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Application of Gibbs sampling (MCMC)
                         - not required
     y_i = x + \beta x_i + \xi_i \xi_i \stackrel{\text{2id}}{\sim} N(o, precision = T)
     garameters: X. B. I.
  priors: X \sim N(0, precision = T_X)
                     \beta \sim N(0, precision = T\beta)
                       T_{\alpha} = T_{\beta} = 0.01, i.e. var = /00.
                    T~ Gamma (shape=a, rate=b)
a = b = 0.00 (.
Full conditional distributions:
p(x | \{x_i, y_i\}_{i=1}^n, \beta, \tau) \propto p(x) p(x) p(x_i, x_i, x_i, \beta, \tau)
       X N(X O, TX). IT N(3; X+BXi, T).
\propto e^{-\frac{1}{2}(T_{x}+n\tau)\left[\chi^{2}-2\cdot\frac{\tau^{\frac{n}{2}}[Y_{i}-\beta\chi_{i})}{T_{x}+n\tau}} \propto \right]
\propto \left[-\frac{1}{2}\left(\frac{\tau^{\frac{n}{2}}[Y_{i}-\beta\chi_{i})}{T_{x}+n\tau}\right) + var = \left(\frac{\tau^{\frac{n}{2}}[Y_{i}-\beta\chi_{i})}{T_{x}+n\tau}\right)^{-1}\right]
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Thm: If we have parameters $\theta_1, \theta_2 - \theta_p$ and data X1 -- Xn, and we know $p(\theta_1 | \theta_2, \theta_3, --\theta_p, \chi_1, --\chi_n) \stackrel{\triangle}{=} P_1$ $P(\theta_2 \mid \theta_1, \theta_3 - - \theta_p, \chi_1 - - \chi_n) \triangleq P_2$ $P(\theta_p \mid \theta_1, \theta_2 - - \theta_{p-1}, \chi_1 - \chi_n) \stackrel{\triangle}{=} P_p$ ⇒ We draw 0, (5) ~ P $\theta_2^{(5)} \sim P_2$ Op ~ Pp. and iterate $5 = 1 \cdots 5$. We get samples { $\theta_1^{(15)}$, $\theta_2^{(15)}$ -- $\theta_p^{(15)}$ } S = 1, which is the same as the posterior samples of {\theta, --- \theta} if $S \rightarrow \infty$. (Algorithm: Gibbs sampling or Gibbs sampler).