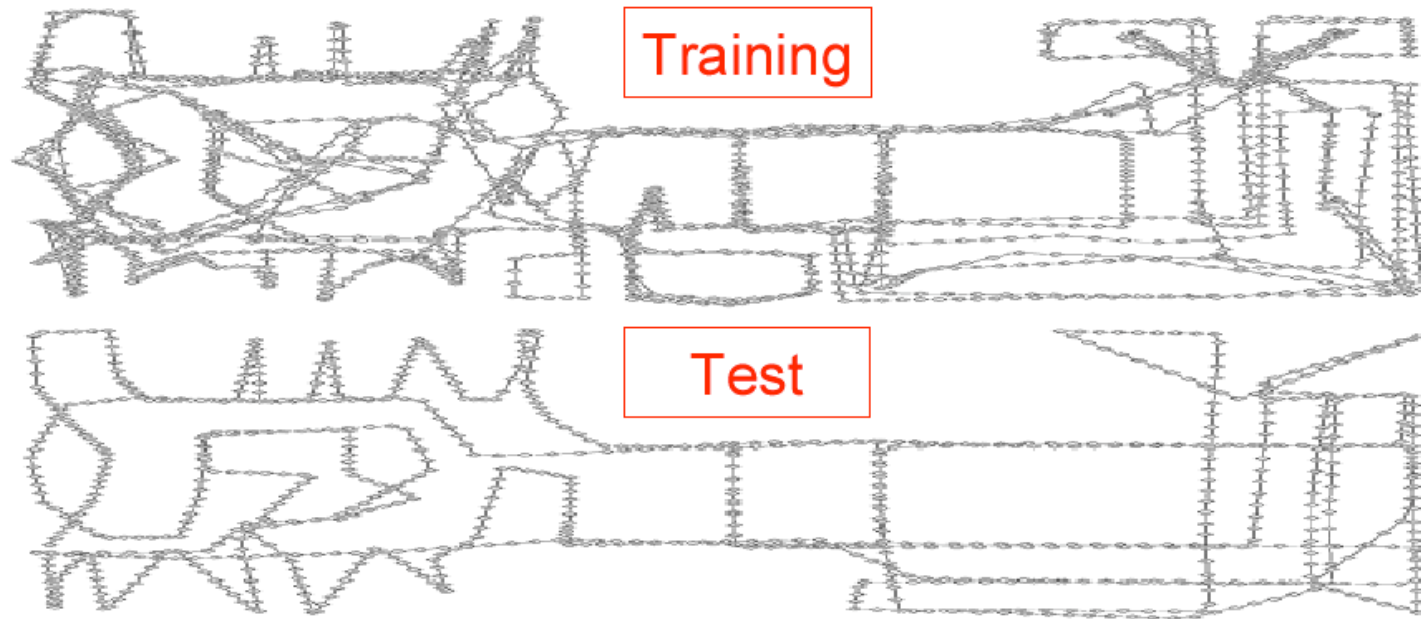


Bayesian Graphical Models for Location Determination

David Madigan
Columbia University

joint work with Wen-Hua Ju, P. Krishnan, and A.S.
Krishnakumar at Avaya Labs Research and Richard P.
Martin and Eiman Elnahrawy at Rutgers CS

Location Determination via Statistical Modeling



Myllymäki et al.

3rd IEEE Workshop on WLANs, September 28, 2001

9

- Data collection is slow, expensive (“profiling”)
- “Productization”
- Either the access points or the wireless devices can gather the data
- Focus on predictive accuracy

The Problem

- Estimate the physical location of a wireless terminal/user in an enterprise
 - Radio wireless communication network, specifically, 802.11-based



Example Applications

- Use the closest resource, e.g., printing to the closest printer
- Security: in/out of a building
- Emergency 911 services
- Privileges based on security regions (e.g., in a manufacturing plant)
- Equipment location (e.g., in a hospital)
- Mobile robotics
- Museum information systems



WhereNet, wireless solutions for tracking and managing assets.

HUMMER FACTORY IMPLEMENTS WHERENET'S WIRELESS SOLUTIONS TO ENHANCE ASSEMBLY LINE OPERATIONS AND EXPEDITE PRODUCTION

Wireless Supply Chain Technology for Military Transportation, Logistics & Security



Wi-Fi Tag for people and asset tracking



T101 Ekahau Wi-Fi Location Tag

[Click here for more information](#)

Real-time location-tracking over your existing Wi-Fi Network!



Ekahau Positioning Engine™ 2.1



AeroScout and Kidspotter launch world's largest Wi-Fi location network for child tracking at LegoLand Denmark.



**Locate.
Manage.
Secure.**

with
WiFi Workplace

Automotive News

SEPTEMBER 8, 2003

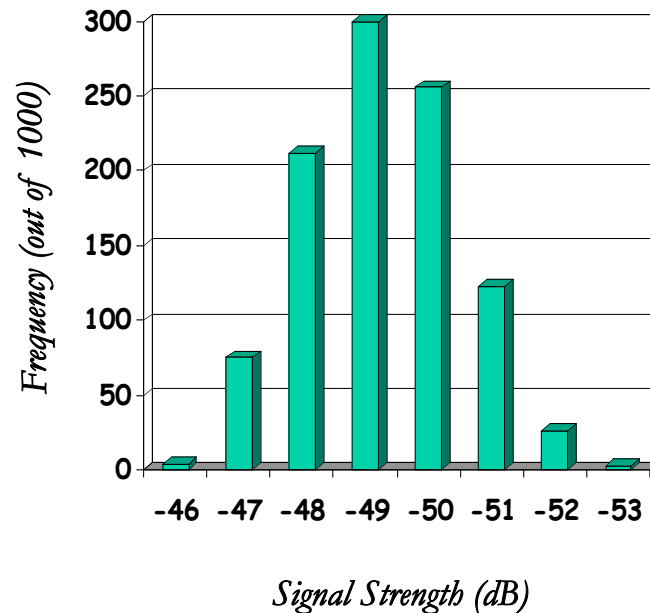
Automakers go wireless to find cars in plants

Physical Features Available for Use

- Received Signal Strength (RSS) from multiple access points
- Angles of arrival
- Time deltas of arrival
- Which access point (AP) you are associated with
- We use RSS and AP association
 - RSS is the only reasonable estimate with current commercial hardware

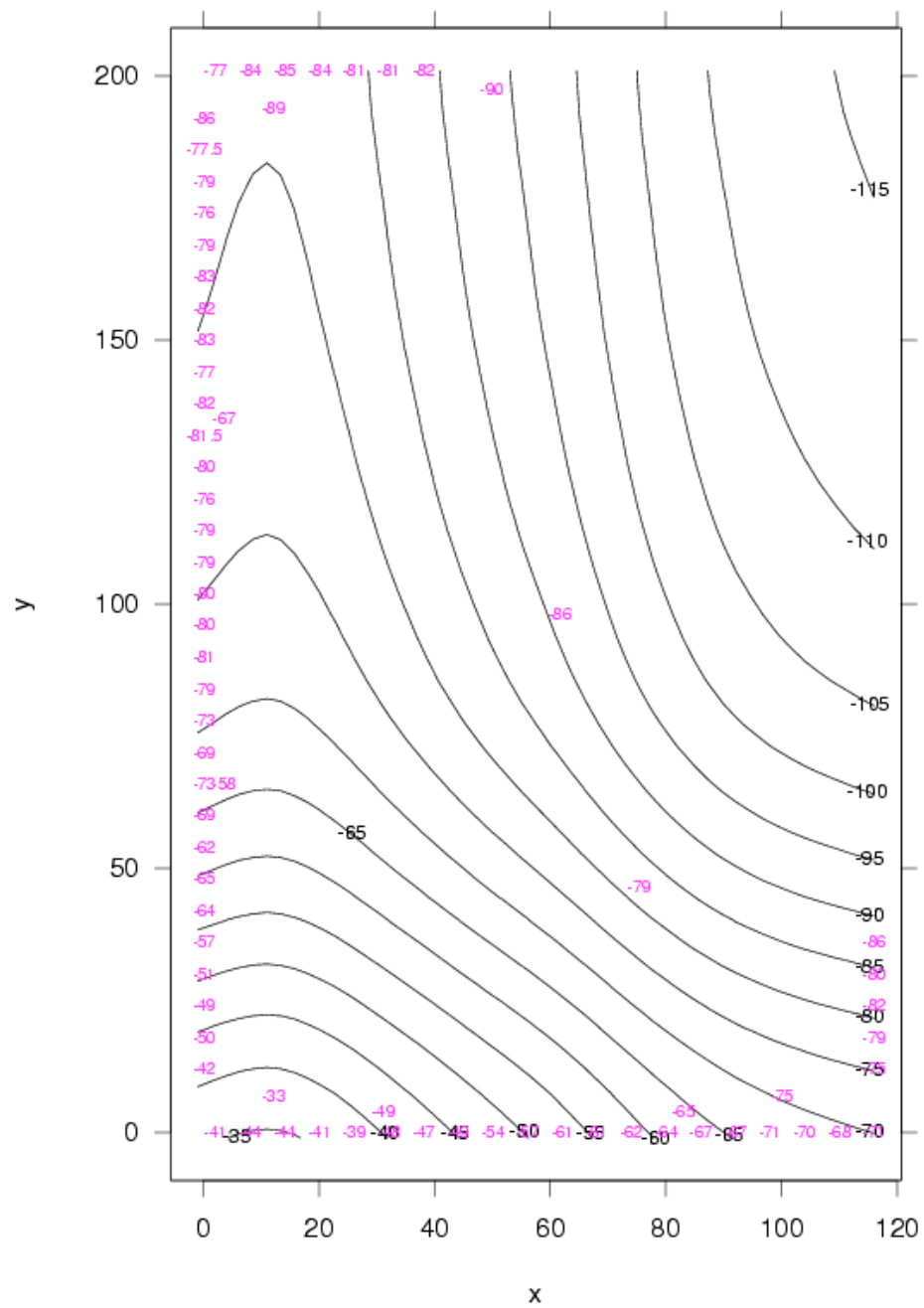
Known Properties of Signal Strength

- Signal strength at a location is known to vary as a log-normal distribution with some environment-dependent σ
- Variation caused by people, appliances, climate, etc.

