Bayesian Positioning in Wireless Networks using Angle of Arrival

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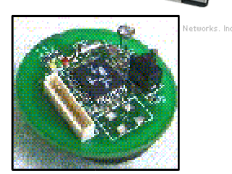
Wireless Explosion

- Technology trends creating cheap wireless communication in every computing device
- Radio offers localization opportunity in 2D and 3D
  - New capability compared to traditional communication networks
- 3 technology communities:
  - **WLAN (802.11x)**
  - Sensor networks (802.15)
  - Cell carriers(3G)

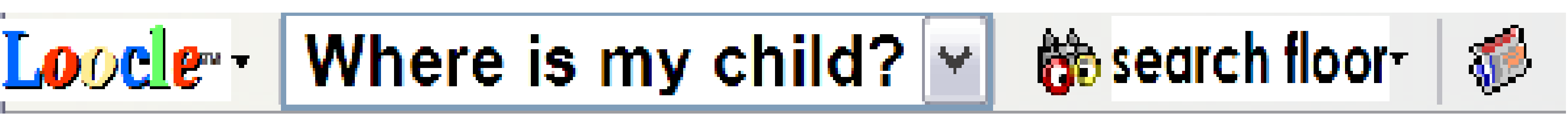


Challenge and Opportunity

- General purpose localization analogous to general purpose communication!
    - Work on any device with little/no modification
    - Supports vast range of performance
    - Will drive new applications

- Challenge: Can we localize all device radios using only the communication infrastructure?
  – How much existing infrastructure can we leverage?

- 1st Application: Search
  – General purpose communication needed for global search
  – Can we make finding objects in the physical space as easy as Google ?



Vision to reality

- Getting closer …

This talk:

- Localize with only existing infrastructure
  - Signal strength-> available on almost all radios
- Ad-hoc
  - **No more labeled data** (our contribution)
- Adding additional infrastructure
  - Directional Antennas

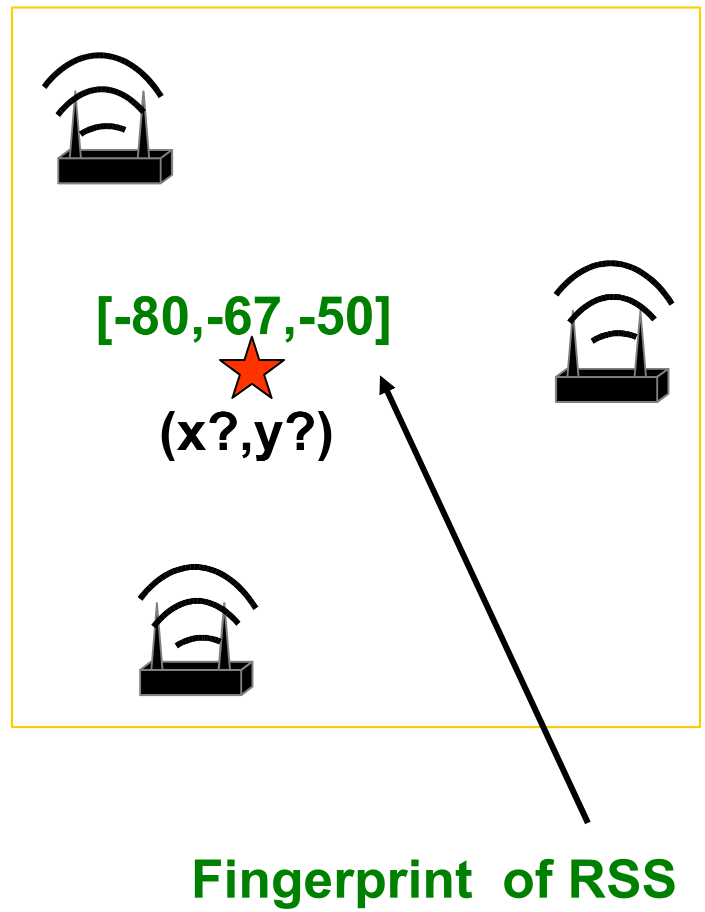
Radio-based Localization

- Signal decays linearly with log distance in laboratory and line of sight settings

