

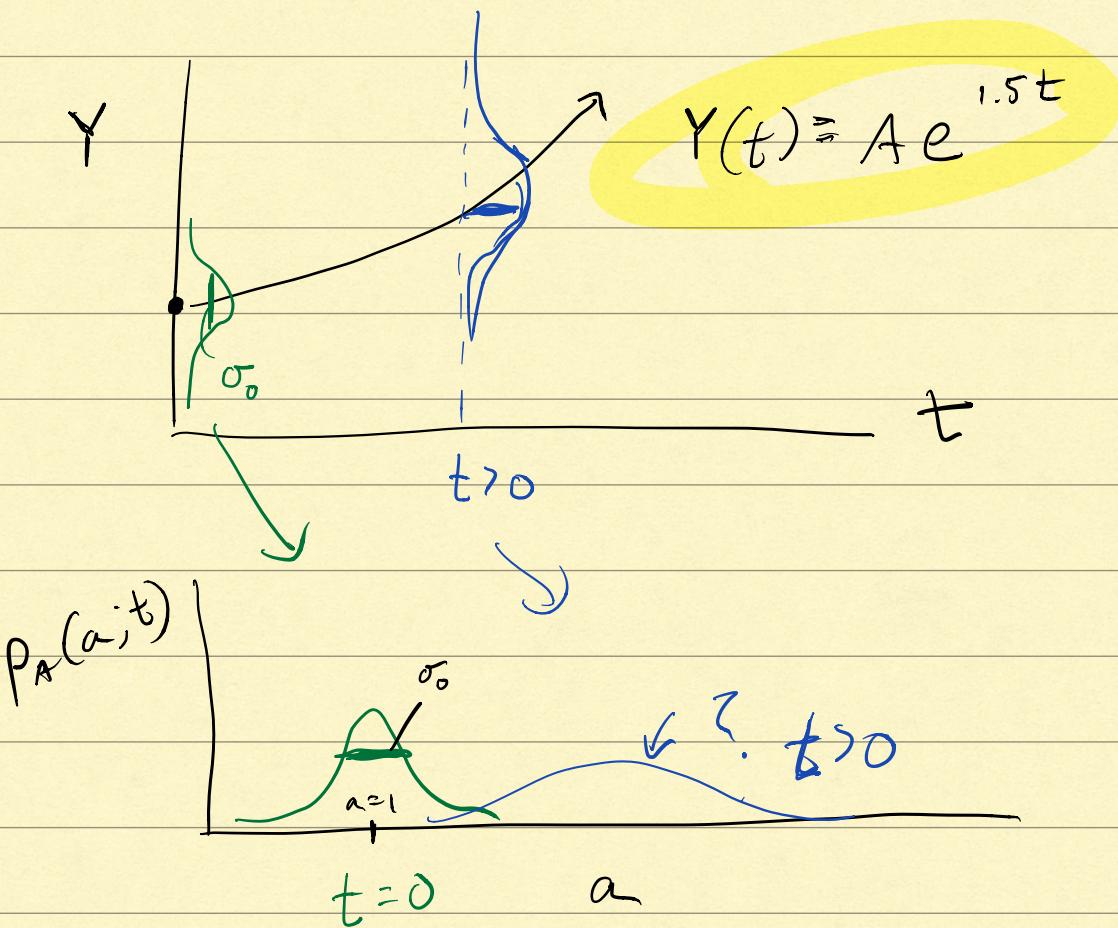
EX

$$\frac{dY}{dt} = (R-1) Y \quad R = 2.5$$

$$Y(0) = A$$

SUPPOSE $A \sim P_A(a)$

$$P_A(a) = \frac{1}{\sqrt{2\pi}\sigma_0} e^{-\frac{(a-1)^2}{2\sigma_0^2}}$$



$$Y = g(A)$$

$$g(a) = a e^{1.5t}$$

$$g^{-1}(y) = \frac{y}{e^{1.5t}} = y e^{-1.5t}$$

$$y = a e^{1.5t}$$

$$\frac{dy}{da} = e^{1.5t}$$

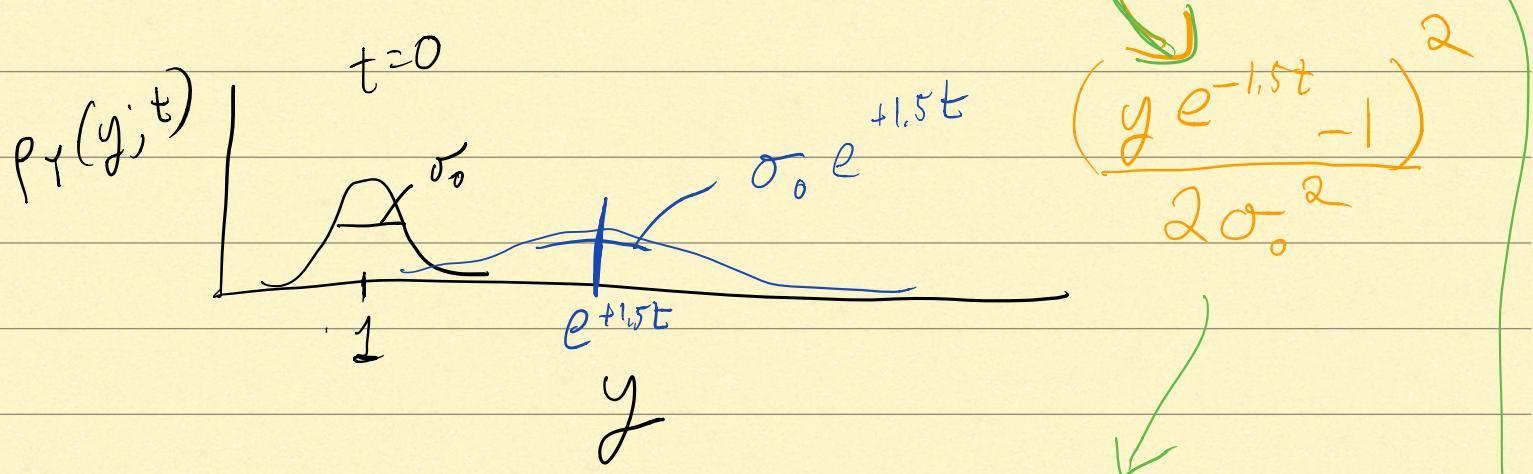


$$\left. \frac{dy}{da} \right|_{a=g^{-1}(y)} = e^{1.5t} \quad x = g(a)$$