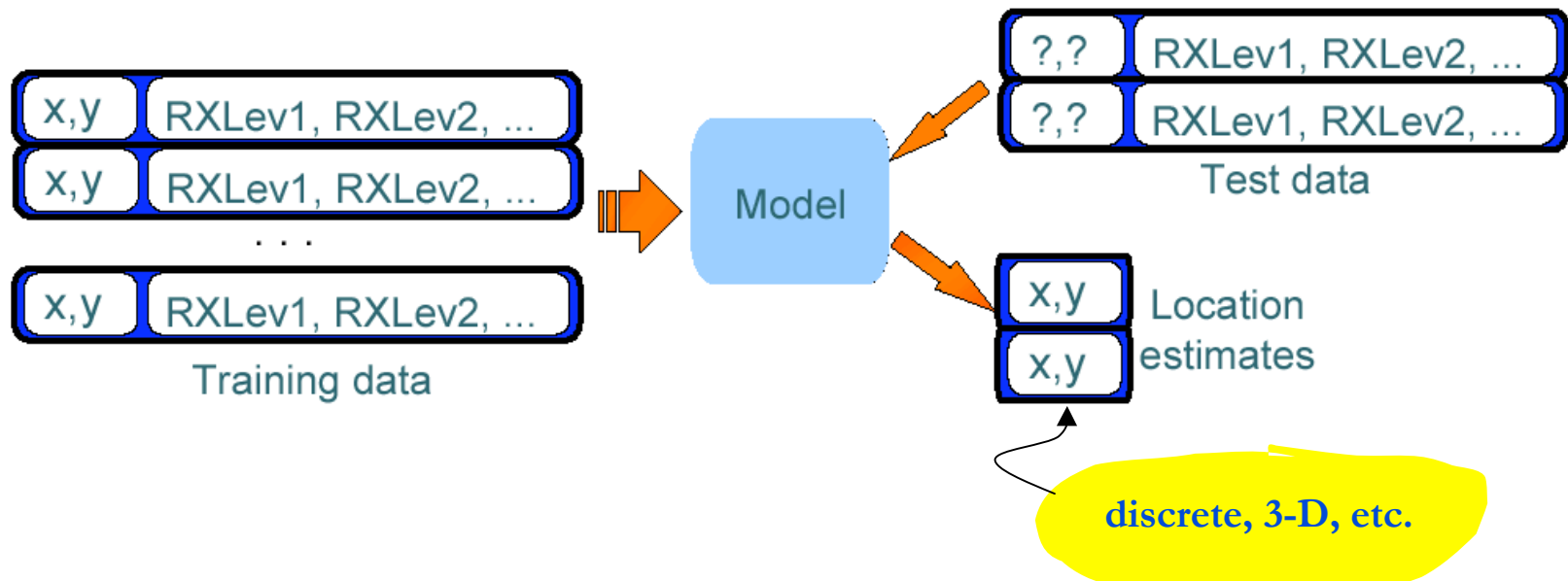


- The Physics: signal strength (SS; in dB) is known to decay with distance (d) as $SS = k_1 + k_2 \log d$

Access point: 1



Prior Work



- Take signal strength measures at many points in the site and do a closest match to these points in signal strength vector space. [e.g. Microsoft's RADAR system]
- Take signal strength measures at many points in the site and build a multivariate regression model to predict location (e.g., Tirri's group in Finland)
- Some work has utilized wall thickness and materials

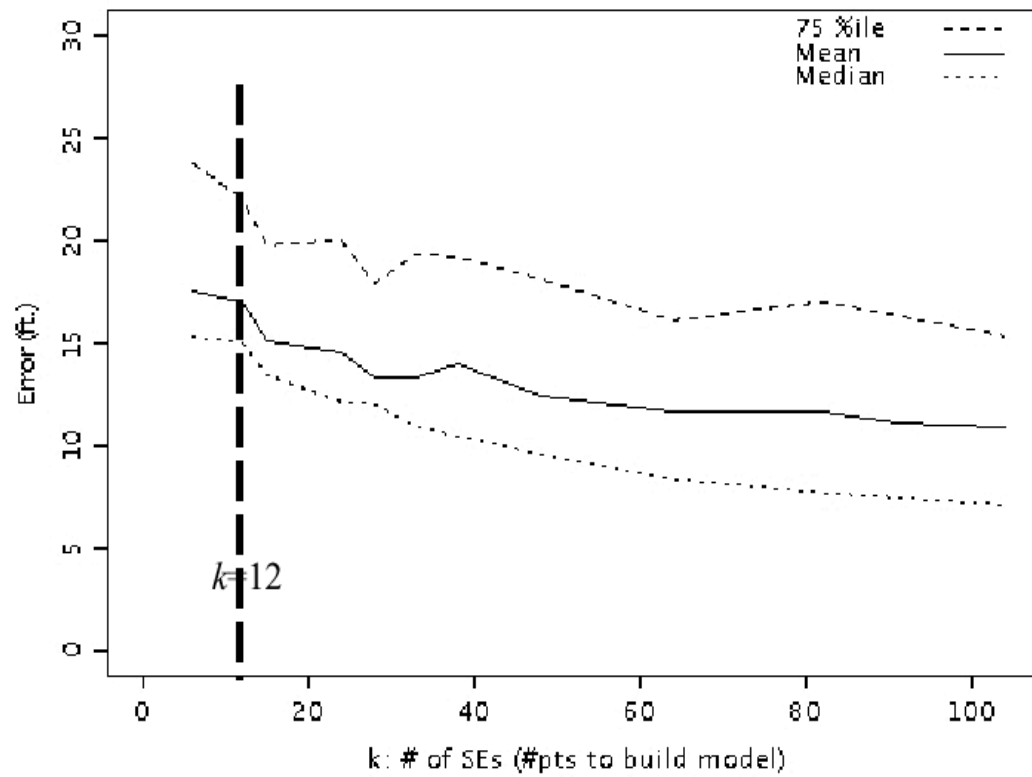
Prior Work

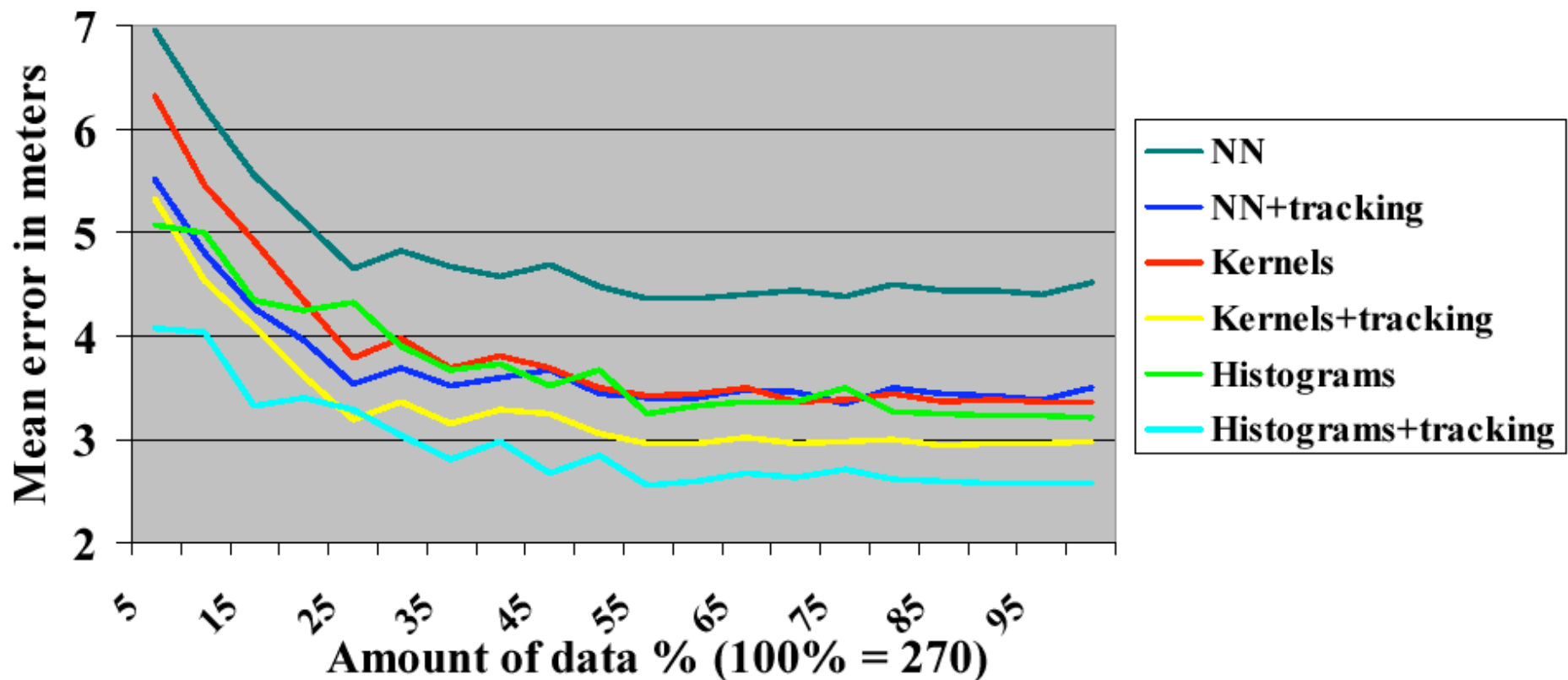
- Use physical characteristics of signal strength propagation and build a model augmented with a wall attenuation factor
- Needs detailed (wall) map of the building; model portability needs to be determined
 - [RADAR; INFOCOM 2000] based on [Rappaport 1992]

Krishnan et al. Results

Infocom 2004

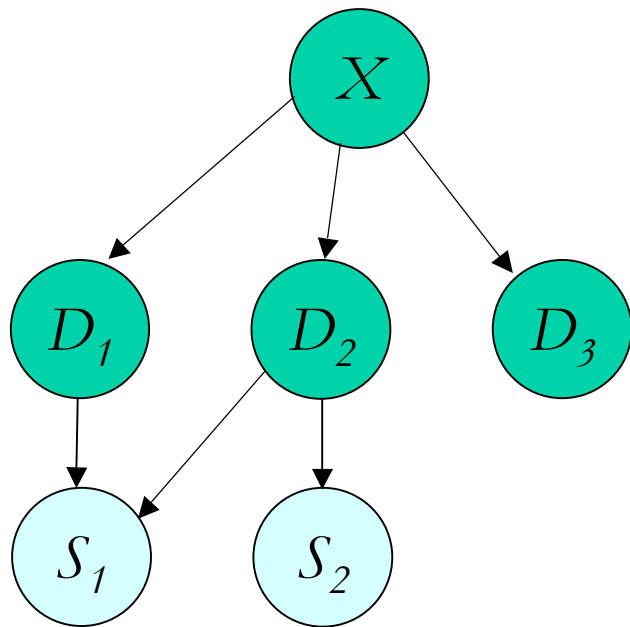
- Smoothed signal map per access point + nearest neighbor





- Best result: mean error 2.57 meters (90% below 4.52 meters) obtained with the probabilistic histogram method with tracking.
- Surprisingly robust with respect to the amount of training data.

