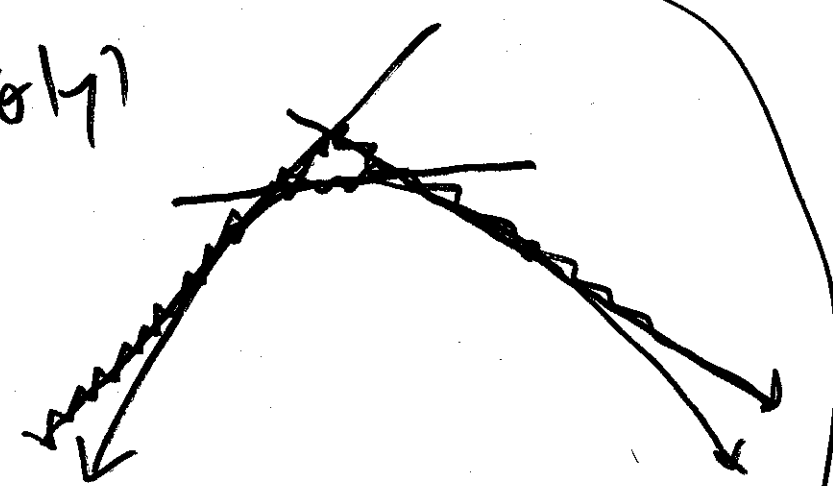




$\log p(\theta|y)$



adaptive
rejection
sampling
(ARS)