$$p_x(x) = p_A(g^{-1}(x)) \left(\frac{dy}{da} \right)^{-1} \quad a = g^{-1}(x)$$

$$p_y(y; t) = \frac{1}{\sqrt{2\pi}\sigma_0} \exp\left(-\frac{(y e^{-1.5t} - 1)^2}{2\sigma_0^2}\right) \cdot e^{-1.5t}$$

$$= \frac{1}{\sqrt{2\pi}\sigma_0 e^{+1.5t}} \exp\left(-\frac{(y - e^{+1.5t})^2}{2\sigma_0^2(e^{+1.5t})^2}\right)$$



$$\frac{(e^{+1.5t})^2 (ye^{-1.5t} - 1)^2}{(e^{+1.5t})^2 20_0^2}$$

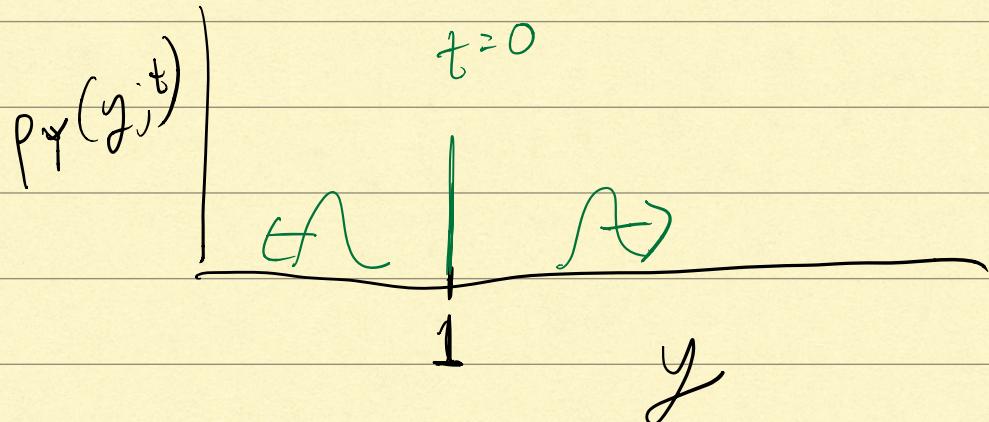
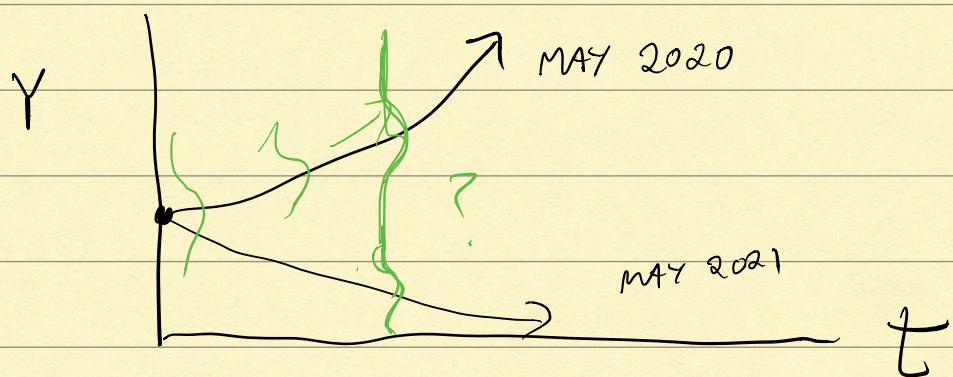
PS 6

