

## Math Preliminaries / Notation

"series expansions / asymptotic approx's / self-consistency"

simple example:  $\epsilon x^2 + x - 1 = 0$

$\Rightarrow$  positive root:  $x = \frac{-1 + \sqrt{1+4\epsilon}}{2\epsilon} = F(\epsilon)$

e.g.  $\epsilon \rightarrow 0$

$\Rightarrow$  Taylor series:  $x \approx F(0) + F'(0)\epsilon + \dots$   
 $= (1) + (-1)\epsilon + \dots$   
 $\quad \uparrow \quad \uparrow$   
 $\quad \text{"leading order"} \quad \text{"next order"}$

$\Rightarrow x \approx F(0)$  if  $F'(0)\epsilon \ll F(0)$

$\Rightarrow$  if  $\epsilon \ll \epsilon^* \equiv \frac{F(0)}{F'(0)} = 1$

$\Rightarrow$  can write this as  $x \approx 1$  ( $\epsilon \ll 1$ )

\* can also do same thing from eq itself  
"dominant balance"

Step 1: guess  $\epsilon x^2 + x - 1 = 0 \Rightarrow x = 1$

small.

"leading order approx"


Step 2: check whether approx is self-consistent

$$\Rightarrow \epsilon x^2 \approx \epsilon (1)^2 = \epsilon \ll 1, x=1$$

$$\Rightarrow \text{self consistent if } \boxed{|\epsilon| \ll 1}$$

$\Rightarrow$  can tell us when approx breaks down:


e.g.  $\epsilon x^2 + x - 1 = 0 \Rightarrow x \approx 1$

$\Rightarrow$  self-consistent when  $\boxed{\epsilon \ll Y_A}$  

compare to:  $\lim_{\epsilon \rightarrow 0} F(\epsilon) = 1$        $\lim_{\epsilon \rightarrow 0} F_A(\epsilon) = 1$

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tells us when wrong:  $x \ll \epsilon x^2, -1 \Rightarrow x = \frac{1}{\sqrt{\epsilon}} \ll 1$

\* step 1       $x = 1 + \delta$   correction term

step 2: substitute into  $\epsilon x^2 + x - 1 = 0$

$$\epsilon (1 + \delta)^2 + (1 + \delta) - 1 = 0$$

$$\Downarrow \quad \epsilon (1 + 2\delta) + (1 + \delta) - 1 = 0$$

$$\Rightarrow \delta = \frac{-\epsilon}{1 + 2\epsilon} \approx -\epsilon$$

$$\Rightarrow \text{e.g. } \in X^5 + X - 1 = 0$$

Useful in practical contexts:

w/ all possible choices of  $\epsilon$

$\Rightarrow$  most are  $\ll 1$ ,  $\gg 1$

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## Probability

① Random variable,  $\hat{X}$ , distributed according to  $p(x)$



$\Rightarrow$  notation  $X \sim p(x)$

② mean (expected value)  $\langle X \rangle \equiv E[X] \equiv \int x p(x) dx$

③ variance:  $\text{Var}(x) \equiv \langle x^2 \rangle - \langle x \rangle^2$

④ Common statistical dist'ns:

$$n \sim \text{Binomial}(N, p) \quad \left[ P(n) = \binom{N}{n} p^n (1-p)^{N-n} \right]$$

$$n \sim \text{Poisson}(\langle n \rangle) = \lim_{\substack{N \rightarrow \infty \\ p \rightarrow 0 \\ \text{fixed } \langle n \rangle = \lambda}} \text{Binom}(N, p) \quad \left[ P(n) = \frac{\lambda^n}{n!} e^{-\lambda} \right]$$

$$x \sim \text{Gaussian}(\mu, \sigma^2) \quad \left[ P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \right]$$

"Normal"

$\Rightarrow$  wikipedia is your friend here!

③ Joint dist'n:  $p(x, y) = \text{prob } \hat{x}=x$   
 &  $\hat{y}=y$

$$\hookrightarrow p(x) = \int p(x, y) dy \quad (\text{marginalization})$$

\* conditional probability  $p(x|y) \equiv \frac{p(x, y)}{p(y)}$  "prob  $\hat{x}=x$ "  
 given  $\hat{y}=y$

\* statistical independence:  $p(x, y) = p(x)p(y)$   
 - or -  $p(x|y) = p(x)$

$\Rightarrow$  for ind. R.V.  $\text{Var}(x+y) = \text{Var}(x) + \text{Var}(y)$

④ Moment generating function

$$H_x(z) = \langle e^{-zx} \rangle = \int e^{-zx} p(x) dx \quad \text{"Laplace transform"}$$

$\Rightarrow H_x(z) \Leftrightarrow p(x)$   
 hard!

e.g. normal R.V.

$$H_x(z) = e^{-\mu z + \frac{1}{2} \sigma^2 z^2}$$

e.g. Poisson:  $H_n(z) = e^{-\lambda(1-e^{-z})}$

$$H_x(z) = \int e^{-zx} p(x) dx$$

$$= \int (1 - zx + \frac{1}{2} z^2 x^2 + \dots) p(x) dx$$

$$= 1 - z \langle x \rangle + \frac{1}{2} z^2 \langle x^2 \rangle + \dots$$

e.g.  $H_x(z) = e^{-\mu z + \frac{1}{2} \sigma^2 z^2} \approx 1 - \mu z + \frac{1}{2} z^2 \sigma^2 + \frac{1}{2} z^2 \mu^2$

$$\Rightarrow \langle x \rangle = \mu, \quad \langle x^2 \rangle = \sigma^2 + \mu^2$$

$$\Rightarrow \text{Var}(x) = \langle x^2 \rangle - \langle x \rangle^2 = \sigma^2$$

shortcut: if  $H_X(z) = \exp[\Phi(z)]$

$$\rightarrow \Phi(z) \approx 0 - \langle x \rangle z + \frac{1}{2} \text{Var}(x) z^2 + \dots$$

$\Rightarrow$  Payoff for independent R.Vs:

$$\begin{aligned} H_{X+Y}(z) &= \langle e^{-z(x+y)} \rangle = \langle e^{-zx} \cdot e^{-zy} \rangle \\ &= \langle e^{-zx} \rangle \langle e^{-zy} \rangle \\ &= H_X(z) H_Y(z) \end{aligned}$$

$$\Rightarrow X = X_1 + X_2 \Rightarrow p(x) = \int dx_1 dx_2 p(x_1) p(x_2) \times \delta(x - x_1 - x_2)$$

$$\begin{aligned} \Rightarrow H_{X_1+X_2}(z) &= \exp\left[-N_1 z + \frac{1}{2} \sigma_1^2 z^2\right] \times \exp\left[-N_2 z + \frac{1}{2} \sigma_2^2 z^2\right] \\ &\rightarrow = \exp\left[-(N_1+N_2)z + \frac{1}{2} (\sigma_1^2 + \sigma_2^2) z^2\right] \end{aligned}$$



## central limit theorem

$X_1, X_2, \dots, X_n$  independent

$\Rightarrow$  then  $\sum_{i=1}^n X_i \rightarrow \text{Gaussian}(n\langle x \rangle, n\text{Var}(x))$

$\Rightarrow \frac{1}{n} \sum_{i=1}^n X_i \sim \text{Gaussian}(\langle x \rangle, \frac{\text{Var}(x)}{n})$

$$\approx \langle x \rangle \pm \frac{\text{Var}(x)}{n}$$