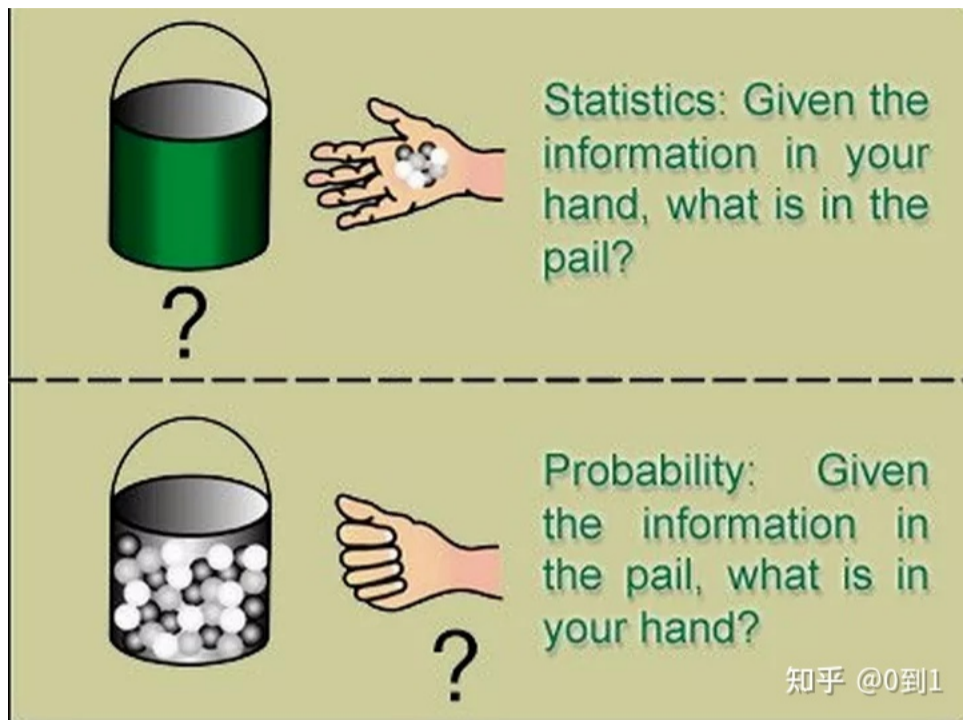


Chapter 23

Probability and Statistics



Probability

sample space S

mutually
exclusive
events

$$P(x_i) = \lim_{n \rightarrow \infty} \frac{\text{number of } x_i \text{ occurs}}{\text{total trials}}$$

Theoretical probability

$$P(x_i) := \frac{\text{number of outcomes } x_i}{\text{total events}}$$

example

1. tossing coins
2. sand

Axioms

1. $0 \leq P \leq 1$
2. $\sum_i P_i = 1$
3. A, B

$$\boxed{A \text{ \& } B \quad A+B} = P(A) + P(B)$$

Conditional Probability

$$P(B|A)$$

$$P(A, B) = P(A) \cdot P(B|A)$$

$$P(B|A) = \frac{P(A, B)}{P(A)} = \frac{n(A, B)}{n(A)}$$

$$P(B|A) = \frac{P(A \cap B)}{P(A)}$$

If A, B are independent,

$$P(A, B) = P(A) \cdot P(B)$$

Bayes' theorem.

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

$$P(B|A) = \frac{P(A \cap B)}{P(A)}$$

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

example.

morbidity 0.5%

accuracy 99%

A: sick

B: diagnosed.

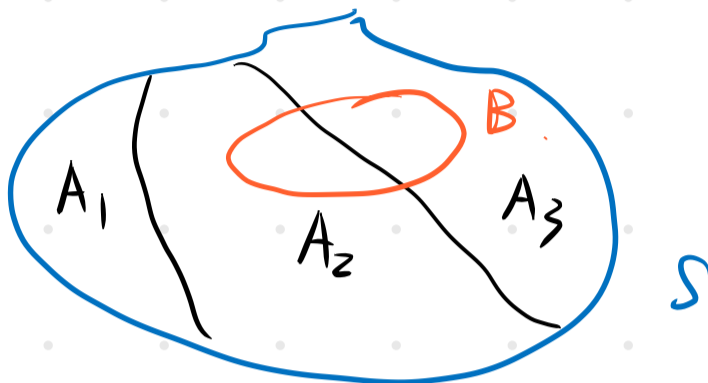
$$\frac{0.005 \times 0.99 \times 0.005}{0.995 \times 0.01 + 0.005 \times 0.99} = 33.2\%$$

more general theorem.