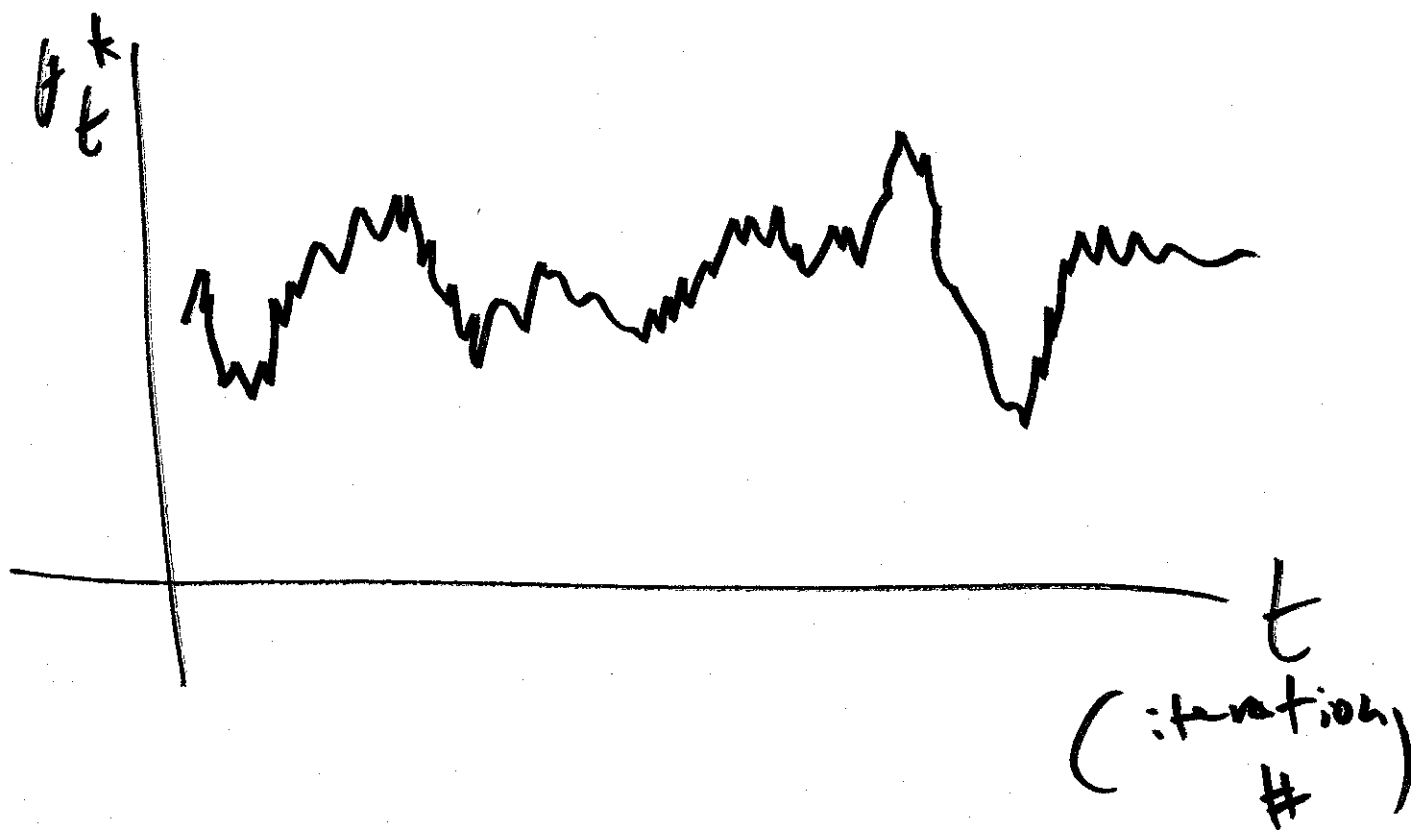
\log concave

3

θ^*	$I(\theta^* \leq 0.15)$
0.17	0
0.11	1
0.48	0
	\vdots

mean $\hat{p}(\theta \leq 0.15 | Y^B)$

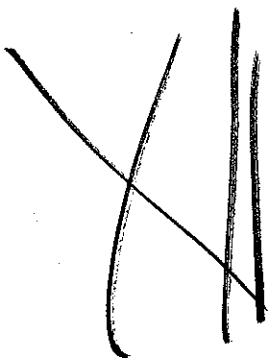
SE $\frac{\hat{p}(1-\hat{p})}{n}$



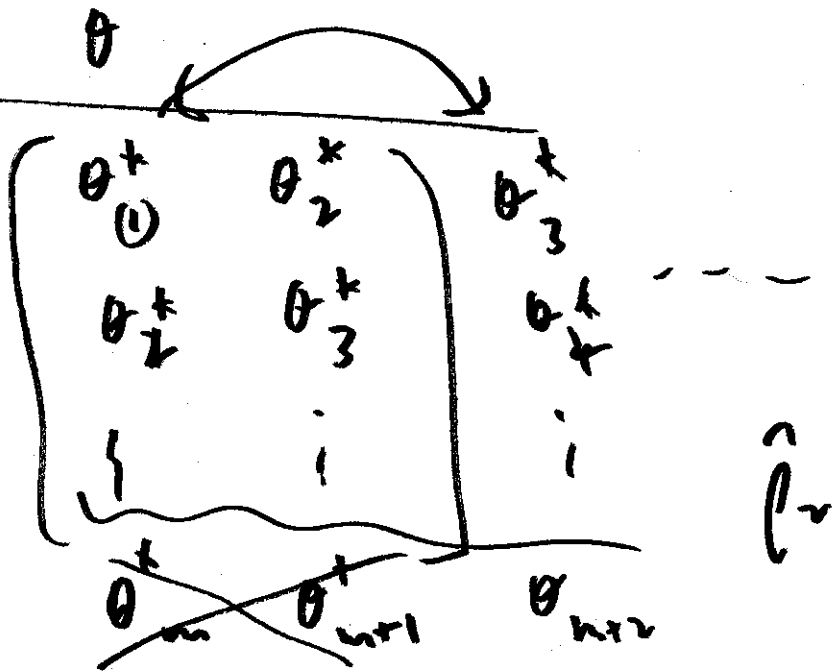
$$p(\theta | y, B) = \underbrace{C}_{\text{length } k} \underbrace{p(\theta | B) \mathcal{L}(\theta | y, B)}_{\text{hard to compute}} \quad \textcircled{+}$$

length k

hard to compute



minimizing



$$\hat{\rho}_i$$

← MCMC

$$\rho_i = \begin{matrix} +.8 \\ +.9 \\ +.95 \end{matrix}$$

target $p(\theta | y)$

proposal distribution (5)



proposal dist $g(\theta^* | x)$

Metropolis

I'm thinking of moving here

has to be symmetric

1) accept all uphill moves

$$\frac{p(\theta^* | y)}{p(\theta_t^* | y)} > 1$$

2) accept any downhill moves

with acceptance probability $\frac{p(\theta^* | y)}{p(\theta_t^* | y)}$

3) if accept $\theta_{t+1}^* = \theta^*$
 don't accept $\theta_{t+1}^* = \theta_t^*$ (??)