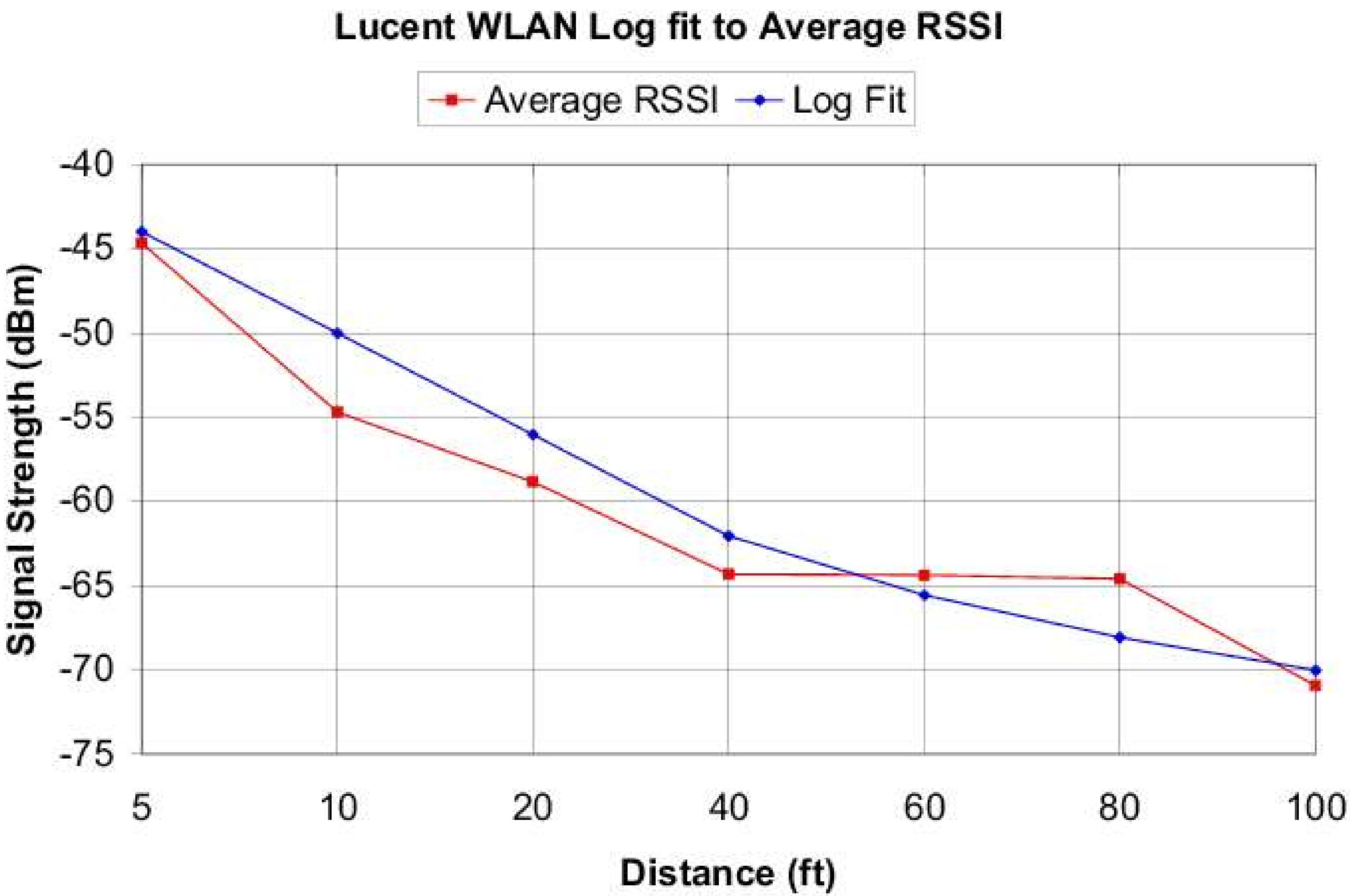
$$S_j = b_{1j} + b_{2j} \log D_j$$

$$D_j = \sqrt{(x - x_j)^2 + (y - y_j)^2}$$

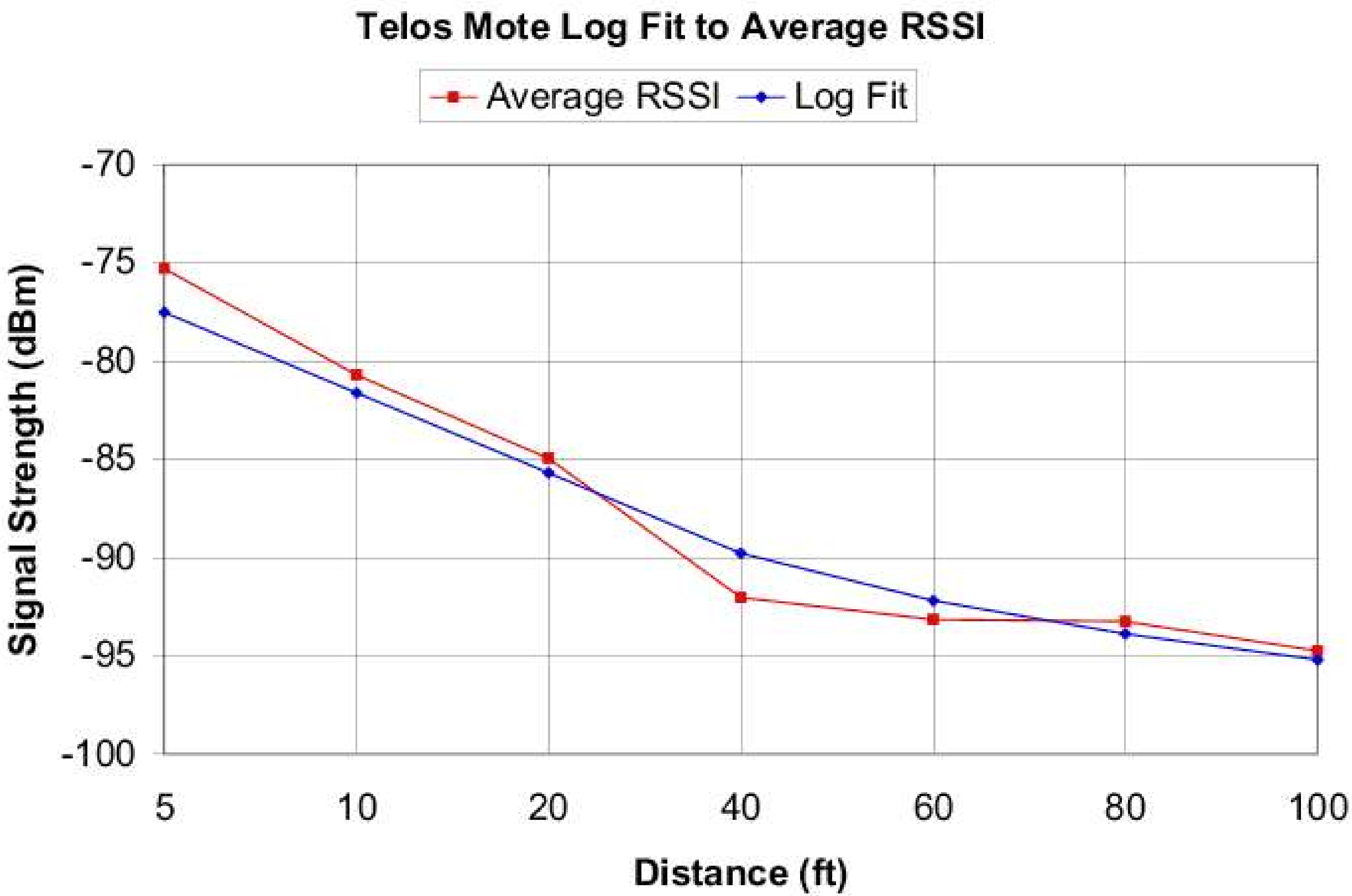
  - Use trilateration to compute (x,y) » Problem solved