$$A_i \quad \bigcup_i A_i = S$$

$A \ B \ C \ S$

$$P(B) = \sum_i P(A_i) P(B|A_i)$$



Permutations and Combinations.

$$P_m^n \quad A_m^n = \frac{m!}{(m-n)!}$$

$$C_m^n \quad \binom{m}{n} = \frac{m!}{n!(m-n)!} \leftarrow C_m^n = \frac{m!}{n!(m-n)!}$$

$$B(n_1, \dots, n_i) = \frac{n!}{n_1! n_2! \dots n_i!}$$

$$\frac{n!}{n_1! n_2! \dots n_i!}$$
 multinomial coefficient.

$$(x_1 + x_2 + \dots + x_m)^n \rightarrow B(\quad) \cdot \underline{x_1}^{n_1} x_2^{n_2} \dots x_m^{n_m}$$

Random Variables.

Mean, deviation, correlation
probability density

$$P(x \leq X \leq x + dx) = f(x) dx$$

$$f(x) \geq 0 \quad \int f(x) = 1$$

example.

1-s electron

$$|\psi| = N e^{-\frac{r}{a}}$$

$$|\psi|^2 = N^2 e^{-\frac{2r}{a}}$$

$$\int |\psi|^2 d^3r = 4\pi N^2 \int e^{-\frac{2r}{a}} r^2 dr$$

$$= \pi a^3 N^2 = 1 \Rightarrow N = \frac{1}{\sqrt{\pi a^3}}$$

Mean and Variance.

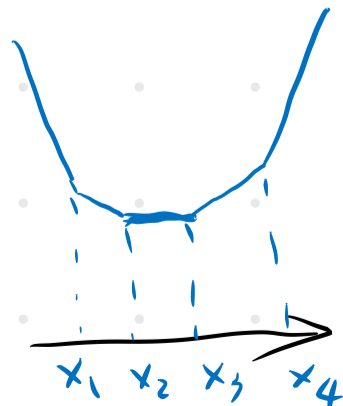
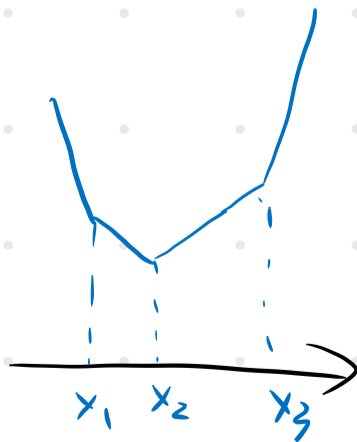
$$\bar{x} = \frac{1}{n} \sum_j x_j$$

$$\langle X \rangle = \sum_i x_i p_i = \int x f(x) dx$$

$$x_g = (x_1 \cdots x_n)^{1/n}$$

$$\frac{1}{x_n} = \frac{1}{n} \left(\frac{1}{x_1} + \cdots + \frac{1}{x_n} \right)$$

$$\boxed{\sum |x_i - \bar{x}|} \leftarrow \hat{x} \rightarrow x_2$$



$$\text{minimize } \sum_i (x - x_i)^2$$

$$\frac{\partial \sum_i (x - x_i)^2}{\partial x} = 2 \sum_i (x - x_i) = 0$$

$$nx = \sum_i x_i$$

$$x = \frac{1}{n} \sum_i x_i$$

method of least squares.

population deviation

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2}$$

$$\begin{aligned} n\sigma^2 &= \sum_{i=1}^n x_i^2 - 2\langle x \rangle \sum_i x_i + n\langle x \rangle^2 \\ &= n(\langle x^2 \rangle - \langle x \rangle^2) \end{aligned}$$

$$\therefore \sigma^2 = \langle x^2 \rangle - \langle x \rangle^2$$

$$\begin{aligned} \sigma^2 &= \sum_j (x_j - \langle x \rangle)^2 p_j \\ &= \int (x - \langle x \rangle)^2 f(x) dx \end{aligned}$$

$$X \quad Y = aX + b$$

$$\langle Y \rangle = a \langle x \rangle + b$$

$$\sigma^2(Y) = a^2 \int (x - \langle x \rangle)^2 f(x) dx$$

$$= a^2 \sigma^2(X)$$

Moments of Probability Distributions.

