_X)^4]$. +1
- **Error Function ($erf(x)$):** Defined as $erf(x) = \frac{2}{\sqrt{\pi}} \int_0^x \exp(-t^2) dt$.
- **Complementary Error Function ($erfc(x)$):** Defined as $erfc(x) = 1 - erf(x) = \frac{2}{\sqrt{\pi}} \int_x^\infty \exp(-t^2) dt$.

3. Assumptions / Conditions

- **PDF Normalization:** For any valid PDF, the total area under the curve must equal 1:
$$\int_{-\infty}^{\infty} f_X(x) dx = 1 .$$
 - **Constants in Expectation:** When calculating expectations, a and b are treated as constants.
 - **Linearity of Expectation:** Assumes that the expectation of a sum of functions is equal to the sum of their individual expectations.
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4. Main Results / Theorems

- **Theorem on Linear Transformation of Expectation:** For any constant a and b ,
$$E [ax + b] = aE [X] + b . +1$$
 - **Theorem on Sum of Functions:** For any function $g (x)$ that is a sum of several other functions $g_k (x)$, the expectation is: $E \left[\sum_{k=1}^N g_k (x) \right] = \sum_{k=1}^N E [g_k (x)] .$
 - **Symmetry and Skewness:**
 - If $C_s > 0$, the PDF is right-skewed.
 - If $C_s < 0$, the PDF is left-skewed.
 - **Kurtosis Significance:** A large value of Kurtosis indicates the random variable X will have a large peak near the mean.
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5. Proofs / Derivations

Derivation of Central Moments ($n = 0, 1, 2$)

- **For $n = 0$ **: $E \left[(X - \mu_X)^0 \right] = E [1] = 1$
- **For $n = 1$ **: Step 1: Expand the expectation: $E [X - \mu_X] = E [X] - \mu_X$. Step 2: Substitute μ_X for $E [X]$: $\mu_X - \mu_X = 0$. *Result:* The first central moment is always 0. +2

- **For $n = 2$ (Variance σ_{X^2}):** Step 1: Start with the definition: $\sigma_{X^2} = E[(X - \mu_X)^2]$. Step 2: Expand the square: $E[X^2 - 2\mu_X X + \mu_{X^2}]$. Step 3: Apply linearity of expectation: $E[X^2] - 2\mu_X E[X] + \mu_{X^2}$. Step 4: Substitute $E[X] = \mu_X$: $E[X^2] - 2\mu_{X^2} + \mu_{X^2}$. Step 5: Simplify: $\sigma_{X^2} = E[X^2] - \mu_{X^2}$. +2
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6. Worked Examples

Example 1: Gaussian PDF and CDF Parameters

Consider a Gaussian Random Variable with mean $m = 3$ and standard deviation $\sigma = 2$.

+2

- **PDF:** $f_X(x) = \frac{1}{\sqrt{2\pi(2^2)}} \exp\left(-\frac{(x-3)^2}{2(2^2)}\right) = \frac{1}{\sqrt{8\pi}} \exp\left(-\frac{(x-3)^2}{8}\right)$. +3
- **CDF:** $F_X(x) = Pr(X \leq x)$, represented as an S-shaped curve centered at $x = 3$.
+2

Example 2: Linearity of Expectation with Constants

If $Y = aX + b$, find $E[Y]$.

- Step 1: $E[Y] = E[aX + b]$.
- Step 2: Using the theorem $E[ax + b] = aE[X] + b$, the result is directly obtained as $a\mu_X + b$.