$$\frac{dY}{dt} = (R-1) Y$$

$$Y(0) = 1$$

$$R \sim p_R(r) =$$

WHAT IS $p_Y(y; t)$?



ROOM 2 CONJECTURE

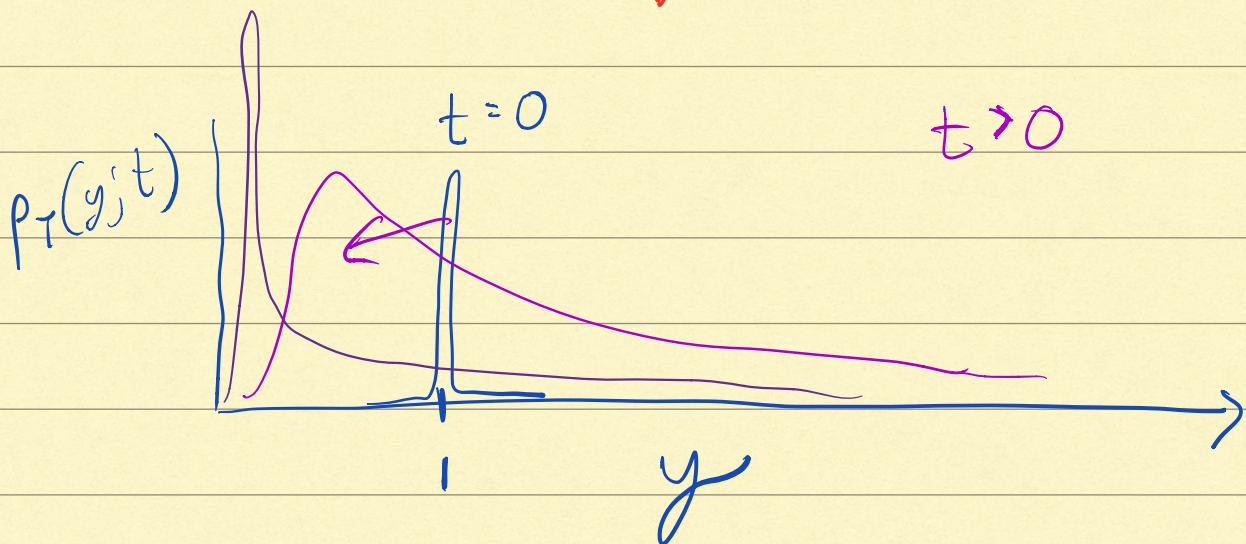
ASSUMING $y > 0$

$$p_Y(y; t) = \frac{1}{\sqrt{2\pi} \sigma_0 t y} \exp\left(-\frac{(\ln y)^2}{2(\sigma_0 t)^2}\right)$$

ROOM 1 CONJECTURE AGREES w/ ROOM 2!

ROOM 3 AGREES!

ROOM 4 AGREES!

