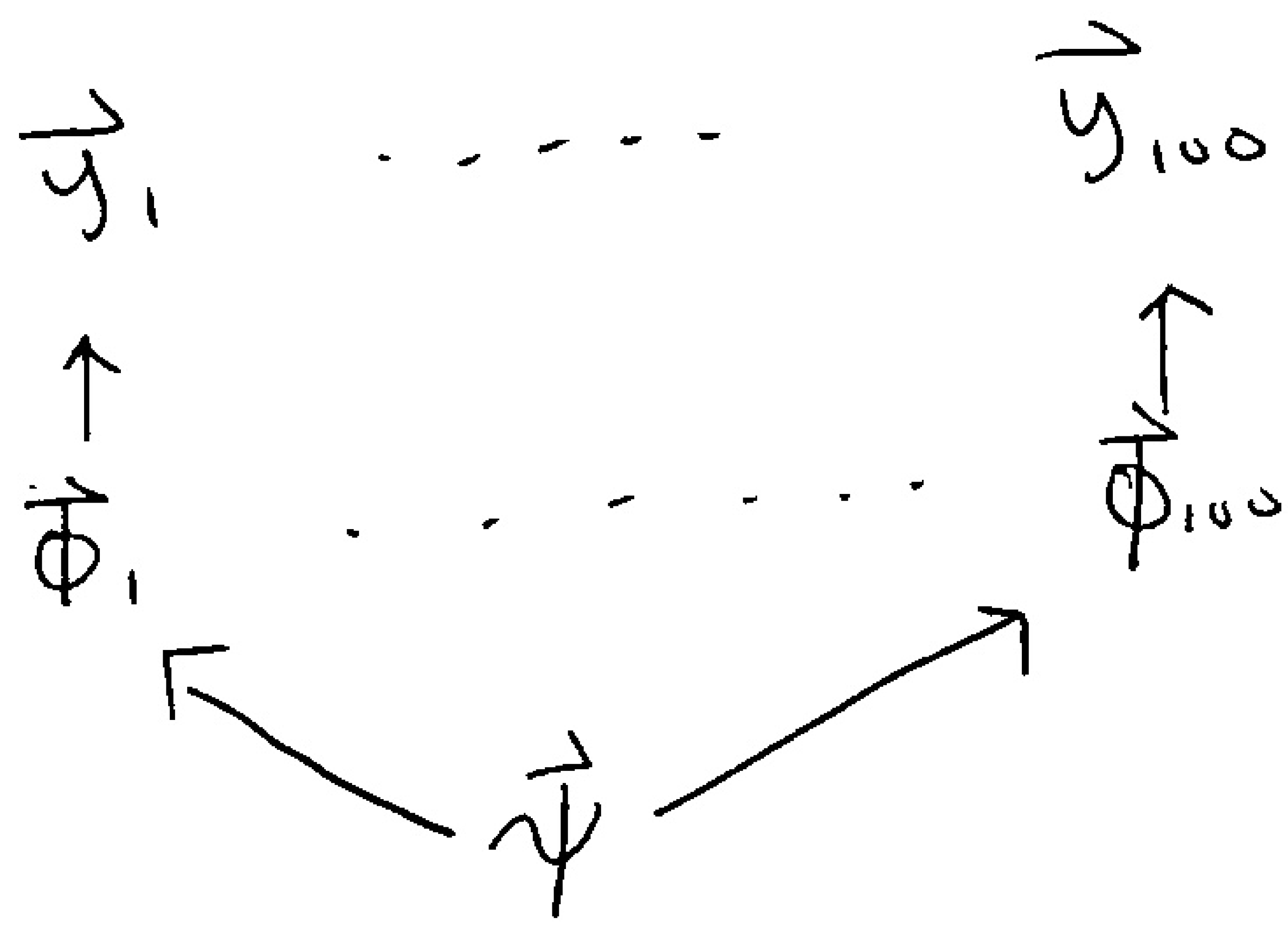
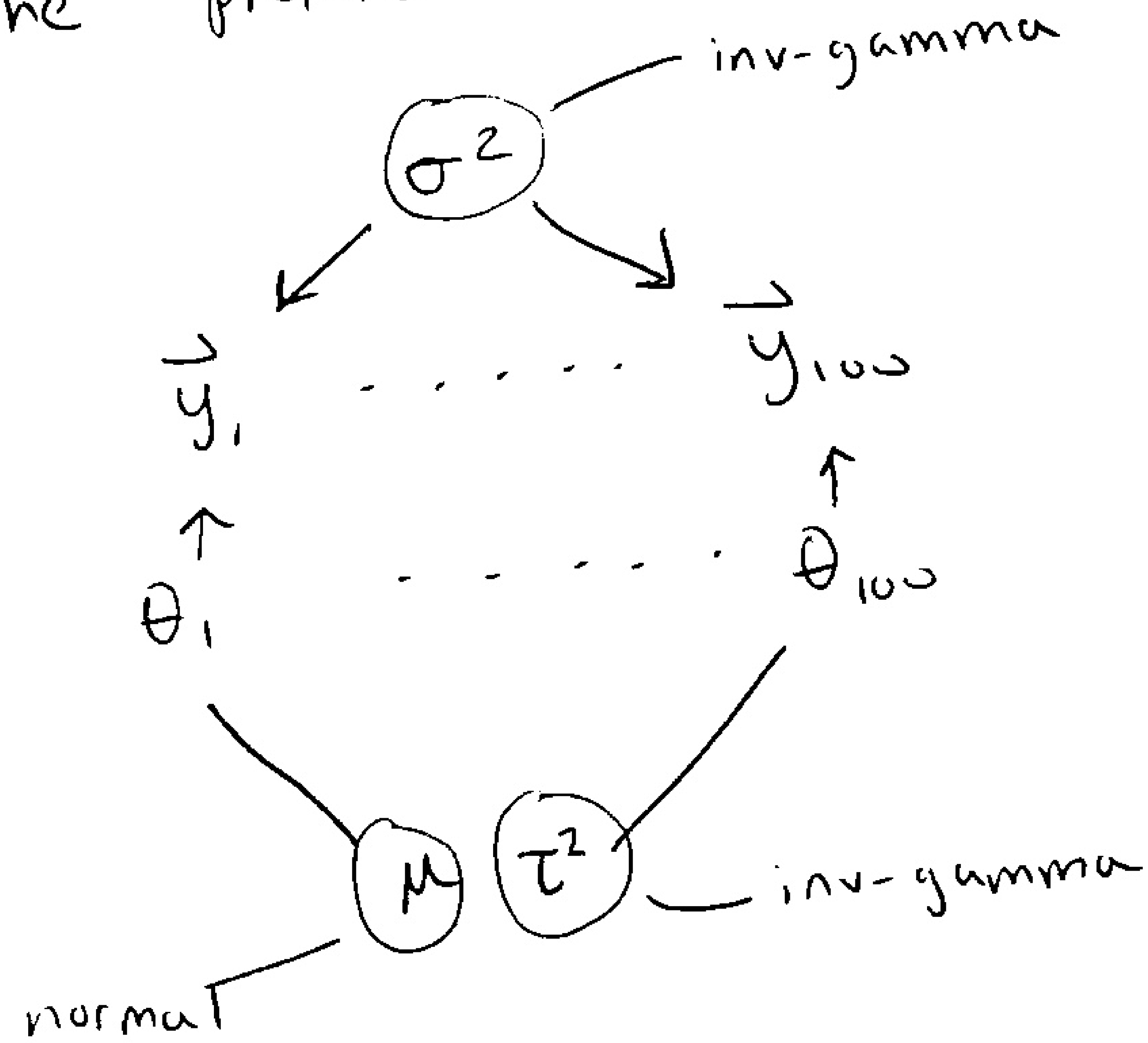
y_{ij} = the score of student i at school j

