## Summary

- In Probability Theory Chebyshev's inequality (also spelled as Tchebysheff's inequality) guarantees that in any probability distribution ,"nearly all" values are close to the mean

- The inequality states that — no more than $1/k^2$ of the distribution's values can be more than *k* standard deviations away from the mean

- According to the inequality, let X be a random variable for which E(X) and V(X) exists. Then for any positive number k ,

  $$P\{|x-\mu| \geq k\sigma\} \leq \frac{1}{k^2} \quad \text{OR} \quad P\{|x-\mu| \leq k\sigma\} \geq 1-\frac{1}{k^2}$$

  The advantage of this theorem is that the theorem applies to any data set regardless of the shape of the distribution of the data.

- Chebyshev does not expect the variable to be non negative but needs additional information to provide a tighter bound. Chebyshev inequality is tight – this means with the information provided, the inequalities provide the most information they can provide

- In probability theory, Markov's inequality gives an upper bound for the probability that a non-negative function of a random variable is greater than or equal to some positive constant

- According to Markov's inequality, Suppose X is a non- negative random variable with finite expectation E(x) .Then for any $\varepsilon > 0$,

  $$P\,(X \geq \varepsilon) \leq \frac{E(X)}{\varepsilon}$$

- The remarkable aspect about Markov's inequality is that the inequality holds for any distribution with positive values, no matter what other features it has