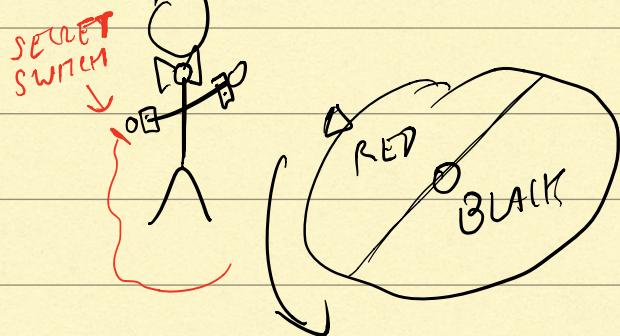


$$P(Y > 1) = \int_1^\infty p_Y(y; t) dy \quad \swarrow$$

$$P(Y < 1) = \int_0^1 p_Y(y; t) dy \quad \swarrow$$

PART II

CASINO worker



SPIN #1

Loss

SPIN #2

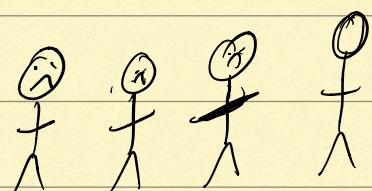
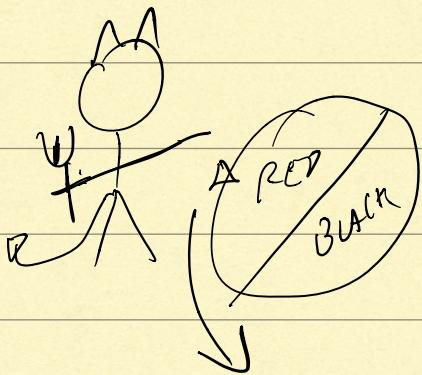
L

SPIN #3

L

PROFESSOR HAHAMA!

$$P(\text{SPIN } \#4 = L) ?$$



SPIN #1

L

SPIN #2

L

SPIN #3

L

$0.5 \in \text{MAJORITY}$

$P > 0.5$

$$P(\text{SPIN } \#4 = L) = ?$$

$0.5 \in \text{MAJORITY}$

PROBABILITY

MODEL

CONSEQUENCES

EX i.i.d.

OBSERVATION

STATISTICS

LEARNING
INFERENCE
CLASSIFICATION

PREDICTION

RECALL

PARAMETER

PROBABILITY DENSITY

$$\text{ex. } p_T(t) = \lambda e^{-\lambda t} = p_T(t; \lambda)$$

PROBABILITY FUNCTION

$$\text{ex. } p_N(k) = \frac{\lambda^k e^{-\lambda}}{k!} = p_N(k; \lambda)$$

THE LIKELIHOOD FUNCTION IS THE PROBABILITY DENSITY (continuous) OR PROBABILITY FUNCTION (discrete), VIEWED AS A FUNCTION OF THE PARAMETERS

$$\text{ex. } L(\lambda) = \lambda e^{-\lambda t}$$

NOTE $\int L(\lambda) d\lambda \neq 1$

STRATEGY: TO FIND A PARAMETER θ FROM AN OBSERVATION X , TAKE

$\text{THB } \theta = \hat{\theta} \text{ THAT MAXIMIZES}$

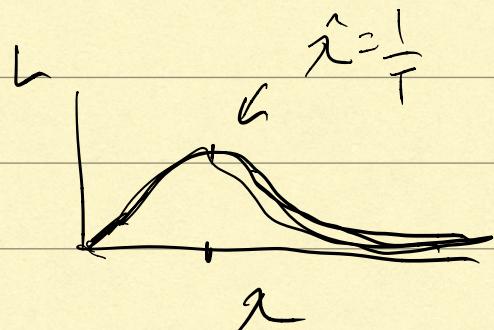
$$L(\theta; x)$$

↳ MAXIMUM LIKELIHOOD ESTIMATION

EX TIME

$$L(\lambda) = \lambda e^{-\lambda t}$$

$$L(\lambda; T) = \lambda e^{-\lambda T}$$



$$\text{MAXIMIZE: } \frac{\partial L}{\partial \lambda} = 0 \dots \hat{\lambda} = \frac{1}{T}$$

EX SUPPOSE THERE ARE N OBSERVATIONS,
ASSUME i.i.d.

$$L(\theta) = \prod_{i=1}^N p(x_i; \theta)$$

EX N NORMAL RANDOM VARIABLES

$$L(\mu, \sigma) = \prod_{i=1}^N \frac{1}{\sqrt{2\pi}} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}}$$

$$\sum_{i=1}^n \frac{1}{\sqrt{2\pi}} \sigma$$

$$\frac{\partial L}{\partial \mu} = 0, \quad \frac{\partial L}{\partial \sigma} = 0, \quad \dots$$

$$\hat{\mu} = \frac{1}{N} \sum_{i=1}^N \tilde{x}_i$$

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

EX UNIFORM RANDOM VARIABLES

$$p_X(x; a, b) = \begin{cases} \frac{1}{b-a} & a < x < b \\ 0 & \text{else} \end{cases}$$