RSS to distance: Outdoor 802.11



RSS to Distance -- Telos Mote Outdoor

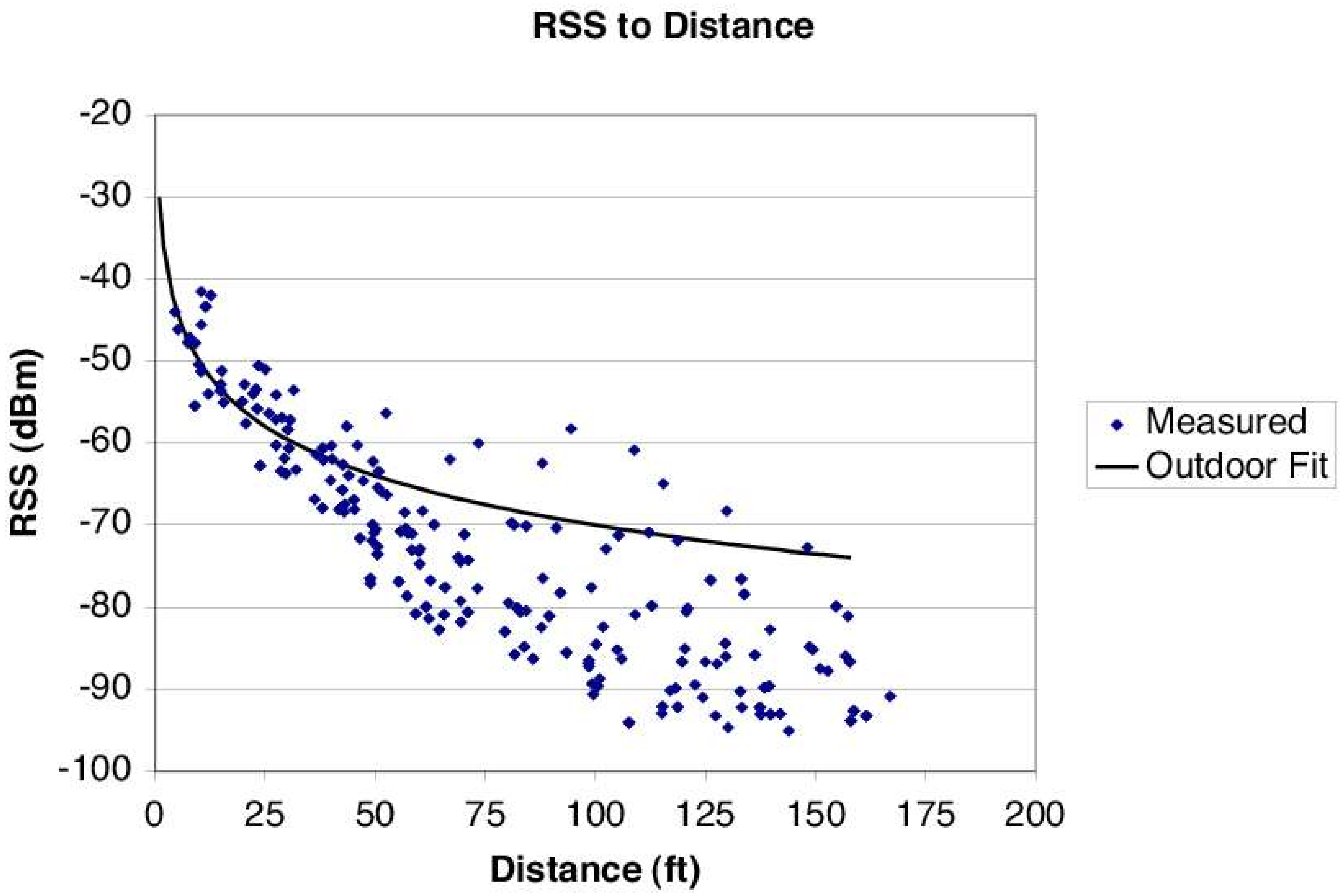


Indoor Localization

- Reality is Bad
  - Noise (could average out)
- Worse ..
  - Multi-path
  - Reflections
  - Attenuation