$$\left\{ \begin{array}{l} (\mu, \sigma^2, r) \sim p(\mu, \sigma^2, r) \\ (y_i | \mu, \sigma^2, r) \stackrel{iid}{\sim} t_r(\mu, \sigma^2) \end{array} \right\} \quad (6)$$

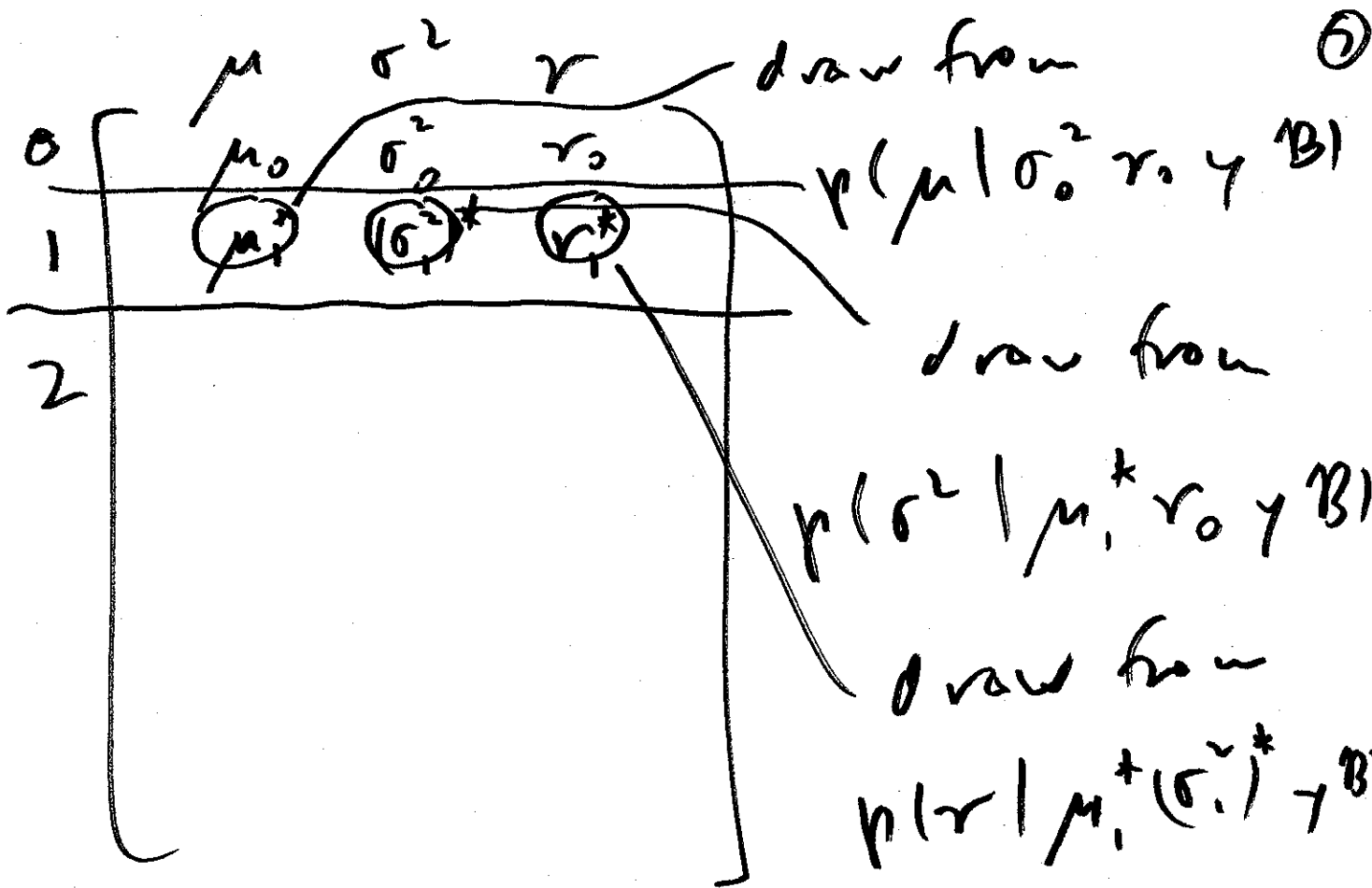
$i = 1, \dots, n$

NB10

$$\theta = (\mu, \sigma^2, r) \quad \left| \quad p(\mu, \sigma^2, r | y, \mathcal{B}) \right.$$

complete post.