Probabilistic Graphical Models



- Graphical model = picture of some conditional independence assumptions
- For example, D_1 is conditionally independent of D_3 given X

Markov Properties for Acyclic Directed Graphs

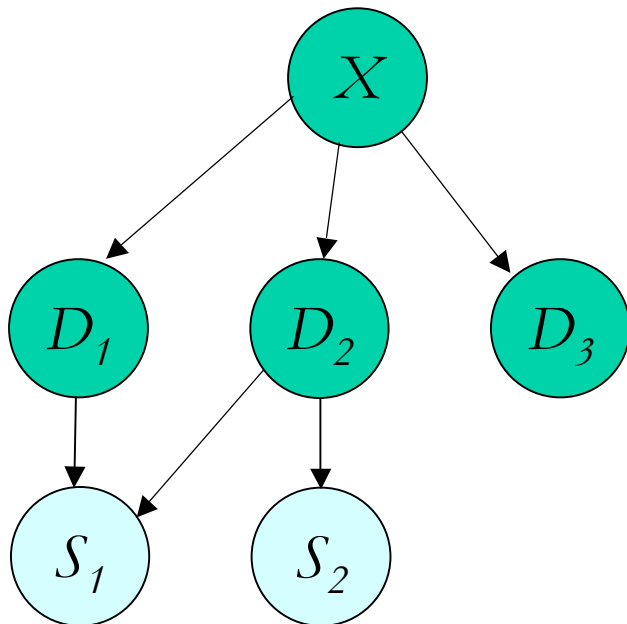
(Bayesian Networks)

(**Global**) S separates A from B in $G_{an(A,B,S)}^m \Rightarrow A \perp\!\!\!\perp B \mid S$

(**Local**) $\alpha \perp\!\!\!\perp nd(\alpha) \setminus pa(\alpha) \mid pa(\alpha)$

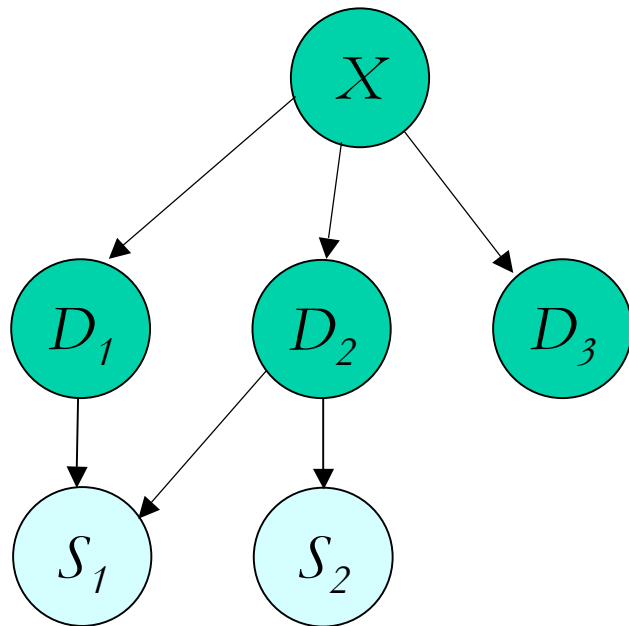
(**Factorization**) $f(x) = \prod f(x_v \mid x_{pa(v)})$

} equivalent



$$\begin{aligned} & p(X, D_1, D_2, D_3, S_1, S_2) \\ &= p(X) p(D_1 \mid X) p(D_2 \mid X) p(D_3 \mid X) \\ & \quad p(S_1 \mid D_1, D_2) p(S_2 \mid D_2) \end{aligned}$$

Monte Carlo Methods and Graphical Models



Simple Monte Carlo: Sample in turn from

$$p(X), p(D_1 | X), p(D_2 | X), p(D_3 | X), \\ p(S_1 | D_1, D_2), \text{ and } p(S_2 | D_2)$$

Gibbs Sampling: Sample in turn from

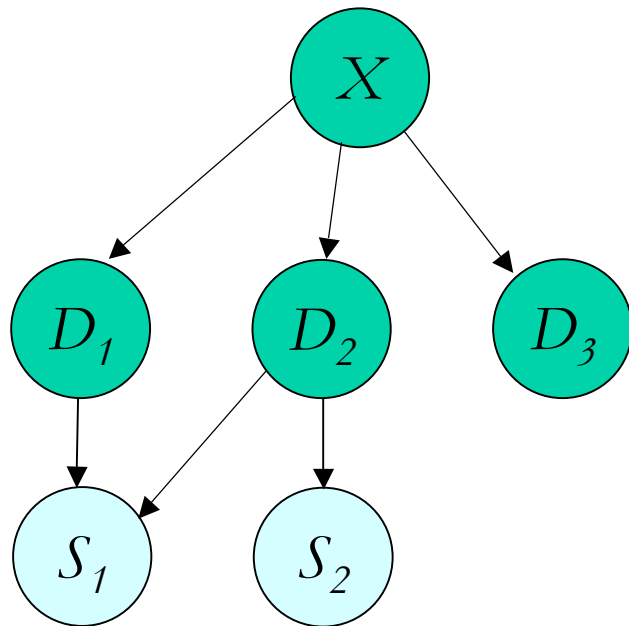
$$p(X \mid D_1, D_2, D_3, S_1, S_2)$$

$$p(D_1 \mid X, D_2, D_3, S_1, S_2)$$

...

$$p(S_2 \mid X, D_1, D_2, D_3, S_1)$$

Full Conditionals from the Graphical Model



$$p(D_1 \mid X, D_2, D_3, S_1, S_2)$$

$$\propto p(X, D_1, D_2, D_3, S_1, S_2)$$

$$= p(X) p(D_1 \mid X) p(D_2 \mid X) p(D_3 \mid X)$$

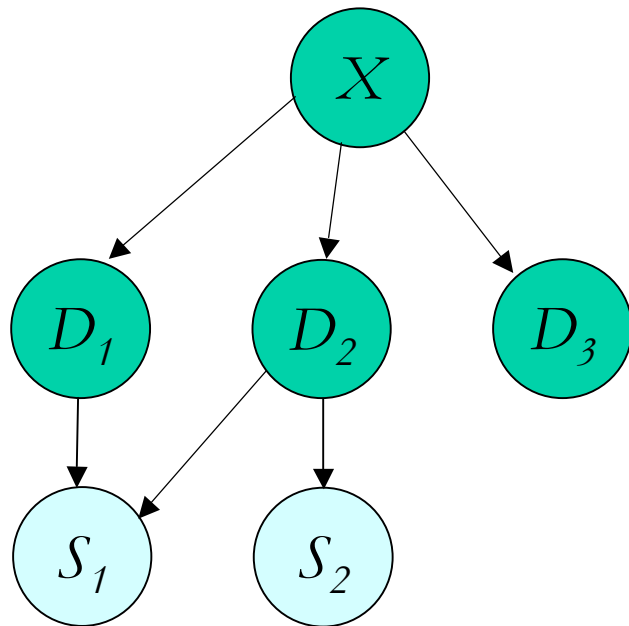
$$p(S_1 \mid D_1, D_2) p(S_2 \mid D_2)$$

$$\propto p(D_1 \mid X) p(S_1 \mid D_1, D_2)$$

BUGS/WinBUGS automates this via adaptive rejection sampling
and slice sampling

Full Conditionals from the Graphical Model

Incorporating Data, etc. Suppose the D 's were observed. Then sample from:



$$p(X \mid D_1, D_2, D_3, S_1, S_2)$$

$$p(S_1 \mid X, D_1, D_2, D_3, S_2)$$

$$p(S_2 \mid X, D_1, D_2, D_3, S_1)$$

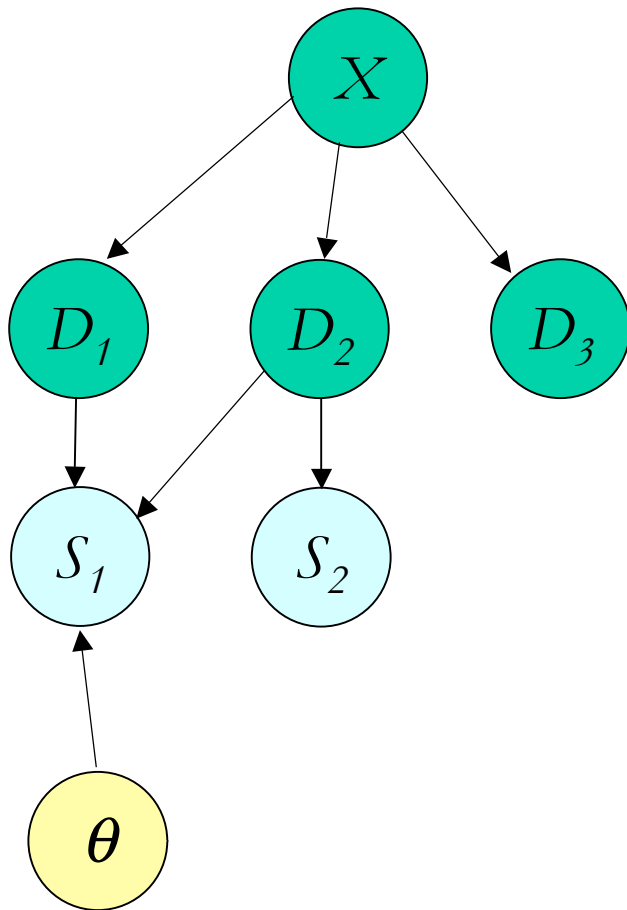
Full Conditionals from the Graphical Model