  Systematic bias

RSS to Distance --- Indoor 802.11

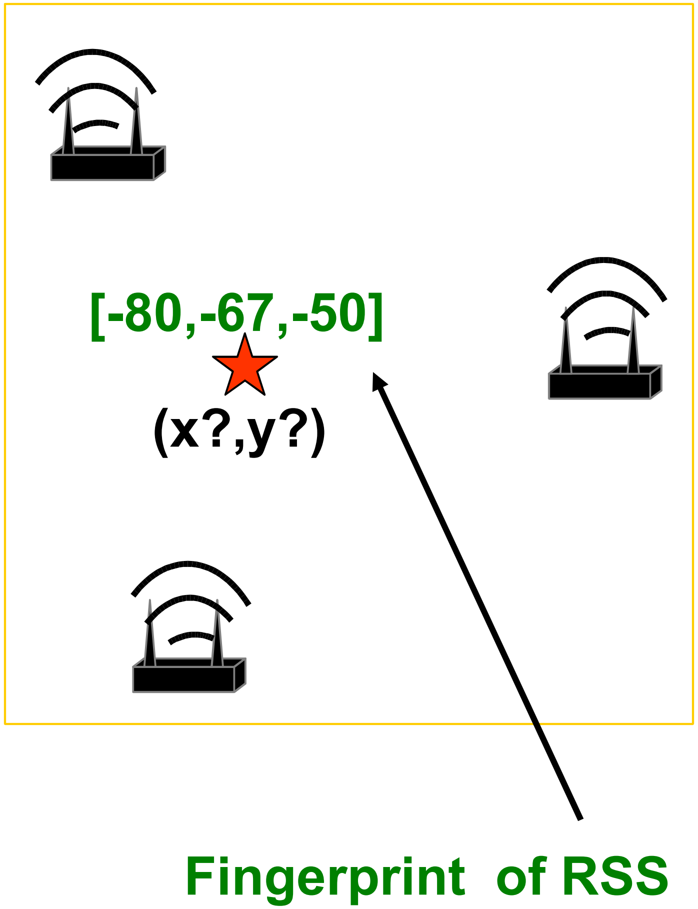


Machine Learning Motivation

- Data generally follows model
  - E.g. 0-50 ft, follows model closely
- Can we use machine learning to automatically obtain signal parameters?
- Identify/ignore noise?
- Match bias to particular regions?

Supervised Learning-based Systems

- Training
- Offline phase
  - Collect **<u>“labeled”</u>** training data [(X,Y), S1,S2,S3,..]
- Online phase
  - Match **<u>“unlabeled”</u>** RSS
  - [(?,?), S1,S2,S3,..] to existing “labeled” training fingerprints

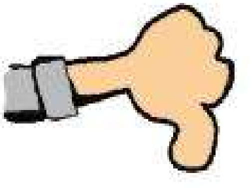


Previous ML Work

- People have tried almost all existing supervised learning approaches
  - Well known RADAR (nearest neighbor)
  - Probabilistic, e.g., Bayes a posteriori likelihood
  - Support Vector Machines
  - Multi-layer Perceptrons
  - …

  [Bahl00, Battiti02, Roos02,Youssef03, Krishnan04,…]

- All have a major drawback



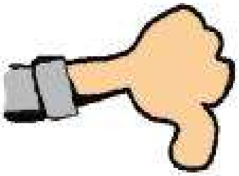
  - Labeled training fingerprints: “profiling”
  - Labor intensive (286 points in 32 hrs => 6.7 min/point)
  - Need to be repeated over the time

Contribution

Used Bayesian Graphical Models (BGM):

- Performance-wise: comparable
- Minimum labeled fingerprints
- Adaptive
- Simultaneously locate a set of objects

- **Advantage: zero-profiling**



  - No more “labeled” training data needed
  - Unlabeled data can be obtained using existing data traffic

Outline

- Motivations and Goals
- Bayesian background
- Prior Work
  - Distance-based Bayesian Models
    - M1, M2, M3
- Angle & Distance model: A1
- Conclusions and Future Work

Bayesian Graphical Models

- Encode dependencies/conditional independence between variables

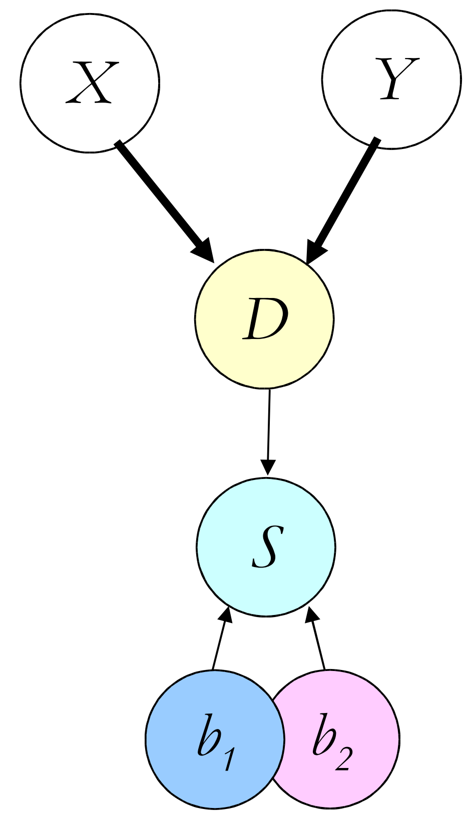
Vertices = random variables
Edges = relationships