$p(\mu \sigma^2, r, y, \mathcal{B})$	full cond. for μ
$p(\sigma^2 \mu, r, y, \mathcal{B})$	_____ σ^2
$p(r \mu, \sigma^2, y, \mathcal{B})$	~~~~~ r



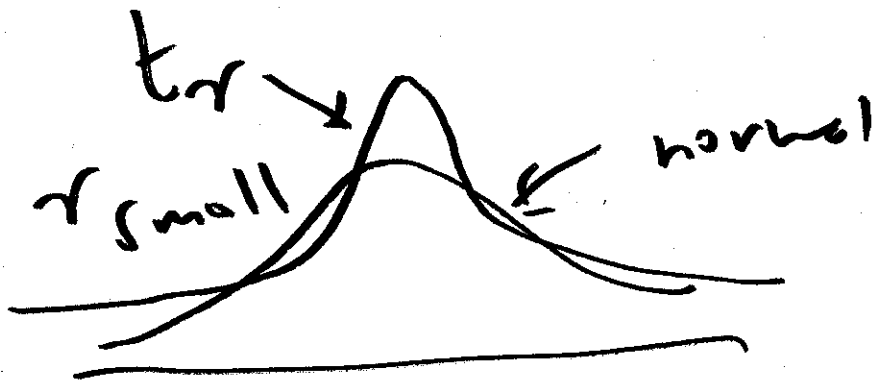
always use most recent values
 of other v parameters

t dist: RS list of $\frac{\bar{y} - \mu}{s/\sqrt{n}}$ (F)

$(Y_i | \mu, \sigma^2) \stackrel{iid}{\sim} N(\mu, \sigma^2)$
 \updownarrow
 unknown

t model for data (sampling dist)

(8)



normal

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

t_{\gamma}

$$\left\{ \begin{array}{l} Y_i \stackrel{\text{indep}}{\sim} N(\mu, \sigma_i^2) \\ \sigma_i^2 \stackrel{iid}{\sim} \text{some dist} \end{array} \right\}$$

