



Markov and Chebyshev Inequalities

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- Assume a simple Bernoulli trial for an event A (e.g. coin is heads).
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- Clearly not likely when n = 1.
- How large does n need to be to get a reasonable estimate of E[A]?

- The weak law of large numbers defines how much we must measure to estimate the mean with a specific accuracy.
- The weak law is simple to prove and helps us understand a stronger method called the Central Limit Theorem.
- Valid when E[X] is finite (e.g. not Cauchy or some Pareto)

- The Weak Law builds on two inequalities or bounds on the probability of something happening: the Markov Inequality and the Chebyshev Inequality.
- Those inequalities estimate properties about a distribution when we only know trivial properties.

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- Chebyshev's Inequality $P[|X E[x]| \ge t] \le \frac{\sigma^2}{t^2}$ when you know mean and variance, the probability of samples falling more than t from the mean is related to the variance and t.

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$$\frac{E[X]}{t} \geq P[X \ge t]$$

Markov Inequality - Rearranged

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$$P[X \ge tE[X]] \le \frac{1}{t}$$

The probability of drawing a sample greater than twice the mean is less than 50%