Example [(X,Y), S], AP at (x_b, y_b)

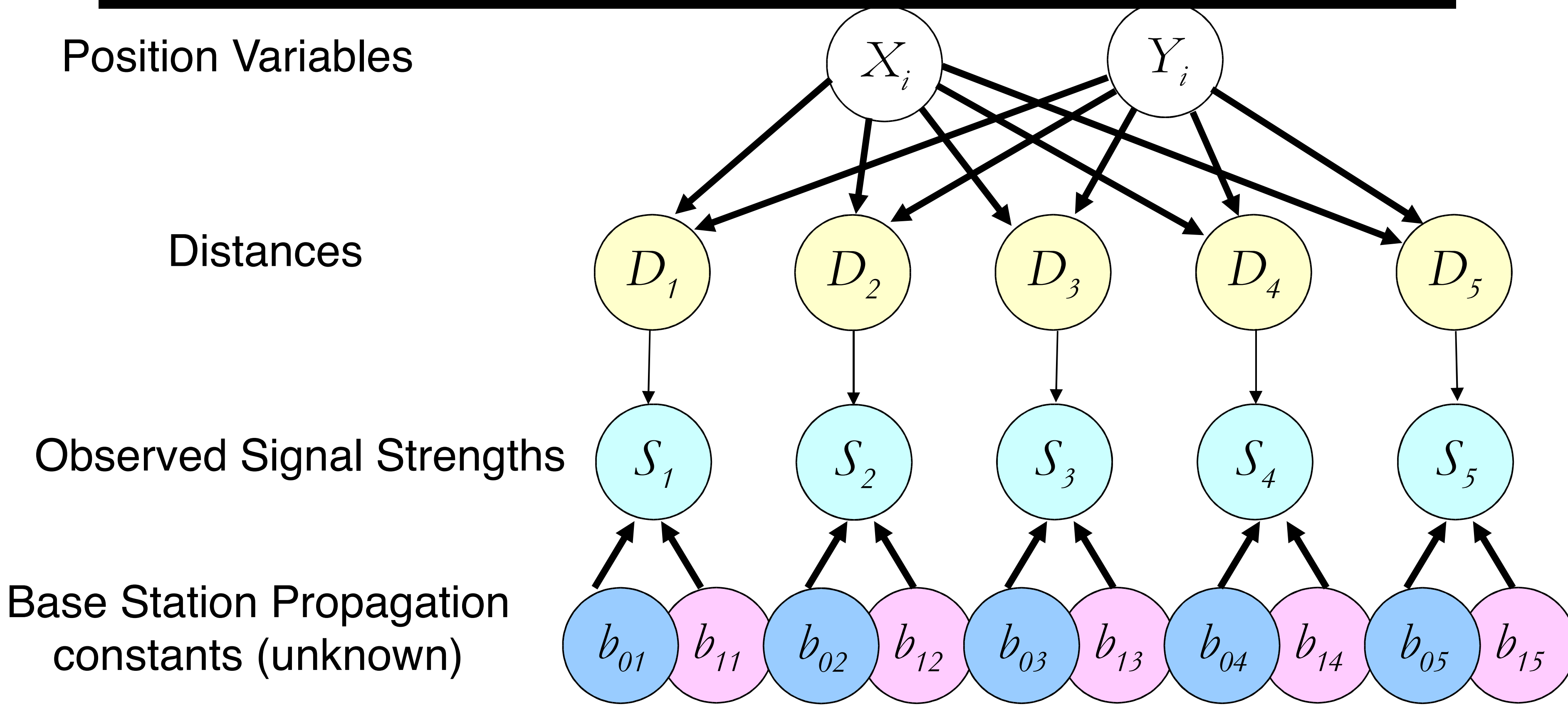
Log-based signal strength propagation

$$S \; b_1 \; b_2 \log D$$

$$D \sqrt{(x \; x_b)^2 \; (y \; y_b)^2}$$



Model 1 (Simple): labeled data



Xi ~ uniform(0, Length) **Yi ~ uniform(0, Width)**

i=1,2,3,4,5 : Si ~ $\mathbf{\mathit{N}(b_{0i}+b_{1i}log(Di),\delta_i)}$**,**

b0i ~ $\mathbf{\mathit{N}(0,1000)}$**, b1i ~** $\mathbf{\mathit{N}(0,1000)}$

Input	Output

Labeled: training

[(x1,y1),(-40,-55,-90,..)]

[(x2,y2),(-60,-56,-80,..)]

[(x3,y3),(-80,-70,-30,..)]

[(x4,y4),(-64,-33,-70,..)]

Unlabeled: mobile object(s)

[(?,?),(-45,-65,-40,..)]

[(?,?),(-35,-45,-78,..)]

[(?,?),(-75,-55,-65,..)]

