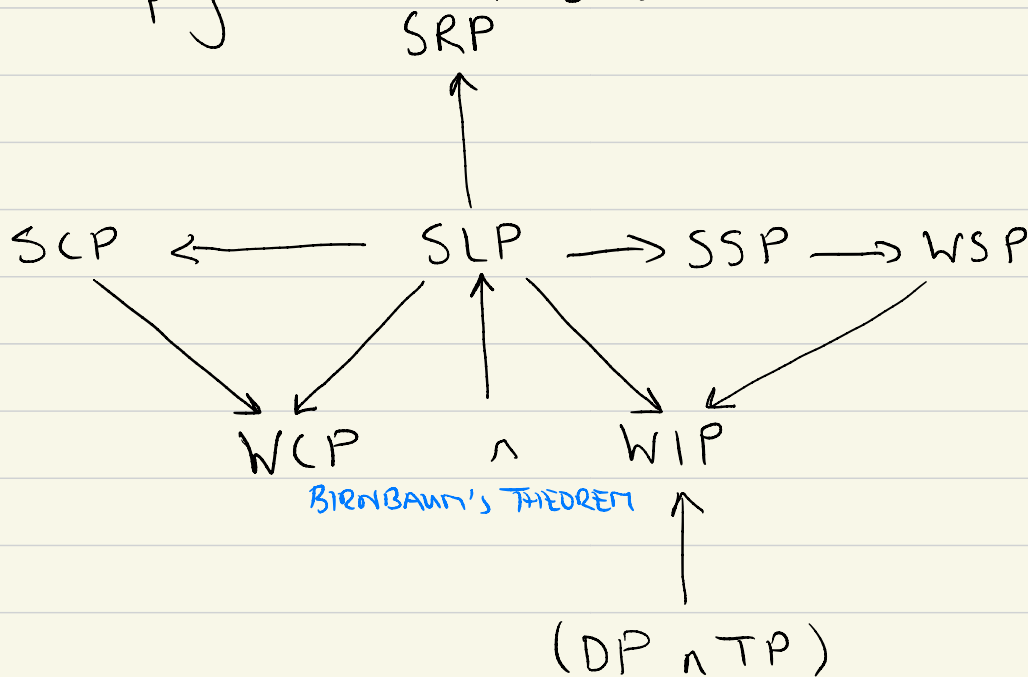


Additional handwritten notes to accompany the Lecture Three Slides.



DP: $\xi = \xi'$ then $E_v(\xi, x) = E_v(\xi', x)$

TP: $g: X \rightarrow Y$ $E_v(\xi, x) = E_v(\xi^g, g(x))$

WIP: $f_x(x|\theta) = f_x(x'|\theta)$ then $E_v(\xi, x) = E_v(\xi, x')$

WCP: Q^* mixture, $E_v(Q^*, (i, x_i)) = E_v(Q^*, x_i)$

SLP: $f_{x_1}(x_1|\theta) = c(x_1, x_2)f_{x_2}(x_2|\theta)$ then $E_v(\xi_1, x_1) = E_v(\xi_2, x_2)$

SSP: $S = s(x)$ sufficient then $E_v(\xi, x) = E_v(\xi^s, s(x))$

WSP: $s(x) = s(x')$ then $E_v(\xi, x) = E_v(\xi, x')$

SRP: $E_v(\xi^T, (x_1, \dots, x_n))$ doesn't depend on θ .

SCP: Y is ancillary, $E_v(\xi, (x, y)) = E_v(\xi^{x|y}, x)$

Key idea of the Bayesian approach: as a function of θ

$$\pi(\theta|x) \propto f_x(x|\theta) \pi(\theta)$$

Posterior \propto Likelihood \times Prior

Strongly likelihood principle is that if, as a function of θ , the likelihoods are proportional then the inference about θ should be the same in each case.

$$\pi_1(\theta | x_1) \propto f_{x_1}(x_1 | \theta) \pi(\theta) \quad (\text{model } \xi^{B,1})$$

$$\pi_2(\theta | x_2) \propto f_{x_2}(x_2 | \theta) \pi(\theta) \quad (\text{model } \xi^{B,2})$$

SLP: suppose $f_{x_1}(x_1 | \theta) \propto f_{x_2}(x_2 | \theta)$ as a function of θ .

$$\begin{aligned} \pi_1(\theta | x_1) &\propto f_{x_1}(x_1 | \theta) \pi(\theta) \\ &\propto f_{x_2}(x_2 | \theta) \pi(\theta) \\ &\propto \pi_2(\theta | x_2) \end{aligned}$$

Thus $\pi_1(\theta | x_1) = \pi_2(\theta | x_2)$. Inferences using $\pi_1(\theta | x_1)$ will be identical as those using $\pi_2(\theta | x_2)$. Bayesian statistics will satisfy the SLP.