CS70 Continuous Probability

Kelvin Lee

kelvinlee@berkeley.edu

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Overview

- Probability Density Function
- 2 Cumulative Distribution Function
- Continuous Joint Distribution
- Expectation and Variance
- Uniform Distribution
- 6 Exponential Distribution

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We interpret f(x, y) as the **probability per unit area** in the vicinity of (x, y).

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$$\operatorname{Var}(X) = \mathbb{E}[X^2] - \mathbb{E}[X]^2 = \int_{-\infty}^{\infty} x^2 f(x) dx - \left(\int_{-\infty}^{\infty} x f(x) dx\right)^2.$$

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$$= \frac{(b-a)^2}{12}.$$



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Problem Time!