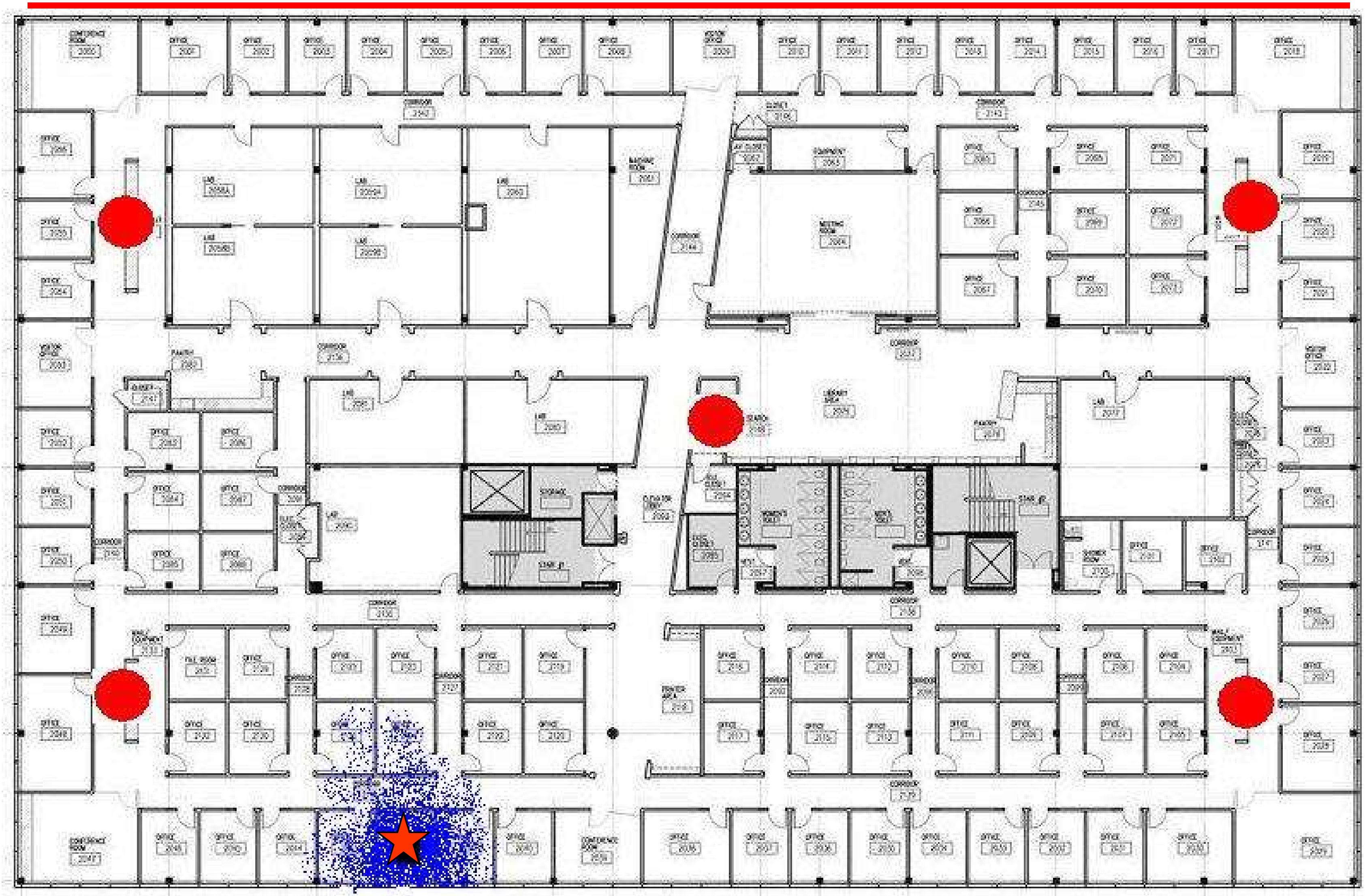
- Probability distributions for all the unknown variables
- Propagation constants
  - b0i, b1i for each Base Station
- **(x,y) for each mobile (?,?)**

