Markov Inequality:
When to use it: If your variable is non-negative and you know its mean but can’t use its variance (or you don’t want to use variance), you can say that it is unlikely to take on a value that is many times larger than its mean (be larger than \( aE[X] \) where \( a \) is big).

For nonnegative random variable \( X \) and any \( a > 0 \),
\[
\Pr[X \geq a] \leq \frac{E[X]}{a}.
\]
Equivalently, for any \( b > 0 \),
\[
\Pr[X \geq bE[X]] \leq \frac{1}{b}.
\]

Chebyshev’s Inequality:
When to use it: If you know your variable’s mean and variance, you can say that it is unlikely to deviate too far from its mean in either direction (have a large value of \( |X - E[X]| \)), and this likelihood goes up with variance.

For any random variable \( X \) and any \( a > 0 \),
\[
\Pr[|X - E[X]| \geq a] \leq \frac{Var[X]}{a^2}.
\]
Equivalently, for any \( b > 0 \),
\[
\Pr[|X - E[X]| \geq bVar[X]] \leq \frac{1}{b^2Var[X]}.
\]
Notice that if \( Var[X] = \sigma^2 \) this becomes
\[
\Pr[|X - E[X]| \geq b\sigma] \leq \frac{1}{b^2}.
\]

Chernoff Bound:
Chernoff-type bounds take many forms. One example is:
When to use it: If your variable is distributed binomially, meaning it is the sum of independent Bernoullis (so \( X = \sum X_i \)), you can say that it is very unlikely that it is far from its mean in either direction.

For any random variable \( X \sim Bin(n, p) \) and any \( \delta \) between 0 and 1,
\[
\Pr[X > (1 + \delta)E[X]] \leq e^{-\frac{\delta^2 E[X]}{3}}
\]
\[
\Pr[X < (1 - \delta)E[X]] \leq e^{-\frac{\delta^2 E[X]}{2}}.
\]