$\vec{y}_j$: vector of scores at school j.

n_j : the # of students to take the exam at school j.



The picture becomes:



$p(\theta_1, \ldots, \theta_{100}, \sigma^2, \tau^2, \mu \mid \vec{y}_1, \ldots, \vec{y}_{100})$

$\propto \quad p(\vec{y}_1, \ldots, \vec{y}_{100} \mid \vec{\theta}, \sigma^2, \tau^2, \mu)\, p(\vec{\theta}, \sigma^2, \tau^2, \mu)$

$\propto \quad p(\vec{y}_1, \ldots, \vec{y}_{100} \mid \vec{\theta}, \sigma^2)\, p(\vec{\theta} \mid \mu, \tau^2) \cdot p(\sigma^2)\, p(\tau^2)\, p(\mu)$

To approx the joint posterior I ^want to^ Gibbs sample.
I need full cond'l posteriors.

$p(\theta_j \mid \cdot) \propto p(y_j \mid \theta_j, \sigma^2) \cdot p(\theta_j \mid \mu, \tau^2)$ normal(,)

$p(\tau^2 \mid \cdot) \propto p(\vec{\theta} \mid \mu, \tau^2) \cdot p(\tau^2)$ inv-gammma(,)

$p(\sigma^2 \mid \cdot) \propto p(\vec{y}_1, \ldots, \vec{y}_{100} \mid \theta, \sigma^2) \cdot p(\sigma^2)$ inv-gamma(,)

$p(\mu \mid \cdot) \propto p(\vec{\theta} \mid \mu, \tau^2) \cdot p(\mu)$ normal. (,)