Solving for the Variables

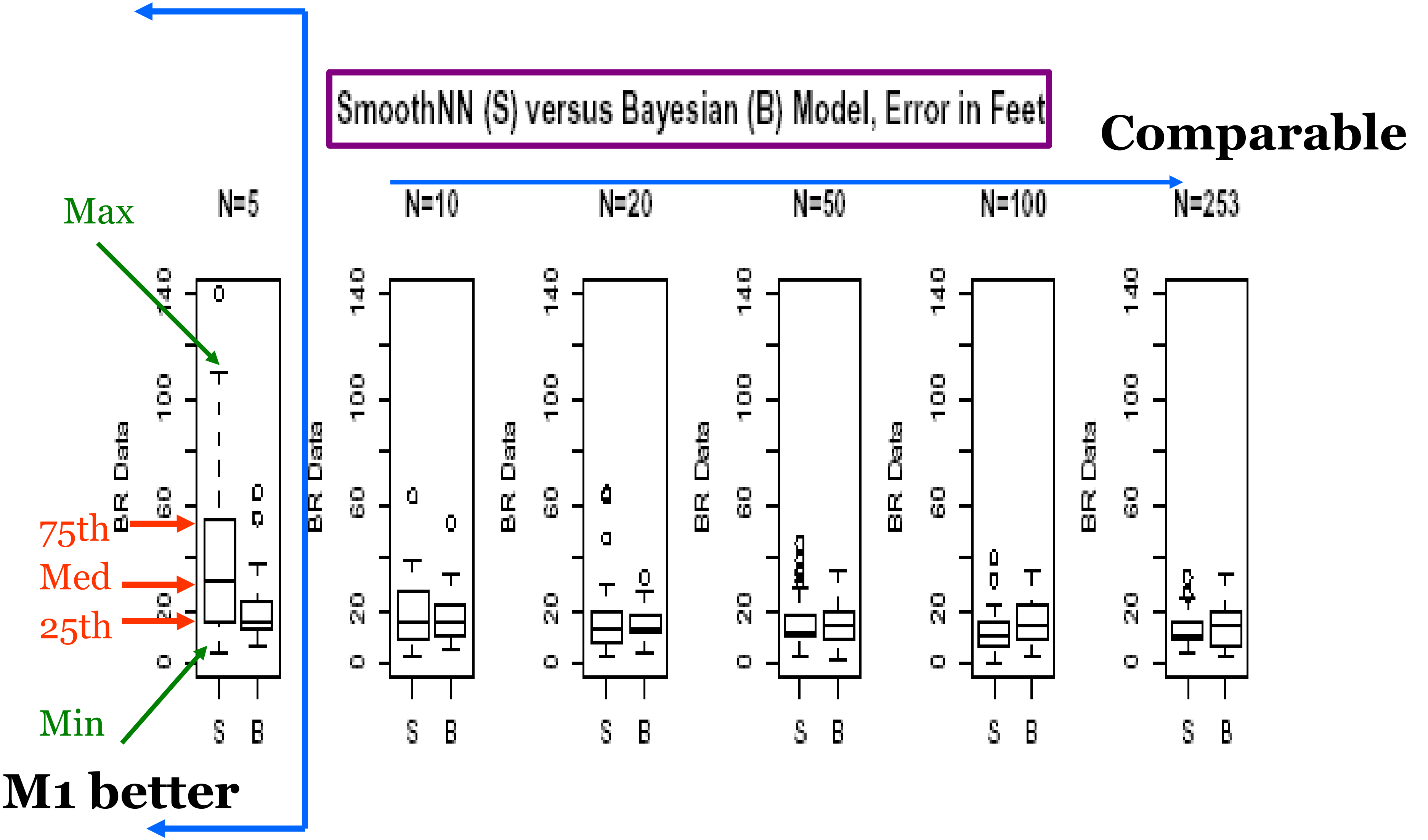
- Closed form solution doesn't usually exist
  - » simulation/analytic approx

- We used **<u>MCMC simulation</u>** (Markov Chain Monte Carlo) to generate predictive samples from the joint distribution for every unknown (X,Y) location

