

## Deceptively simple problem

## STAT 530: Partial Identification

Mar. 22, 2010

$X \sim \text{Bernoulli}(r)$  in population.

Infer  $r$  from random sample.

**Slight twist:**  $X$  not measured well

(e.g. perhaps some subjects give wrong answer on questionnaire)

Measure  $X^*$  instead of  $X$  on sampled subjects, where

$$SN = Pr(X^* = 1 | X = 1)$$

$$SP = Pr(X^* = 0 | X = 0)$$



Still looks relatively simple, presuming some info. on misclassification rates

## MCMC

$X^* \sim \text{Bernoulli}\{rSN + (1-r)(1-SP)\}$  in population.

Say decide on prior:

$$p(r, SN, SP) \propto I_{(0,1)}(r)I_{(a,1)}(SN)I_{(b,1)}(SP)$$

### Two issues

- MCMC and parameterization
- Information flow

### Example

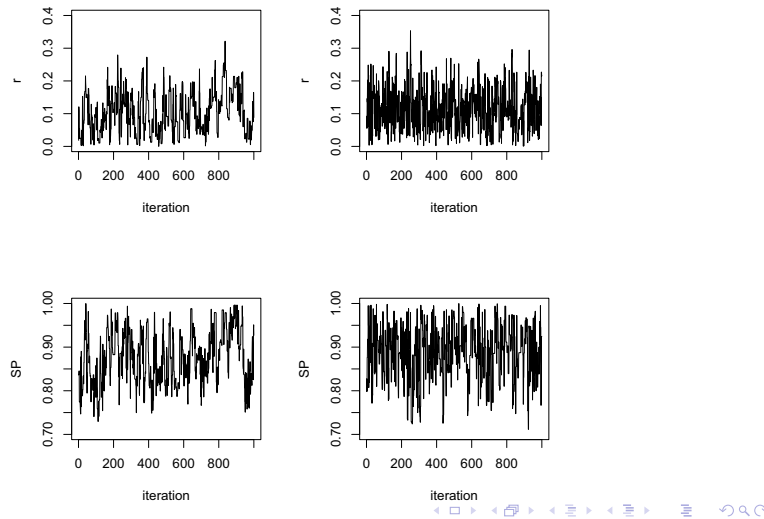
- Data: 20/100 have  $X^* = 1$
- Prior information:  $a = 0.9$ ,  $b = 0.7$

1. Univariate RWMH in original parameterization  $(r, SN, SP)$ , tuned to have approx. 50% acceptance rate for each component.
2. Univariate RWMH in new parameterization  $(\tilde{r}, SN, SP)$ , tuned to have approx. 50% acceptance rate for each component.

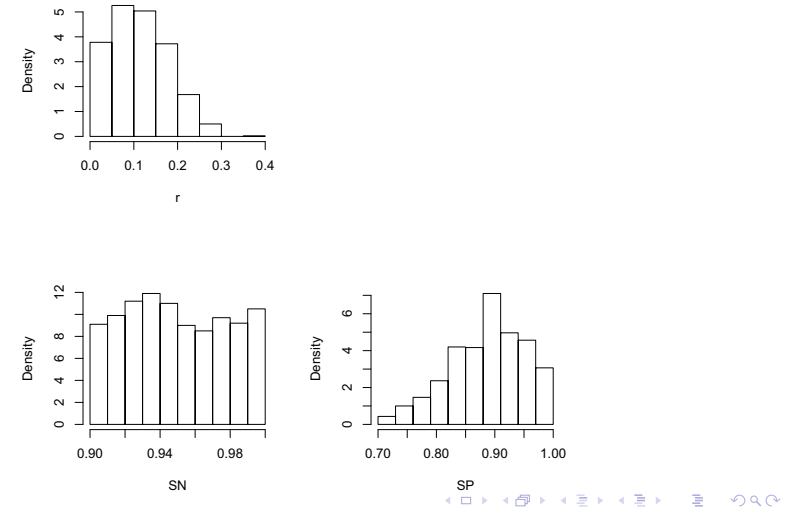
Intuition for why 2 might work better?



## Traceplots



Information flow:  
Where does the 'extra-prior' info. about  $SP$  come from???



## Intuition

Whereas  $r$  and  $(SN, SP)$  are independent *a priori*,  
 $\tilde{r}$  and  $(SN, SP)$  are **dependent a priori**  
 Thus we learn about  $\tilde{r}$  directly from the data,  
 and the prior dependence then implies something about  $(SN, SP)$   
 [Also bear in mind that the quantity of most interest,  $r$ , can be regarded as a function of  $(\tilde{r}, SN, SP)$ .]

## More formally

As  $n \rightarrow \infty$

$p(\tilde{r}|\text{Data}) \rightarrow$

$p(SN, SP|\text{Data}) \rightarrow$

## We have just seen a simple example of a **partially identified** model

Arise somewhat generally when data are imperfect, but one isn't sure to what extent.

Characterized by the large-sample limit of the posterior distribution on the parameter of interest being:

- narrower than the prior
- wider than a single point

Point estimators (e.g. posterior mean) are necessarily biased.

But interval estimators (e.g. credible interval) reflect this appropriately.