Incorporating Data, etc. Suppose the D 's were observed. Then sample from:

$$p(X \mid D_1, D_2, D_3, S_1, S_2)$$

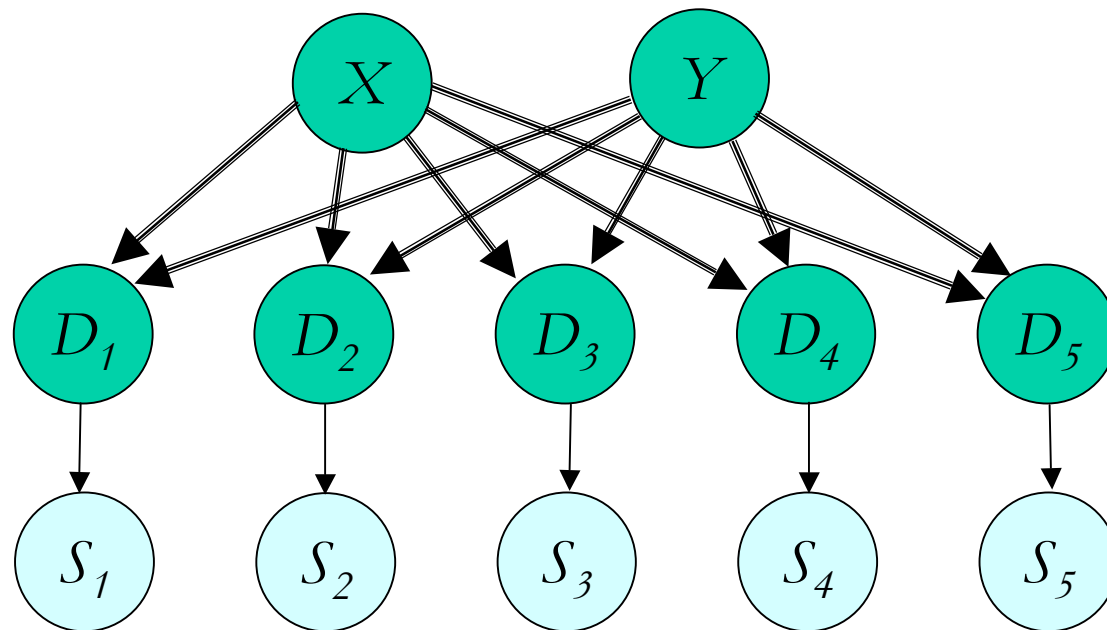
$$p(S_1 \mid X, D_1, D_2, D_3, S_2)$$

$$p(S_2 \mid X, D_1, D_2, D_3, S_1)$$



Bayesian Analysis. Treat “parameters” the same as everything else.

Bayesian Graphical Model Approach



$$X, Y \sim \text{unif}$$

$D_i(X, Y)$ = distance to the i th access point

$$S_i \sim N(b_{i0} + b_{i1} \log D_i, \sigma_i^2), \quad i = 1, \dots, 5$$

average

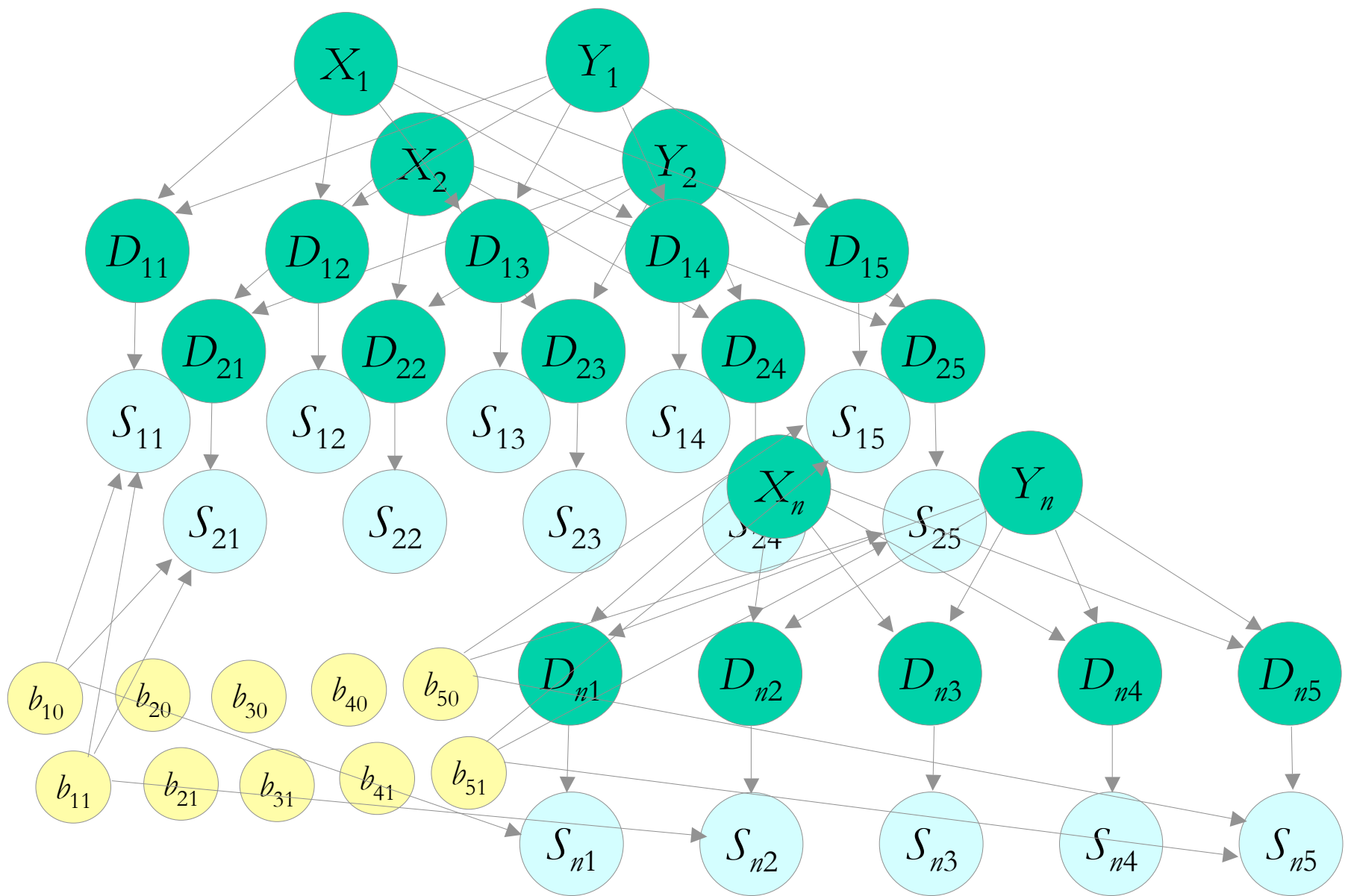
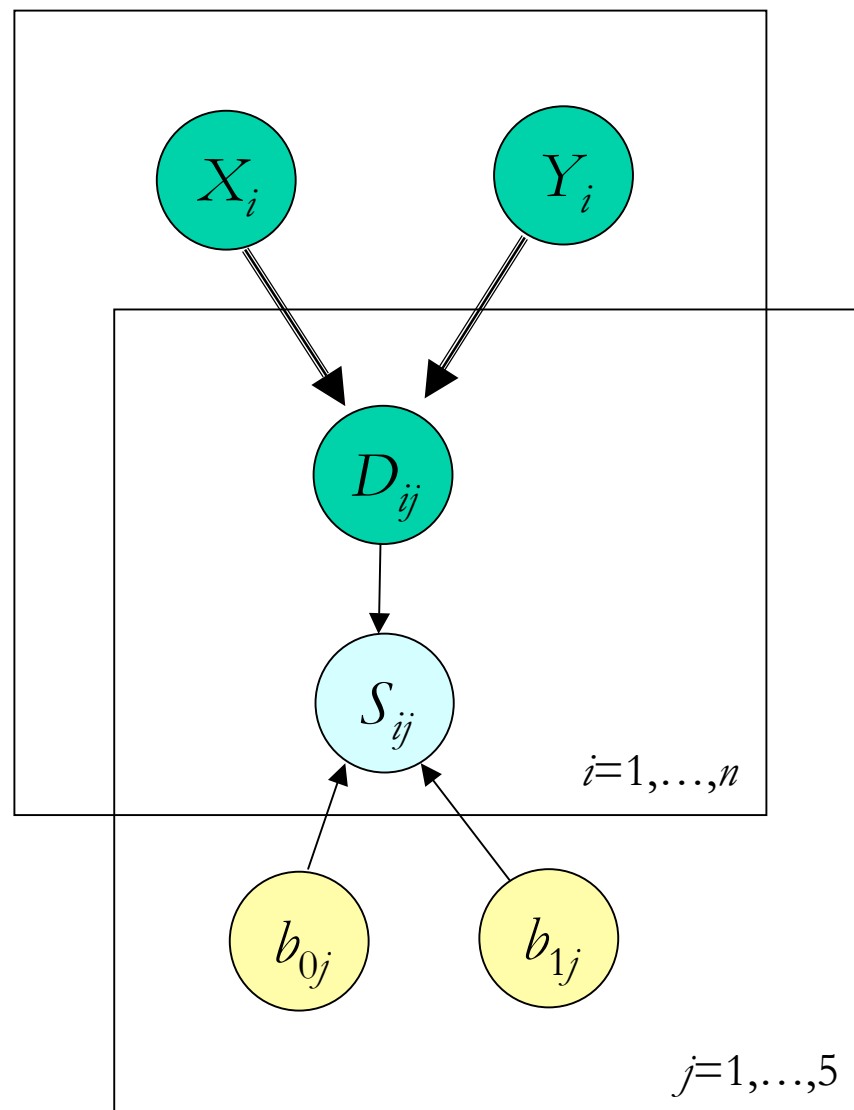
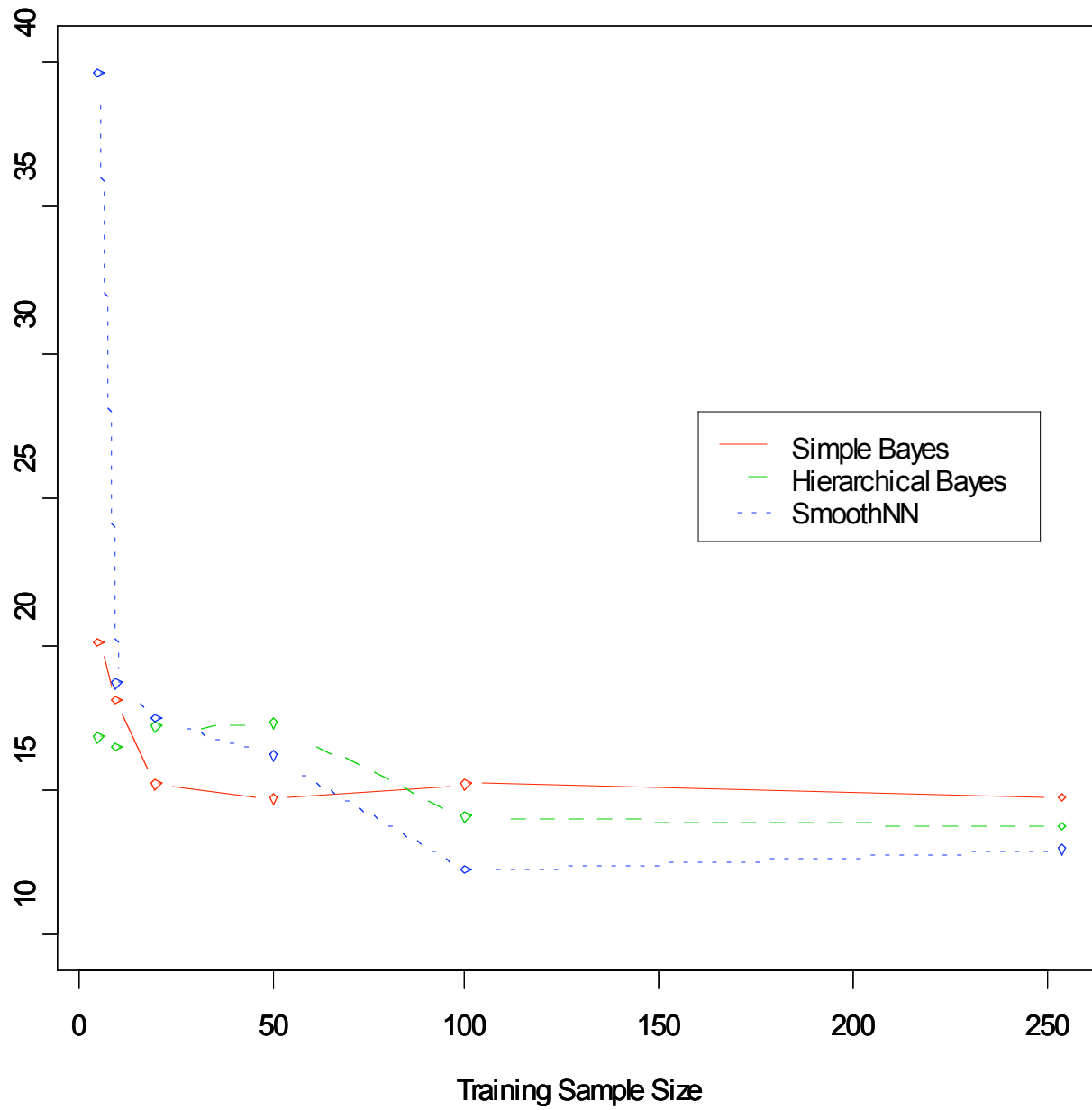