矩

$$\begin{aligned}\langle (x - \langle x \rangle)^k \rangle &= \sum (x_j - \langle x \rangle)^k P_j \\ &= \int_{-\infty}^{+\infty} (x - \langle x \rangle)^k f(x) dx\end{aligned}$$

moment-generating function.

$$\langle e^{tx} \rangle = \int e^{tx} f(x) dx = 1 + t \langle x \rangle + \frac{t^2}{2!} \langle x^2 \rangle$$

Therefore

$$\begin{aligned}\langle x \rangle &= \left. \frac{d \langle e^{tx} \rangle}{dt} \right|_{t=0} \\ \langle x^2 \rangle &= \left. \frac{d^2 \langle e^{tx} \rangle}{dt^2} \right|_{t=0}\end{aligned}$$

example

1 2 3 4

$$P(3) = \frac{1}{6}$$

$$P(4) = \frac{1}{6}$$

$$P(5) = \frac{1}{3}$$

$$P(6) = \frac{1}{6}$$

$$P(7) = \frac{1}{6}$$

$$M = \langle e^{tx} \rangle = \frac{1}{6} (e^{3t} + e^{4t} + 2e^{5t} + e^{6t} + e^{7t})$$

$$M' = \frac{1}{6} (3e^{3t} + 4e^{4t} + 10e^{5t} + 6e^{6t} + 7e^{7t})$$

$$M'' = \frac{1}{6} (9 + 16 + 50 + 36 + 49)$$

$$M'(t=0) = 5 = \langle x \rangle \quad \langle x^2 \rangle = \frac{80}{3}$$

$$\sigma^2 = \langle X^2 \rangle - \langle X \rangle^2 = \frac{80}{3} - 5 = \frac{5}{3}$$

Covariance and Correlation

$$f(x, y) = f(x)g(y) \Leftrightarrow \text{independent.}$$

$$\text{cov}(X, Y) = \langle (X - \langle X \rangle)(Y - \langle Y \rangle) \rangle$$

independent.

$$\int (x - \langle x \rangle) f(x) dx \int (y - \langle y \rangle) g(y) dy = 0$$

normalized covariance = correlation

$$-1 \leq \frac{\text{cov}(X, Y)}{\sigma(X)\sigma(Y)} \leq 1$$

proof:

$$Q = \langle [a(x - \langle x \rangle) + c(y - \langle y \rangle)]^2 \rangle \geq 0$$

$$= a^2 \langle (x - \langle x \rangle)^2 \rangle + 2ac \text{cov}(X, Y) + c^2 \langle (y - \langle y \rangle)^2 \rangle$$

$\underbrace{\qquad\qquad\qquad}_{\sigma^2(X)} \qquad\qquad\qquad \underbrace{\qquad\qquad\qquad}_{\sigma^2(Y)}$

its discriminant

$$4c^2 \text{cov}^2(X, Y) - 4c^2 \sigma^2(X) \sigma^2(Y) \leq 0$$

$$\text{cov}^2(X, Y) \leq \sigma^2(X) \sigma^2(Y)$$

$$Y = aX + b$$

$$\frac{\text{cov}(X, aX + b)}{\sigma(X) \sigma(X)} = \frac{\langle X - \langle X \rangle \rangle (aX - a\langle X \rangle)}{\sigma(X) \sigma(X)} = \pm 1$$

$$Y = aX + b \Leftrightarrow \pm 1$$

Marginal Probability Distribution

$$\begin{aligned} F(x) &= \int f(x, y) dy \\ G(y) &= \int f(x, y) dx \end{aligned}$$

Conditional Probability Distribution

$$P(X = x | Y = y_0)$$

$$f(x, y_0)$$

Binomial Distribution

example b $P = \frac{1}{6}$

4 times

$$P(S = s) = \binom{4}{s} a^s b^{4-s} \quad a + b = 1$$

$$P(S = s) = \binom{n}{s} p^s q^{n-s} \quad p + q = 1$$

example. moment-generating function

$$\begin{aligned}\langle e^{ts} \rangle &= \langle e^{t(s_1 + s_2 + \dots + s_n)} \rangle \\ &= \langle e^{ts_1} \rangle \langle e^{ts_2} \rangle \langle e^{ts_3} \rangle \dots \\ &= (\langle e^{ts_1} \rangle)^n\end{aligned}$$

$$\langle e^{ts_1} \rangle = pe^t + q$$

$$\langle e^{ts} \rangle = (pe^t + q)^n$$

$$\frac{\partial \langle e^{ts} \rangle}{\partial t} \Big|_{t=0} = \underline{np e^t (pe^t + q)^{n-1}} \Big|_{t=0} = np$$

$$\frac{\partial^2 \langle e^{ts} \rangle}{\partial t^2} \Big|_{t=0} = np e^t (pe^t + q)^{n+1} + n(n-1)p^2 e^{2t} (pe^t + q)^{n-1} \Big|_{t=0}$$

$$\langle S^2 \rangle = np + n(n-1)p^2$$

$$\sigma^2(S) = \langle S^2 \rangle - \langle S \rangle^2 = npq$$

Poisson Distribution.