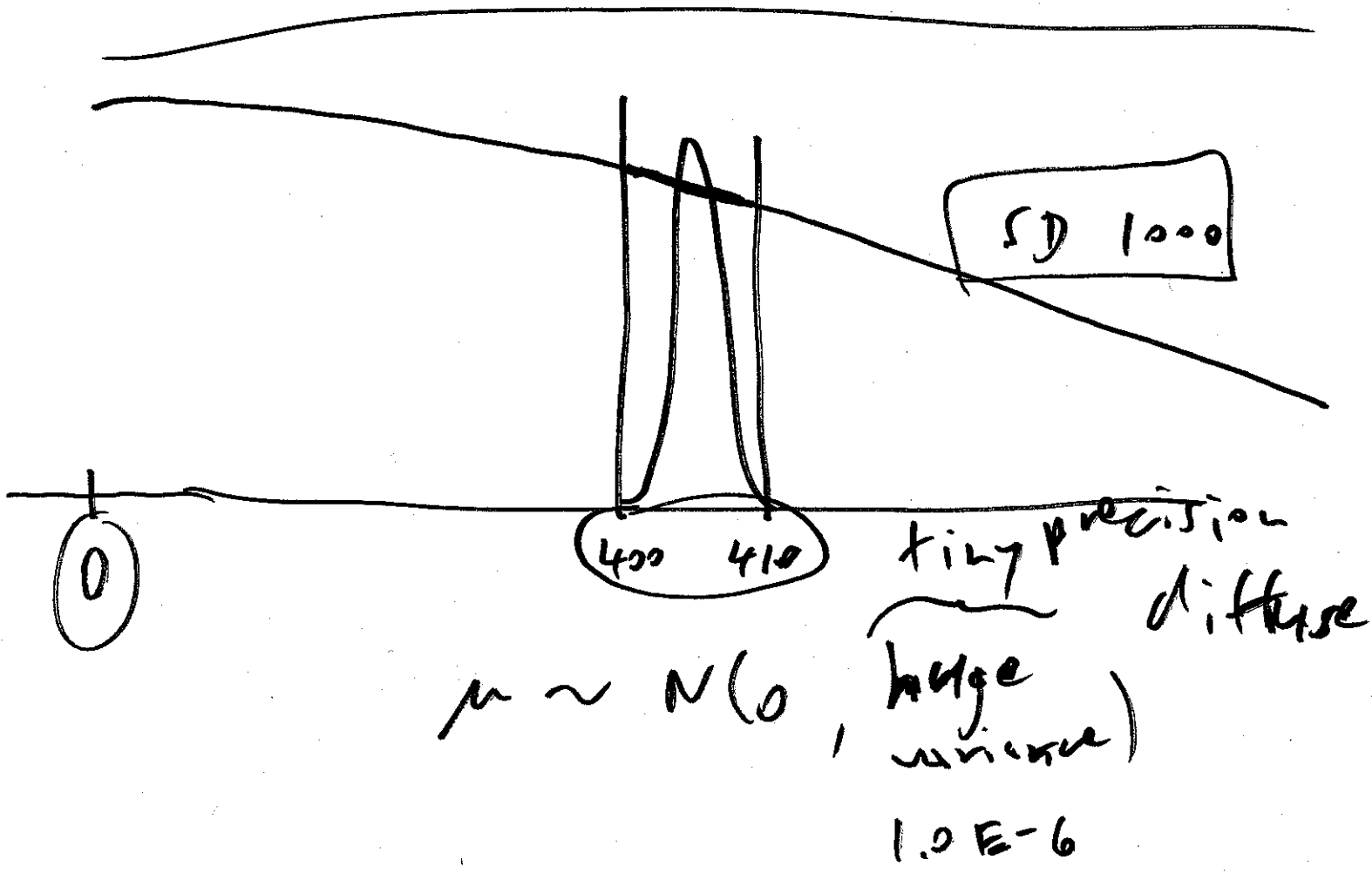
$$r$$

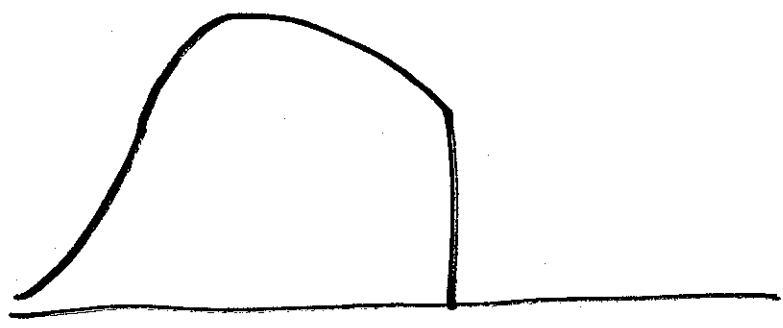
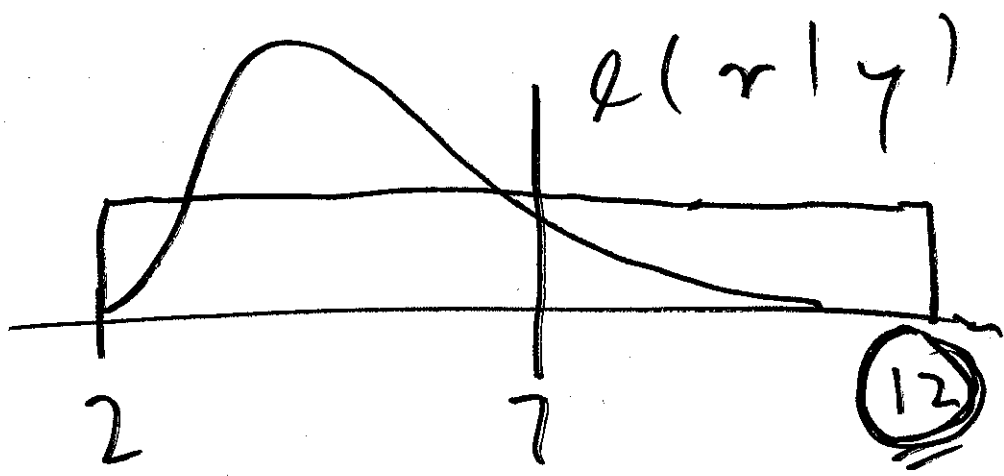
$$(\sigma^2 | x)$$