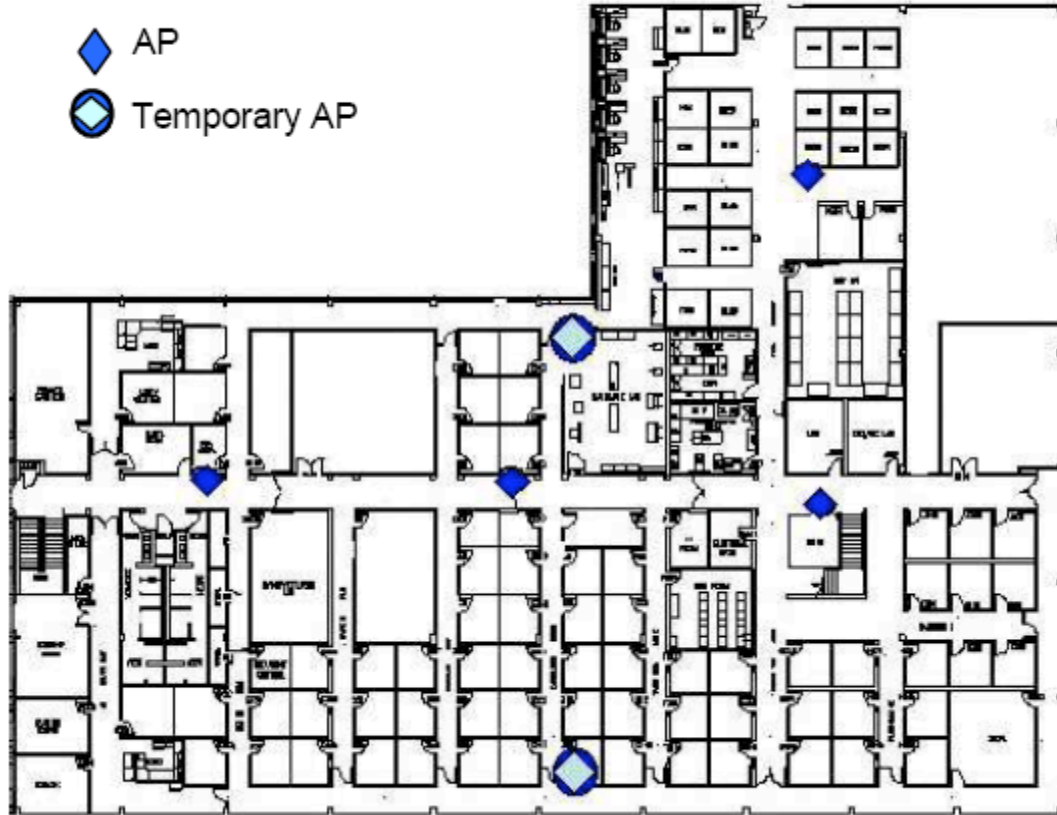
Plate Notation



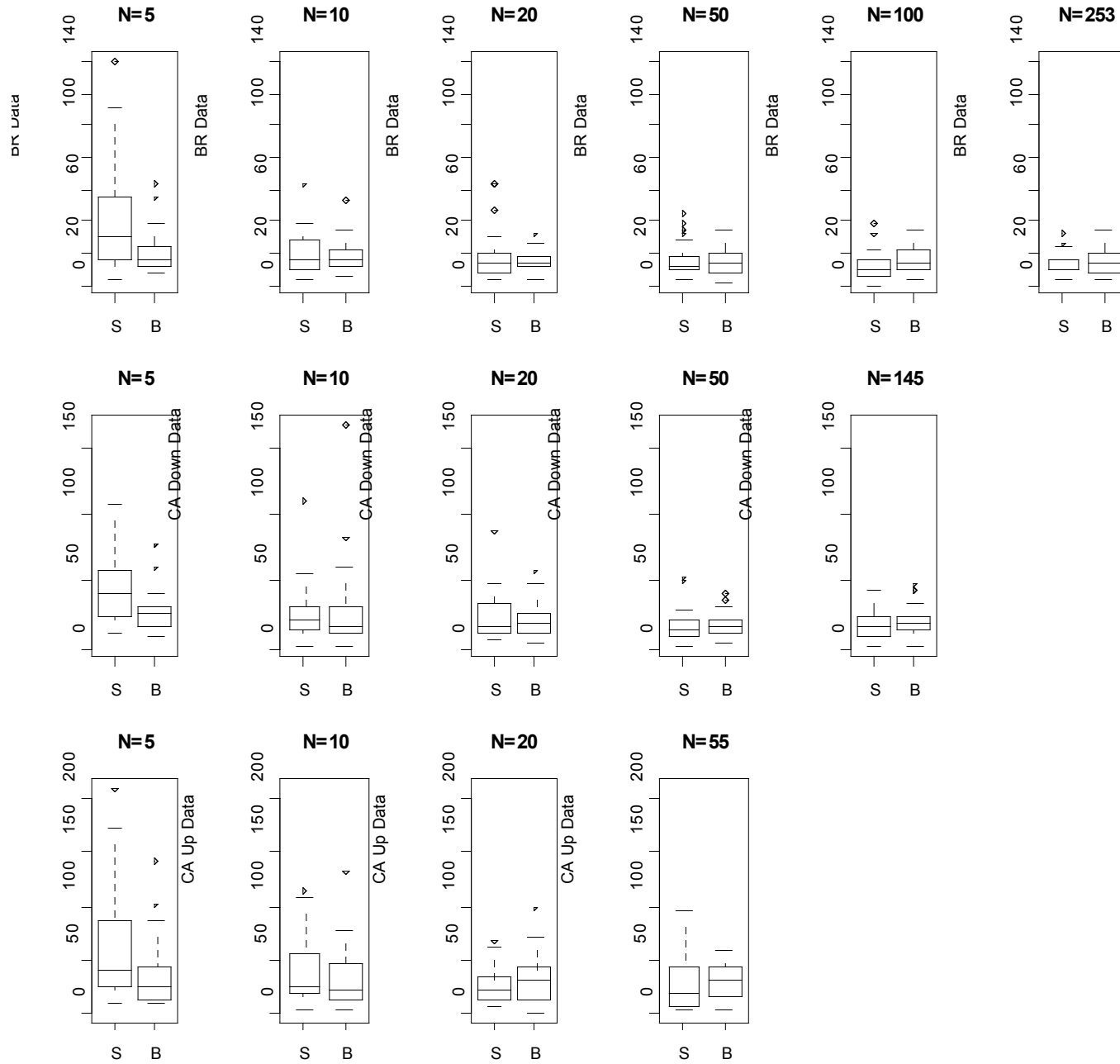
Leave-one-out error (feet)