example

Decay, Poisson noise.

repeated at a constant rate of probability.

$$\underline{P_n(t+dt)} = P_n(t) P_0(dt) + P_{n-1}(t) P_1(dt)$$

$$P_1(dt) = \mu dt \ll 1 \quad P_0(dt) = (1 - \mu) dt$$

$$\frac{dP_n(t)}{dt} = \frac{P_n(t+dt) - P_n(t)}{dt} = \underline{\mu P_{n-1}(t) - \mu P_n(t)}$$

$$n=0 \quad \frac{dP_0(t)}{dt} = -\mu P_0(t) \Rightarrow P_0(t) = e^{-\mu t}$$

$$P_n(t) = \frac{(\mu t)^n}{n!} e^{-\mu t} \quad P_n(0) = \delta_{n0}$$

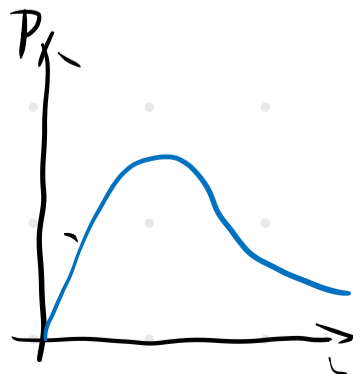
$$\boxed{\mu t \rightarrow \mu} \quad P(n) = \frac{\mu^n}{n!} e^{-\mu} \quad \text{Poisson distribution}$$

$$\langle X \rangle = \sum_{n=1}^{\infty} n \cdot \left(\frac{\mu^n}{n!} \right) e^{-\mu} = \cancel{e^{-\mu}} \cdot \mu \sum_{n=1}^{\infty} \frac{\mu^{n-1}}{(n-1)!} = \mu$$

$$\begin{aligned} \langle X^2 \rangle &= e^{-\mu} \sum (n^2 \frac{\mu^n}{n!}) = e^{-\mu} \sum_{n=1}^{\infty} \left[\frac{\mu^n e^{\mu}}{(n-2)!} + \frac{\mu^n}{(n-1)!} \right] \\ &= \mu^2 + \mu \end{aligned}$$

$$\sigma^2 = \mu$$

$$\begin{aligned} \langle e^{tx} \rangle &= \sum_{n=0}^{\infty} \frac{\mu^n}{n!} e^{-\mu} e^{tn} = e^{-\mu} \sum_{n=0}^{\infty} \frac{(\mu \cdot e^t)^n}{n!} \\ &= e^{-\mu} \cdot e^{\mu \cdot e^t} \\ &= \exp(\mu(e^t - 1)) \end{aligned}$$



Relation to Binomial Distribution

$$P(S=s) = \frac{n!}{s!(n-s)!} p^s q^{n-s} \quad \begin{array}{l} n \rightarrow +\infty \\ p \rightarrow 0 \end{array} \quad np \rightarrow \mu$$

$$n! \sim \sqrt{2\pi n} \left(\frac{n}{e}\right)^n$$

$$\begin{aligned} \frac{n!}{(n-s)!} &\sim \left(\frac{n}{e}\right)^n \cdot \left(\frac{e}{n-s}\right)^{n-s} \sim \left(\frac{n}{e}\right)^s \left(\frac{n}{n-s}\right)^{n-s} e^s \\ &= \left(\frac{n}{e}\right)^s \left(1 + \frac{s}{n-s}\right)^{n-s} \\ &= n^s \end{aligned}$$

$$\begin{aligned} q^{n-s} &= (1-p)^{n-s} \quad p = \frac{\mu}{n} \\ &= \left(1 - \frac{\mu}{n}\right)^n \underbrace{\left(1 - \frac{\mu}{n}\right)^{-s}} \rightarrow 1 \\ &= e^{-\mu} \end{aligned}$$

$$\begin{aligned} P(S=s) &= \frac{n!}{s!(n-s)!} p^s q^{n-s} \\ &\sim \frac{n^s}{s!} p^s e^{-\mu} \\ &= \boxed{\frac{\mu^s}{s!} e^{-\mu}} \quad \text{Poisson distribution} \end{aligned}$$

