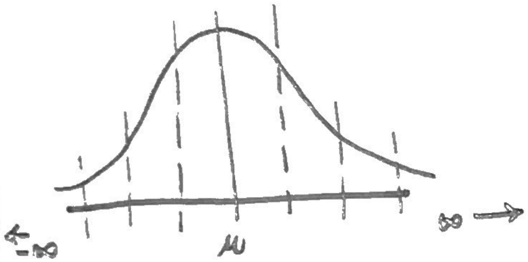
Normal(μ, σ^2)

$N(\mu, \sigma^2)$



- Symmetry around μ
- Empirical Rule
- Standard normal
- Continuous $\Rightarrow$ Density $\left(\text{Area under curve} = 1\right)$

$\Rightarrow P(X=0)=0$

No equal sign probability

rnorm

Random observations from normal(μ, σ^2)

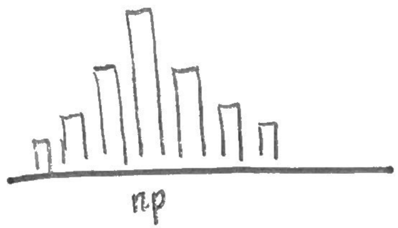
pnorm $P(X \le k) = P(X < k) + P(X = k)$
$= P(X < k) + 0$
$= P(X < k)$

qnorm

Gives you k s.t. $P(X \le k) =$ value of your choice

Binomial(n, p)

$P(X=k) = \binom{n}{k}(p)^k(1-p)^{n-k}$



Mean $= np$

SD $= \sqrt{np(1-p)}$

- Discrete $\Rightarrow$ probability is the value corresponding to bars (area)
- fixed # of independent trials (n)
- success probability is p

rbinom

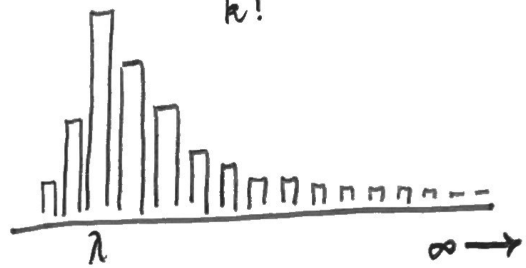
Random obs from Bin(n, p)

pbinom $P(X \le k)$

dbinom $P(X = k)$

Poisson(λ)

$P(X=k) = \dfrac{e^{-\lambda}\lambda^k}{k!}$



Mean $= \lambda$

SD $= \sqrt{\lambda}$

- Discrete
- "rare" events
- fixed rate of happenings expected during some unit of time (λ)

rpois

Random ob's from Poisson(λ)

ppois $P(X \le k)$, probability of bar and all less

$P(X \ge 100) = 1 - P(X < 100)$
$= 1 - \text{ppois}(99, \lambda)$

dpois

probability of one $X = k$,
$P(X=k)$, one bar

Central Limit Theorem

With large **n**, any distribution with mean and finite variance

$\Rightarrow$ sampling distribution of sample mean $\sim N(\mu, \frac{\sigma}{\sqrt{n}})$

ALSO NECESSARY

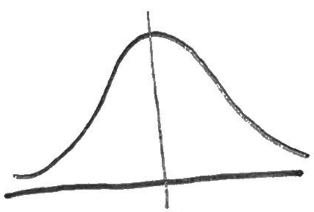
- $np \geq 10$ $\quad n(1-p) \geq 10$
- POPULATION at least 20% greater than n (sample size)

Law of Large Numbers

As n n n n gets bigger, your sample statistic gets closer and closer to the true parameter.

Sampling Distribution

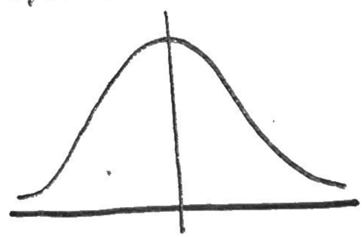
Distribution of SAMPLE MEAN/PROPORTION only!



μ

Sampling Distribution of $\bar{x}$ (sample mean)

$\sim N(\mu, \frac{\sigma}{\sqrt{n}})$



p

Sampling Distribution of $\hat{p}$ (sample proportion)

$\sim N(p, \sqrt{\frac{p(1-p)}{n}})$