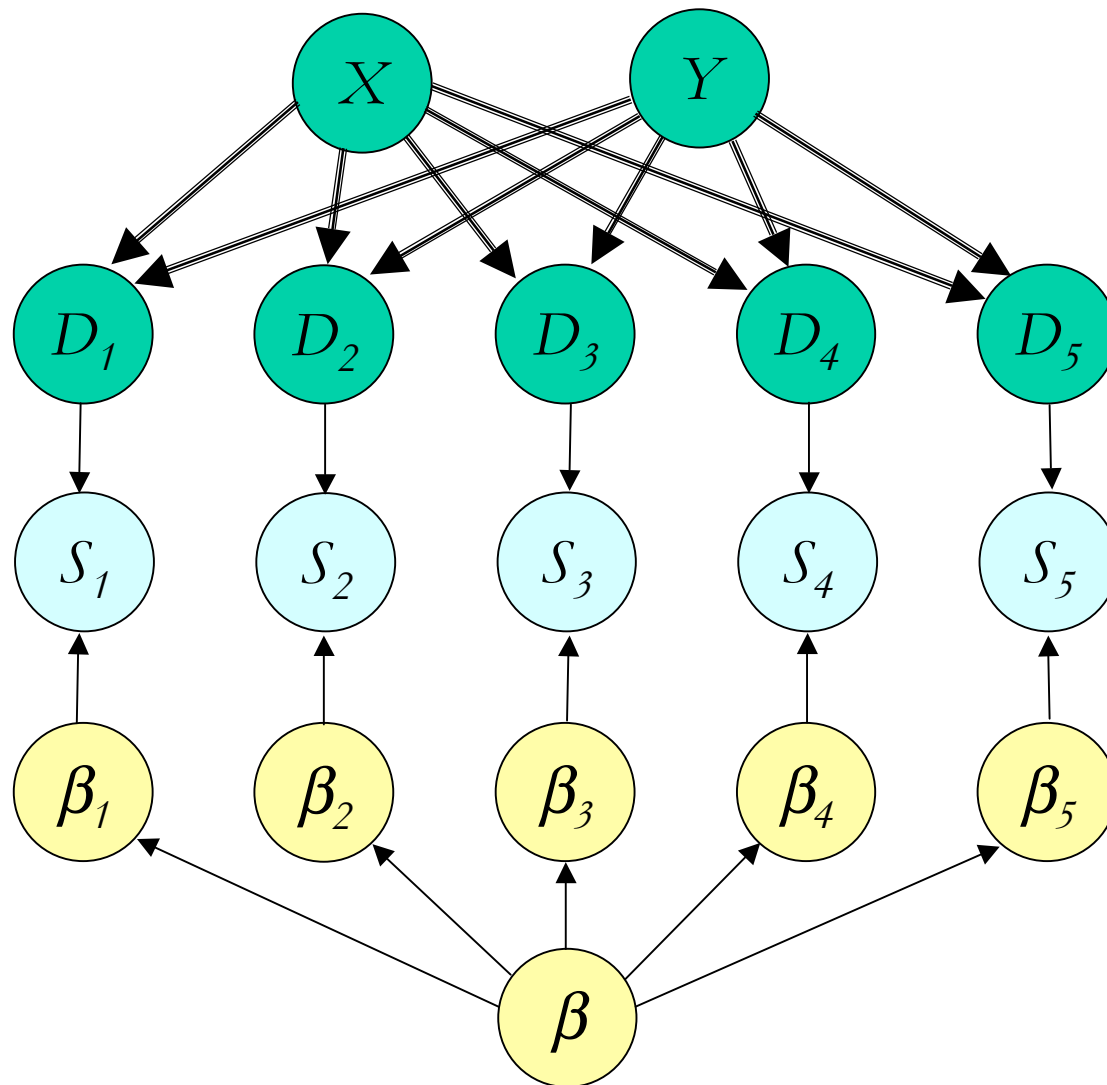
- ◆ AP
- ◈ Temporary AP



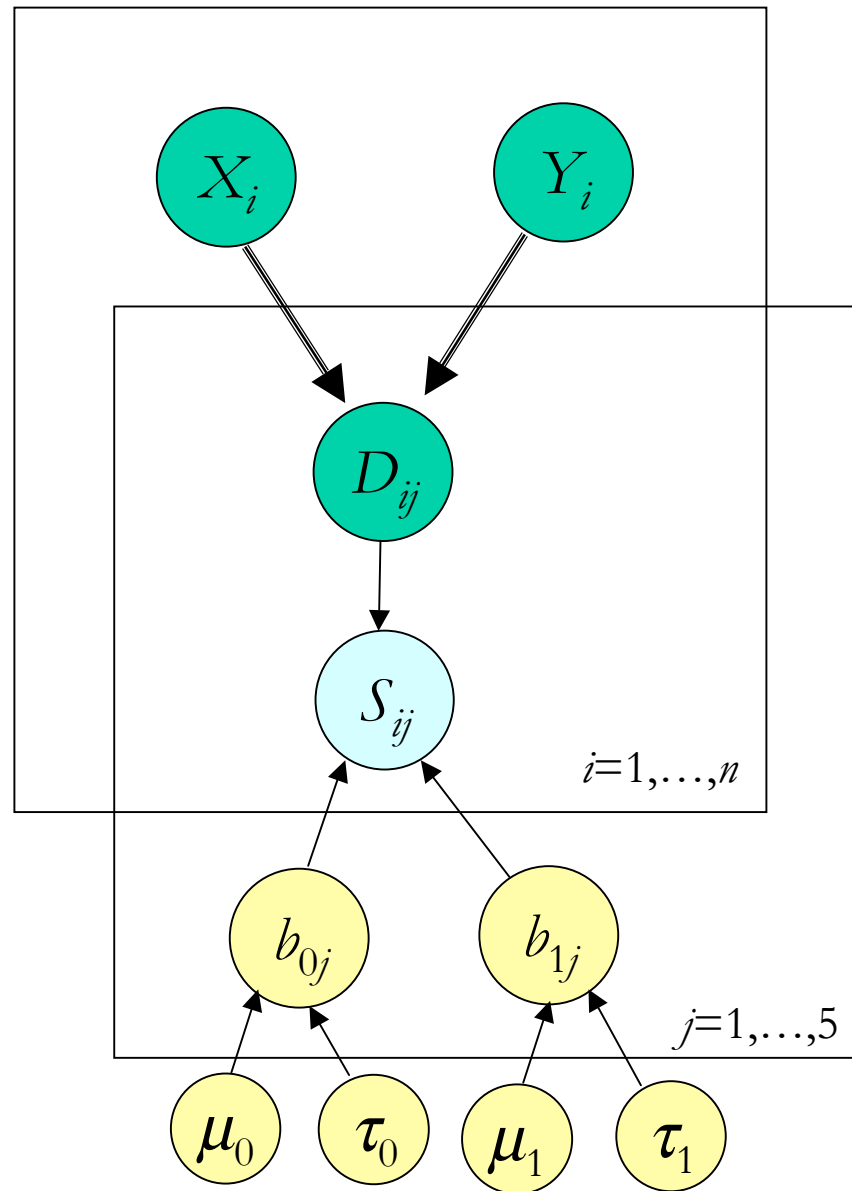
SmoothNN (S) versus Bayesian (B) Model, Error in Feet