Gauss' Normal Distribution

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

limits of Poisson and Binominal Distributions

$$p(n) = \frac{\mu^n}{n!} e^{-\mu}$$

$$\ln p(n) = \underbrace{n \ln \mu} - \mu - \ln \sqrt{2\pi n} - \underbrace{n \ln n + n}$$

$$n \rightarrow \mu + \nu$$

$$= (\mu + \nu) \ln \left(1 - \frac{\nu}{\mu + \nu}\right) + \nu - \ln \sqrt{2(\mu + \nu)\pi}$$

$$\ln(1-x) \downarrow \sum_{t=1}^{\infty} \frac{x^t}{t(\mu + \nu)^{t-1}} + \nu - \ln \sqrt{2\pi(\mu + \nu)}$$

$$\ln p(n) \approx -\frac{\nu^2}{2\mu} - \ln \sqrt{2\pi\mu}$$

$$p(n) \sim \frac{1}{\sqrt{2\pi\mu}} e^{-\frac{\nu^2}{2\mu}}$$

Transformations of Random Variables.

$$X \rightarrow Y \quad y = y(x)$$

$$\int f(x) dx = \int g(y) dy \Rightarrow g(y) = f(x) \cdot \frac{dx}{dy}$$

$$\begin{matrix} X, Y & \rightarrow & U(X, Y) & V(X, Y) \\ f & g & u & v \end{matrix}$$

$$g(u, v) = f(x(u, v), y(u, v)) |J|$$

$$|J| = \left| \frac{\partial(x, y)}{\partial(u, v)} \right| = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix}$$

Addition

$$x = x$$

$$J = 1$$

$$z = x + y$$

$$g(z) = \int_{-\infty}^{+\infty} f_1(x) f_2(z-x) dx$$

$$= \sqrt{2\pi} (f_1 * f_2)(z)$$

$$\langle e^{itx} \rangle = \left| \int e^{itx} f_1(x) dx \right| = \sqrt{2\pi} f^T(t)$$

$$g^T(t) = \sqrt{2\pi} f_1^T(t) f_2^T(t)$$

$$g(z) = \int e^{-izt} f_1^T(t) f_2^T(t) dt$$

$$\langle e^{itz} \rangle = \langle e^{itx} \rangle \langle e^{ity} \rangle \quad (z=x+y)$$

Multiplication

$$x = x$$

$$J = \frac{1}{x}$$

$$z = xy$$

$$g(z) = \int_{-\infty}^{+\infty} f_1(x, \frac{z}{x}) \frac{dx}{|x|}$$

$$= \int f_1(x) f_2(\frac{z}{x}) \frac{dx}{x}$$

Gamma Distribution

$$X \sim N(0, \sigma^2)$$

$$Y = X^2$$

$$\text{fix } dx = g(y) dy$$

$$f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}}$$

$$g(y) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{y}{2\sigma^2}} \cdot \frac{\sqrt{y}}{2} \quad y > 0$$

$$0 \quad y \leq 0$$

$$z = \frac{y}{2\sigma^2}$$

$$\int g(z) dz = \frac{1}{\sqrt{\pi}} \int_0^{+\infty} z^{-\frac{1}{2}} e^{-z} dz = \frac{\Gamma(\frac{1}{2})}{\sqrt{\pi}} = 1$$

gamma distribution

$$g(p, \sigma; y) = \begin{cases} 0, & y \leq 0 \\ \frac{y^{p-1} e^{-\frac{y}{2\sigma^2}}}{(2\sigma^2)^p \Gamma(p)} & y > 0 \end{cases}$$

$$[g(p, \sigma)]^T(t) = \frac{1}{\sqrt{2\pi}} \frac{1}{(1 - 2i\sigma^2 t)^p}$$

$$\langle e^{itx} \rangle = \frac{1}{(1 - 2i\sigma^2 t)^p}$$

Statistics

error propagation

$$x_j = \bar{x} + e_j \quad \sum_j e_j = 0$$

$$\begin{aligned} \bar{f}(x) &= \frac{1}{n} \sum f(x_j) = \frac{1}{n} \sum f(\bar{x} + e_j) \\ &= f(\bar{x}) + \frac{1}{n} f'(\bar{x}) \sum e_j + \frac{1}{2n} f'' \sum e_j^2 \\ &= f(\bar{x}) + \frac{1}{2} \sigma^2 f''(\bar{x}) + \dots \end{aligned}$$

