The weak law of Large Numbers
Let $X_{1}, X_{2},$ be a sequence of independent $Y_{1}, Y_{2},$ be a sequence of independent $Y_{2}, Y_{2},$ pack having the same mean $Y_{2}$ and having finite variance. Then $X_{1} = \frac{1}{n} \sum_{i=1}^{n} X_{i}$ $X_{2},$ We have that $X_{1} = \frac{1}{n} \sum_{i=1}^{n} X_{i}$ $X_{2} = \frac{1}{n} \sum_{i=1}^{n} X_{i}$ $X_{2} = \frac{1}{n} \sum_{i=1}^{n} X_{i}$ $X_{3} = \frac{1}{n} \sum_{i=1}^{n} X_{i}$ $X_{4} = \frac{1}{n} \sum_{i=1}^{n} X_{i}$ That is that the sample averages converge in probability to the common (population) mean $Y_{2}$ .
$\forall \varepsilon > 0$ , we have that $\sqrt{\chi} = \frac{1}{n} \sum_{i \in \Lambda} \chi_i$
$\lim_{n\to\infty} P([X_n - \mu] \geqslant \varepsilon) = 0$ $\mu = C[X_i]$
That is that the sample averages converge in probability to the common (population) mean u.
Proof: using Chebychev's inequality.  Convergence in probability is "weaker" than almost sure convergence (strong LLN).  Not all X: are "almost sure" to converge but the sample mean, for "n" large.
Not all X: are "almost sure" to converge but the sample mean, for -n " large.
Reference: Trobability and Statistics, 2nd ed., Michael J. Evans and Jeffrey S. Rasenthal, 2009.