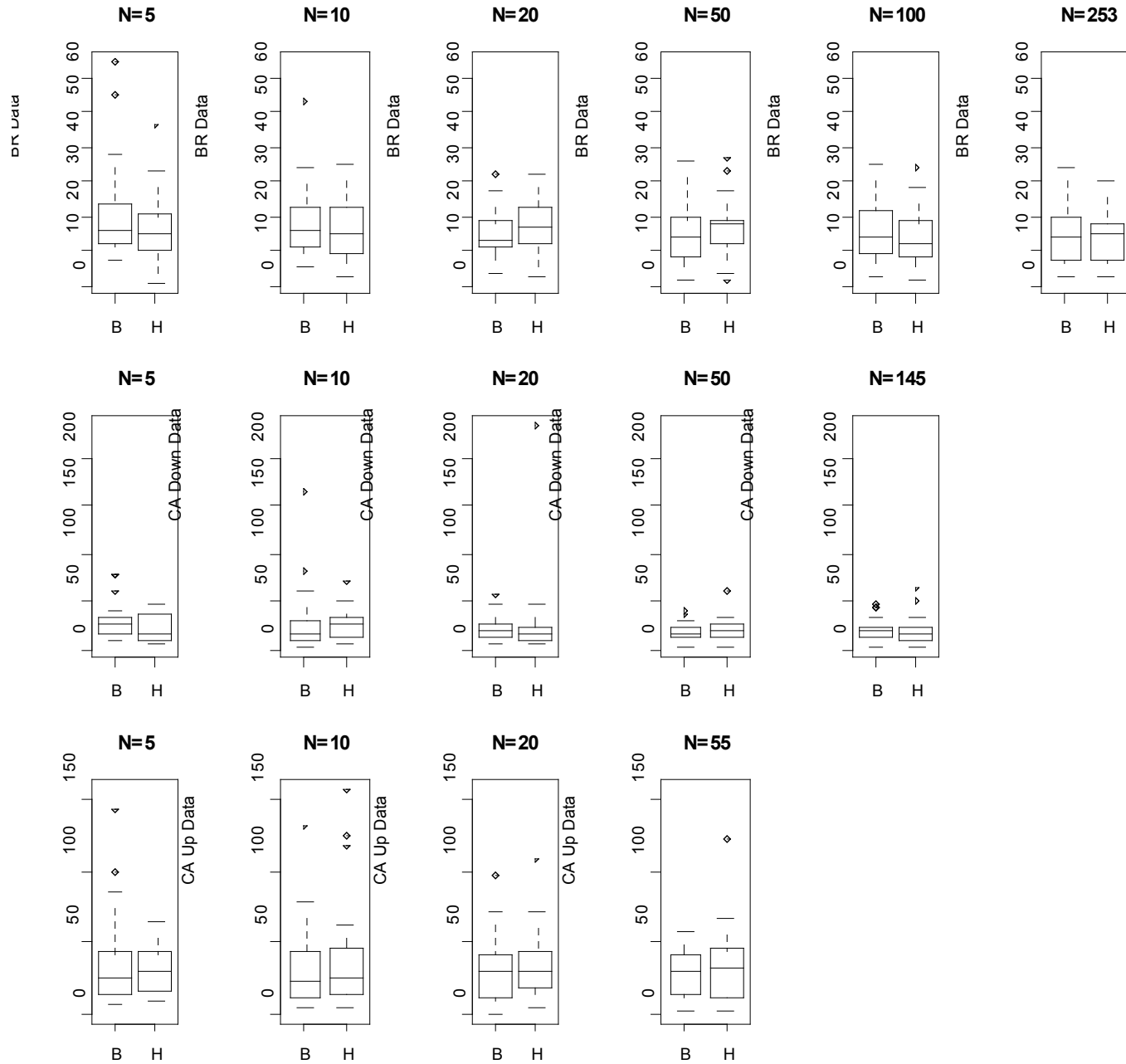
Hierarchical Model



Hierarchical Model



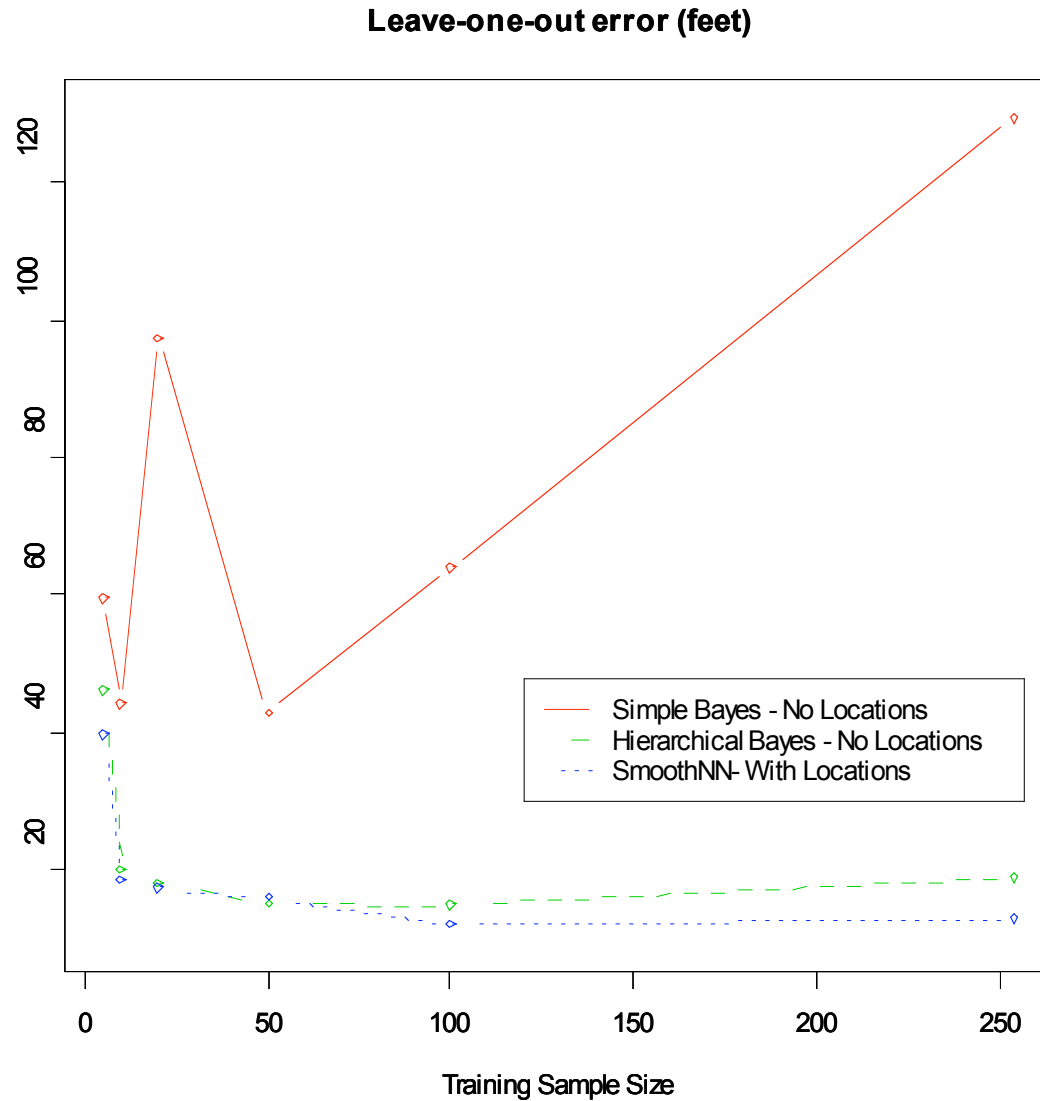
Simple Bayesian (B) versus Hierarchical Bayesian (H) Model, Error in Feet



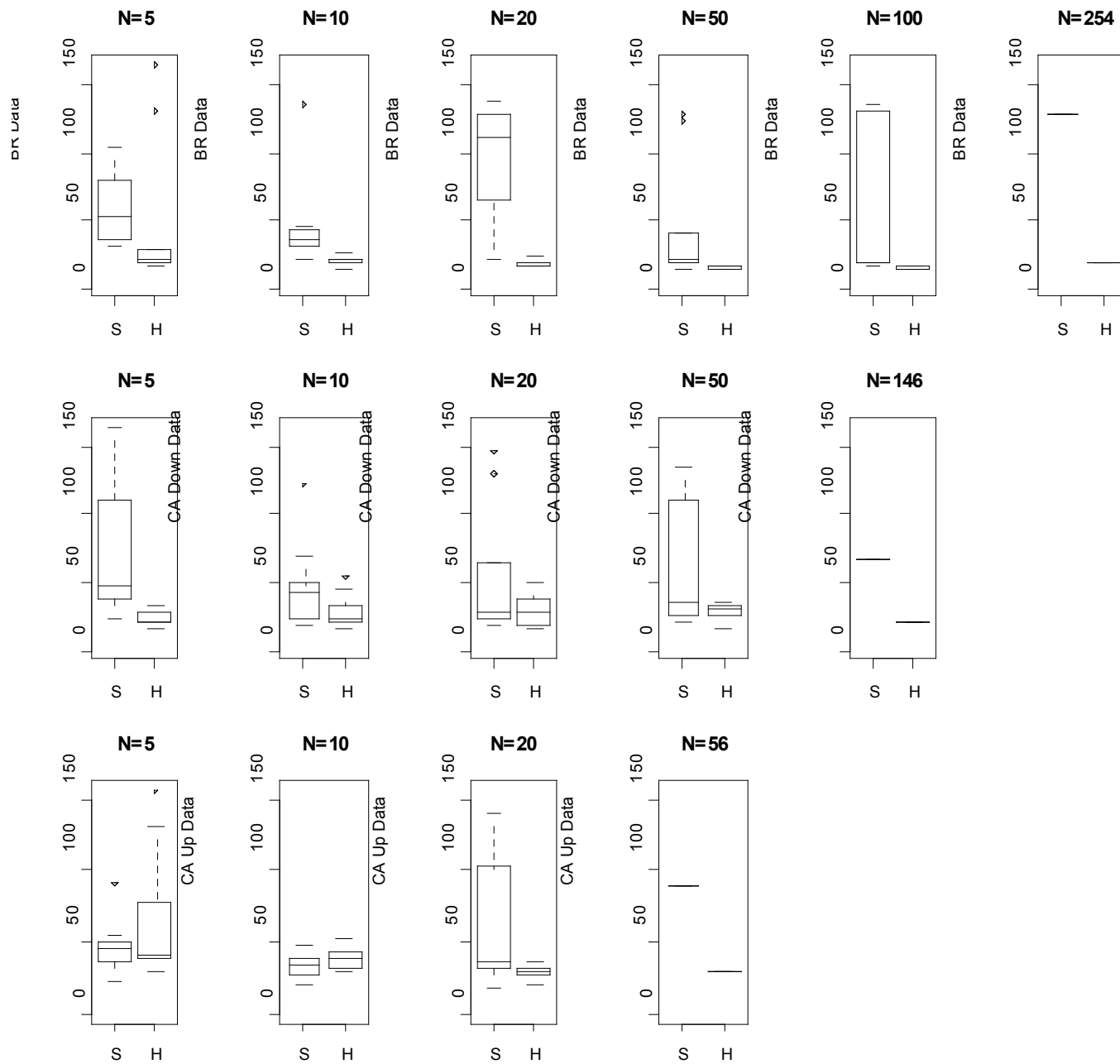
Pros and Cons

- Bayesian model produces a predictive distribution for location
- MCMC can be slow
- Difficult to automate MCMC (convergence issues)
- Perl-WinBUGS (perl selects training and test data, writes the WinBUGS code, calls WinBUGS, parses the output file)

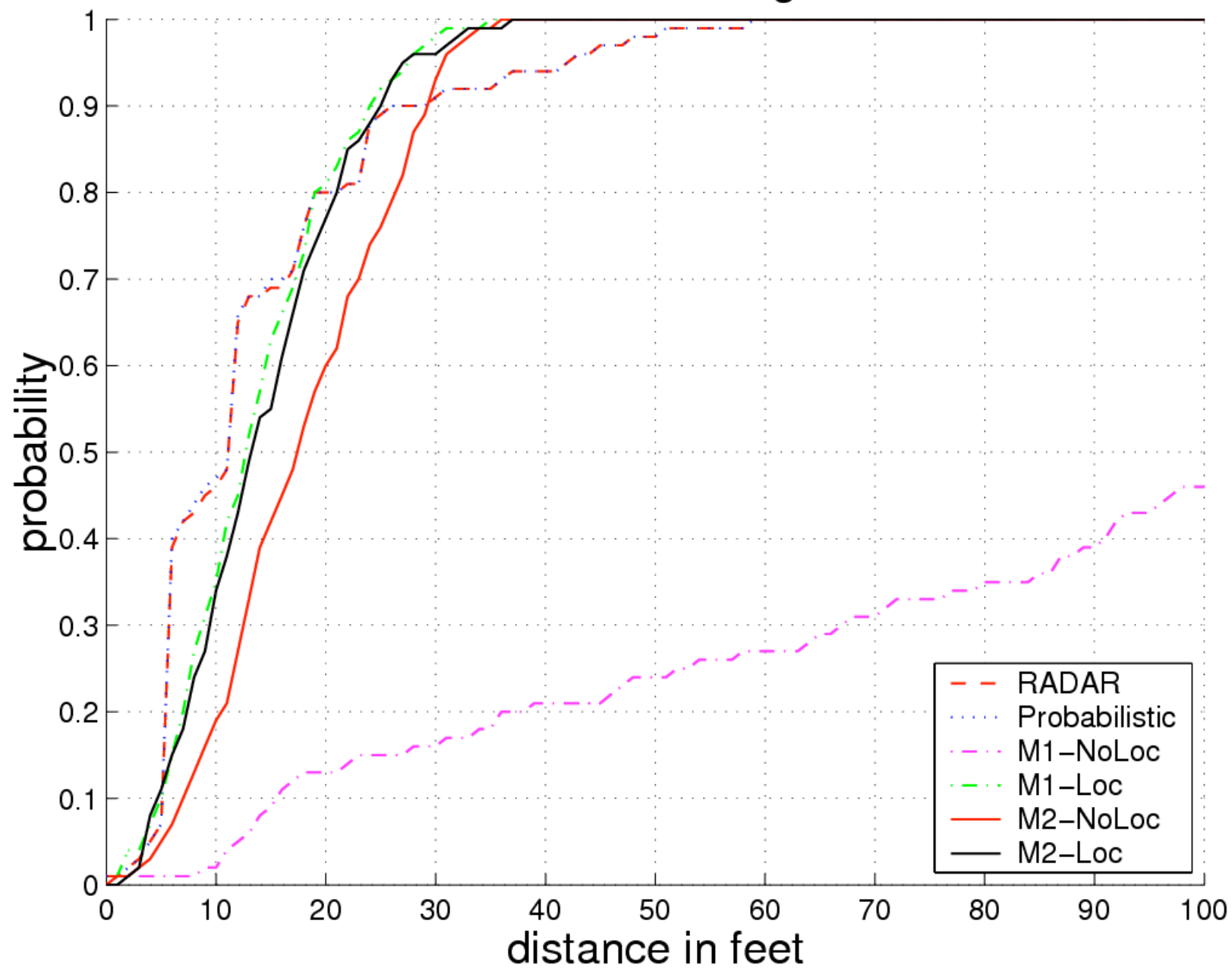
What if we had no locations in the training data?