$$(\mu | \sigma^2, x)$$

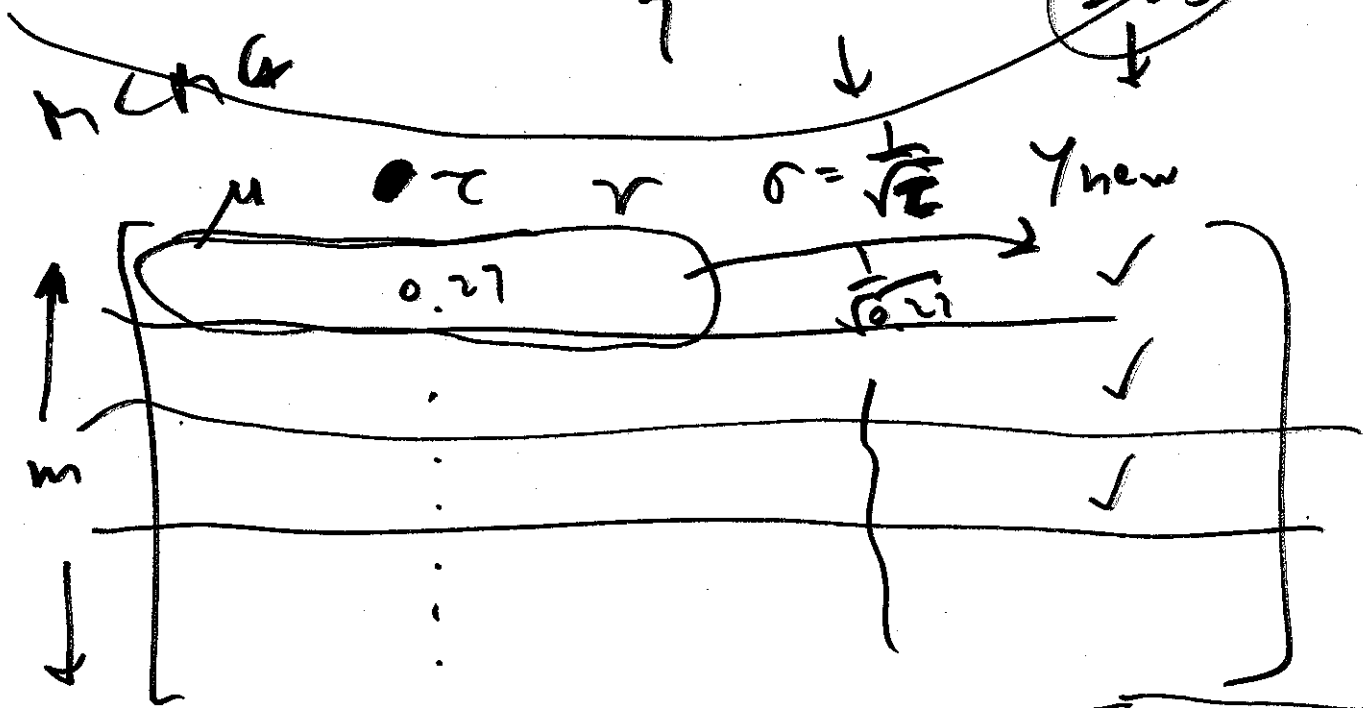
$$(\lambda_i | r, x, x')$$

$$(y_i | \lambda_i, \sigma^2, \mu)$$





~~IED~~



mean $E(\mu | \gamma, B) =$

$$P(\mu | \gamma, B) = \iint p(\mu, z, r | \gamma, B) dz dr$$

$$\int \mu p(\mu | \gamma, B) d\mu$$

$$p(y_{n+1} | y^B) = \int \int p(y_{n+1} | \theta | y^B) p(\theta) d\theta \quad (1)$$

$$\theta = (\mu, \sigma, \tau) = \int \int p(y_{n+1} | \theta | y^B) p(\theta | y^B) d\theta$$

$$= \int \int p(y_{n+1} | \theta | y^B) p(\theta | y^B) d\theta$$

$$y \leftrightarrow \begin{cases} x \\ y|x \end{cases} \quad \text{under } \left\{ \begin{array}{l} \theta \\ \theta | y^B \end{array} \right\}$$

$$(y_{n+1} | y^B) \leftrightarrow \left\{ \begin{array}{l} (\theta | y^B) \\ \cancel{(y_{n+1} | \theta | y^B)} \\ (y_{n+1} | \theta | y^B) \end{array} \right\}$$

