Solutions for Questions Based on Central Limit Theorem (CLT) and Uniformly Minimum Variance Unbiased Estimator (UMVUE) Selected Topics and Numericals on Probability and Statistics

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• Suppose X_1, X_2, \ldots is an i.i.d. sequence of random variables with common variance $\sigma^2 > 0$.

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- (d) Degenerate at 0

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• CLT states:

$$rac{ar{X}_n-\mu}{\sigma/\sqrt{n}} \xrightarrow{d} N(0,1)$$

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• Thus, the correct answer is (c) $N(0, 2\sigma^2)$.

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- S^2 is a biased estimator for σ^2 .
- To correct this bias, we use:

$$\hat{\sigma}^2 = \frac{n}{n-1}S^2 = \frac{1}{n-1}\sum_{i=1}^n X_i^2$$

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