Results with No Locations: Simple (S), Hierarchical (H), Error in Feet



Error CDF Across Algorithms



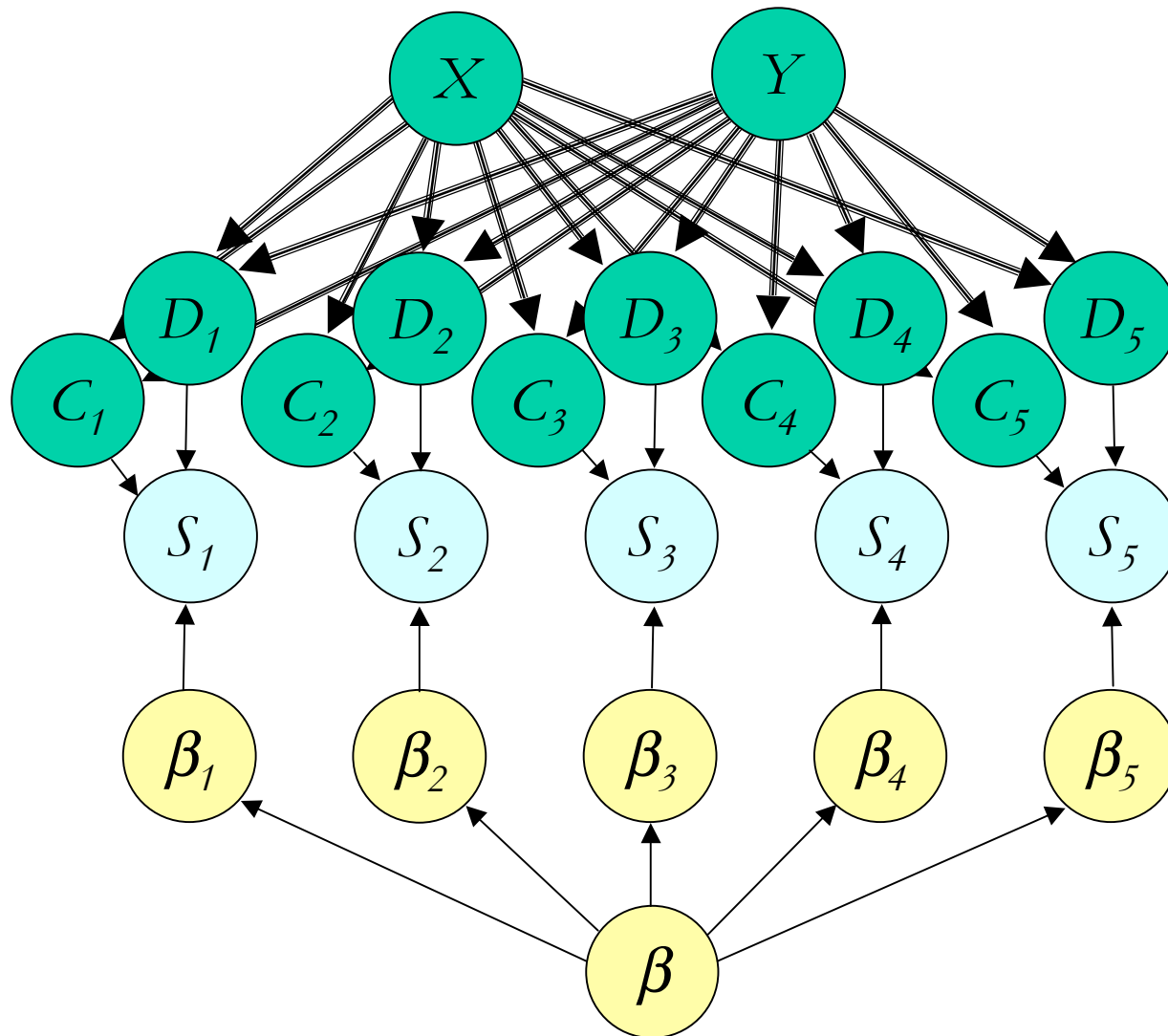
Zero Profiling?

- Simple sniffing devices can gather signal strength vectors from available WiFi devices
- Can do this repeatedly
- Locations of the Access Points

Why does this work?

- Prior knowledge about distance-signal strength
- Prior knowledge that access points behave similarly
- Estimating several locations simultaneously

Corridor Effects



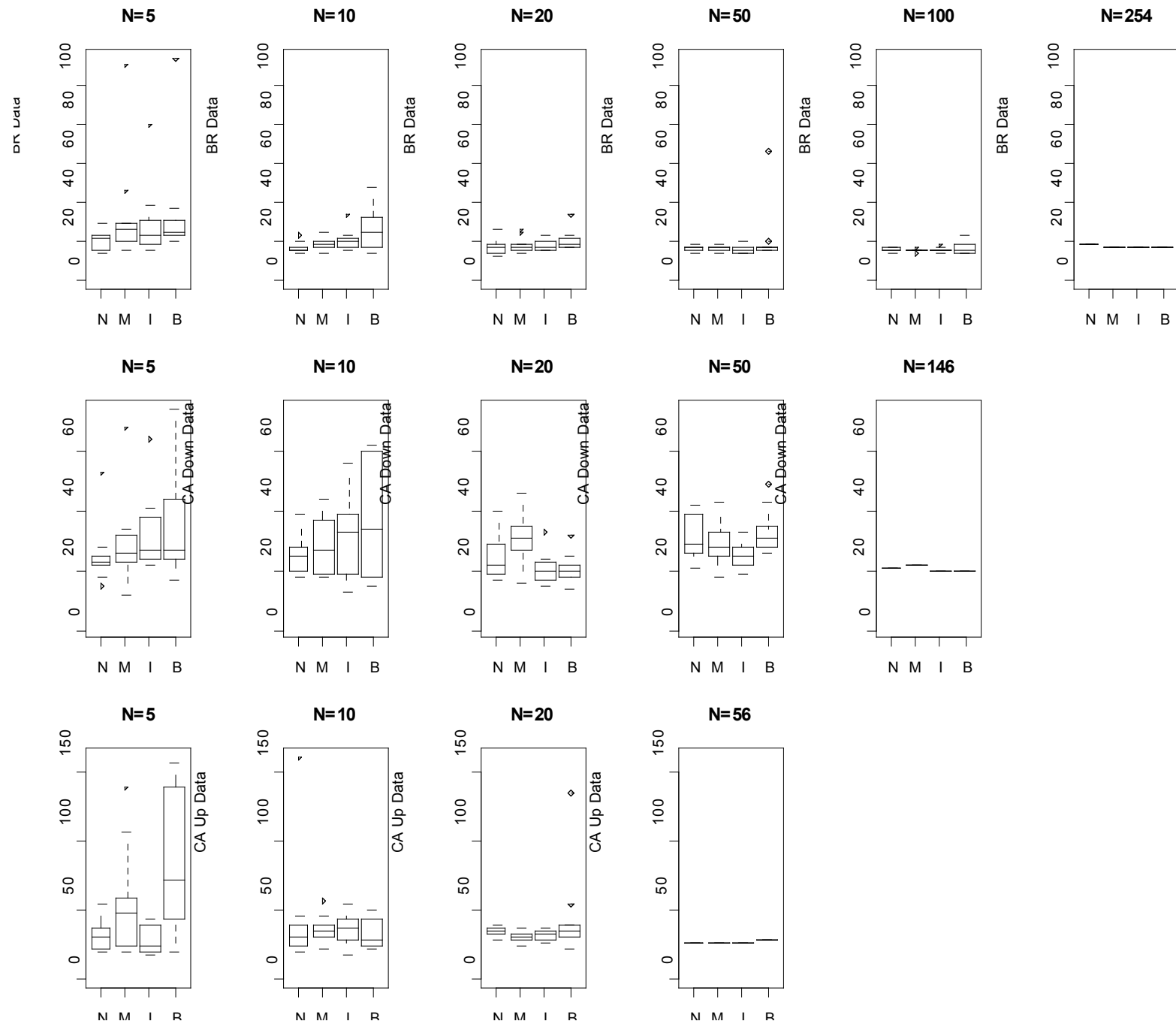
Results for N=20, no locations

| corridor main effect | corridor -distance interaction | average error |
|----------------------------|--------------------------------------|------------------|
| 0 | 0 | 20.8 |
| 0 | 1 | 16.7 |
| 1 | 0 | 17.8 |
| 1 | 1 | 17.3 |

with mildly informative prior on the distance main effect...

| corridor main effect | corridor -distance interaction | average error |
|----------------------------|--------------------------------------|------------------|
| 0 | 0 | 16.3 |
| 0 | 1 | 14.7 |
| 1 | 0 | 15.8 |
| 1 | 1 | 15.9 |

Corridor Effect: None (N), Main (M), Interaction (I), Both (B), Error in Feet



Discussion

- Informative priors
 - Convenience and flexibility of the graphical modeling framework
 - Censoring (30% of the signal strength measurements)
 - Repeated measurements & normal error model
 - Tracking
-
- Machine learning-style experimentation is clumsy with perl-WinBUGS