$$\begin{aligned} \sigma^2(f) &= \frac{1}{n} \sum_j (f_j - \bar{f})^2 \approx \frac{1}{n} (f'(\bar{x}))^2 \sum e_j^2 \\ &= [f'(\bar{x})]^2 \sigma^2 \end{aligned}$$

$$f(\bar{x} \pm \sigma) = f(\bar{x}) \pm f'(\bar{x}) \sigma$$

two variant.

$$\begin{aligned} \sigma^2(f) &= \frac{1}{rs} \sum \sum (f_{jk} - \bar{f})^2 & f_x &= \frac{\partial f}{\partial x} \\ &= \frac{1}{rs} \sum \sum (f_x u_j + f_y v_k)^2 \\ &= \frac{f_x^2}{r} \sum u_j^2 + \frac{f_y^2}{s} \sum v_k^2 \end{aligned}$$

$$\sigma^2(f) = f_x^2 \sigma_x^2 + f_y^2 \sigma_y^2$$

Repeated Measurement

$$\sigma \quad \frac{\sigma}{n}$$

$$s^2 = \frac{1}{n} \left(\sum_j v_j^2 \right)$$

$$e_j = x_j - \bar{x}$$

$$= \frac{1}{n} \sum_{j=1}^n (e_j + \alpha)^2$$

$$= \frac{1}{n} \sum_j (e_j^2 + \alpha^2)$$

$$\alpha^2 \approx \frac{s^2}{n}$$

$$s^2 \left(1 - \frac{1}{n}\right) = \frac{1}{n} \sum e_j^2$$

$$= \frac{1}{n} \sum_j (x_j - \bar{x})^2$$

$$s = \sqrt{\frac{\sum_j (x_j - \bar{x})^2}{n-1}}$$

sample standard deviation

The χ^2 Distribution

$$\chi^2 := \sum_{j=1}^n \left(\frac{u_j - u(t_j, a, \dots)}{\sigma_j} \right)^2$$

$$u_j \sim N$$

$$\chi^2 = \sum_{j=1}^n \chi^2$$

$$\chi \sim N$$

a	b	a+b
c	d	c+d
a+c	b+d	n

$$g(x^2=y) = \frac{y^{\frac{n}{2}-1} e^{-\frac{y}{2}}}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})}$$

$$P(x^2 > y_0) = \int_{y_0}^{\infty} g(y) dy$$

Student t Distribution

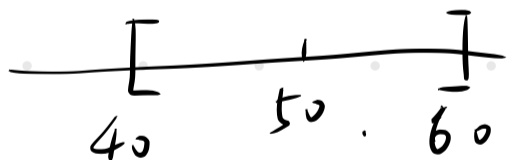
W. S. Gosset

$$T = \frac{Y \sqrt{n}}{\sqrt{S}}$$

$$Y = \frac{1}{n} \sum_j x_j - \mu \quad x_j \sim N$$

$$f_n(T) = \frac{\Gamma(\frac{n+1}{2})}{\sqrt{\pi n} \Gamma(\frac{n}{2})} \left(1 + \frac{t^2}{n}\right)^{-\frac{n+1}{2}}$$

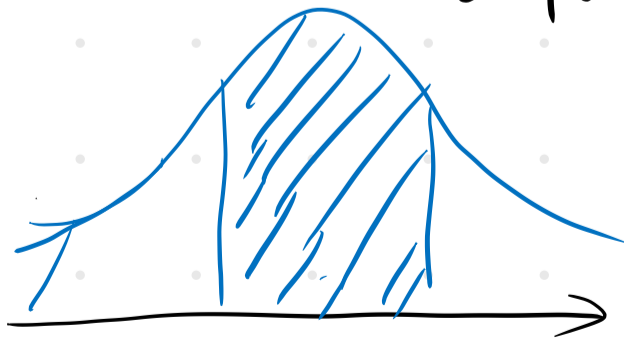
Confidence interval



$x = 0.50 \pm 0.10$ with 90% confidence

$$P(-c_p < t < +c_p) = P$$

$$P(-\infty < t < +\infty) = \frac{1+P}{2} \equiv \hat{P}$$



The end