Example Output



Performance results

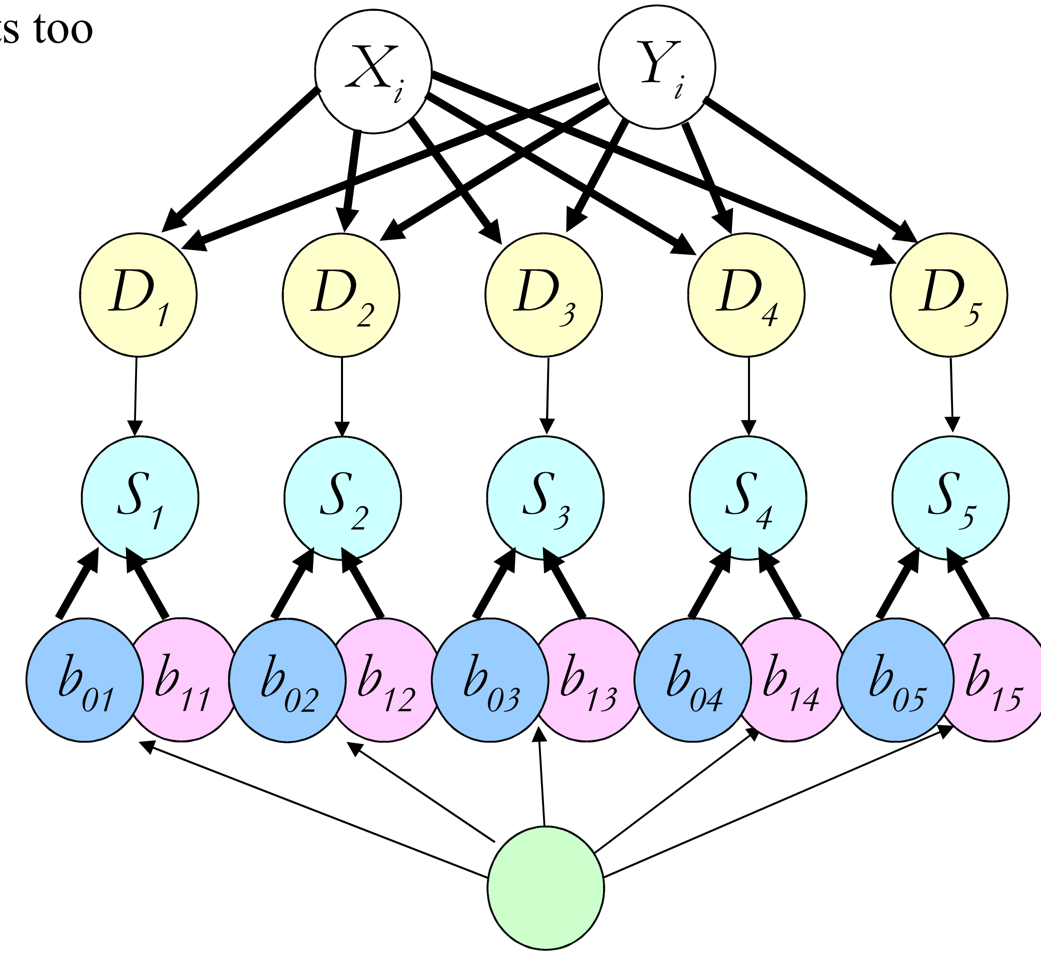


Model 2 (Hierarchical): labeled data

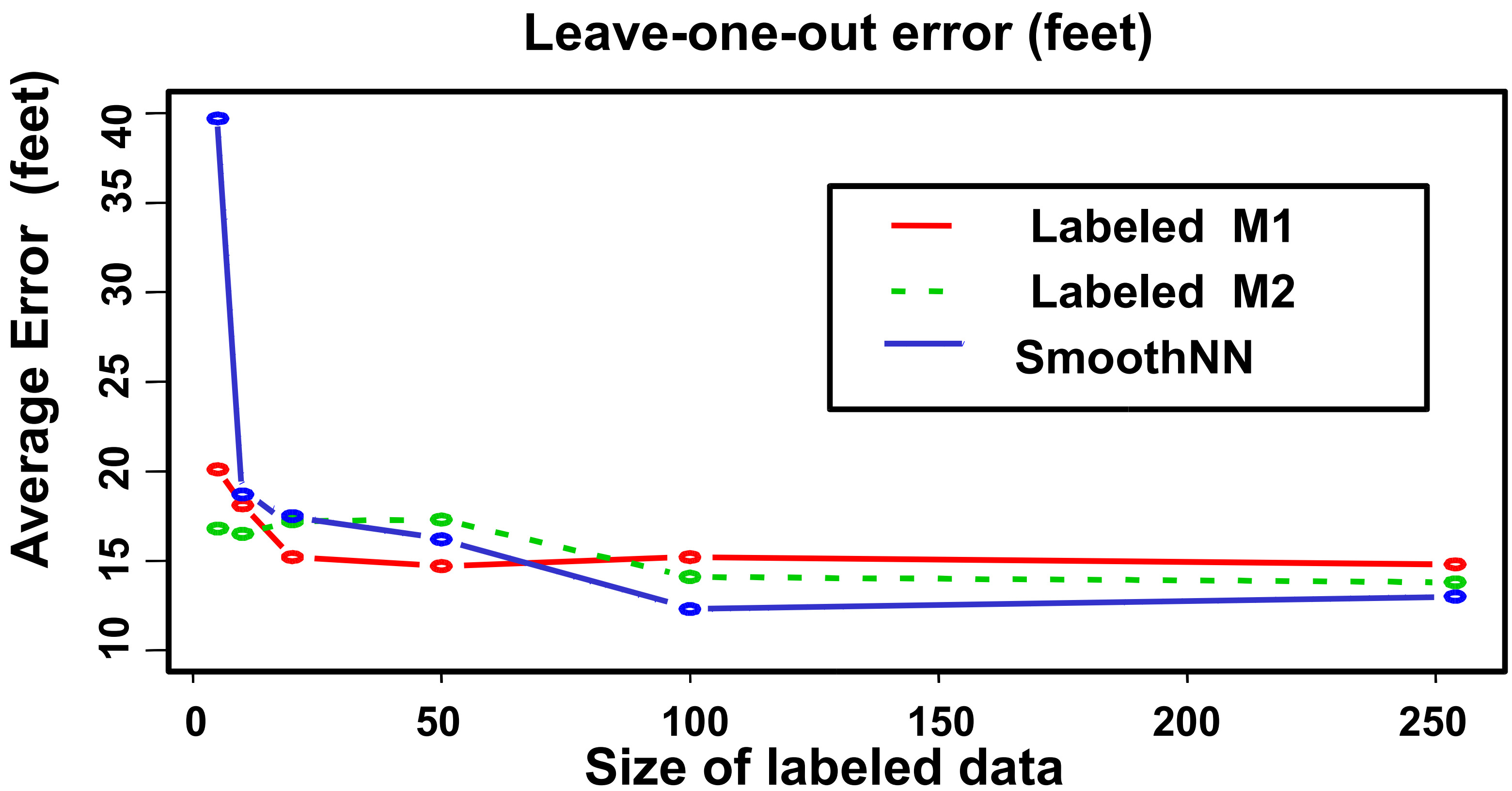
Allowing any signal propagation constants too constrained!

<u>Assume all base-stations parameters normally distributed around a hidden variable with a mean and variance</u>

- Intuition:
  - Same hardware should generate same signal propagation constants
  - Systematic bias in different environments (e.g. a closet)



M1, M2, SmoothNN Comparison



M2 similar to M1, but better with very small training sets

<u>Both comparable to SmoothNN</u>

No Labels

- Challenge: Position estimates without labeled data
- Observe signal strengths from existing data packets (unlabeled by default)
- **<u>No more running around collecting data..</u>**
- **<u>Over and over.. and over..</u>**

Input

~~**Labeled: training**~~

~~[(x1,y1),(-40,-55,-90,..)]~~

~~[(x2,y2),(-60,-56,-80,..)]~~

~~[(x3,y3),(-80,-70,-30,..)]~~

~~[(x4,y4),(-64,-33,-70,..)]~~

Unlabeled: mobile object(s)

[(?,?),(-45,-65,-40,..)]

[(?,?),(-35,-45,-78,..)]

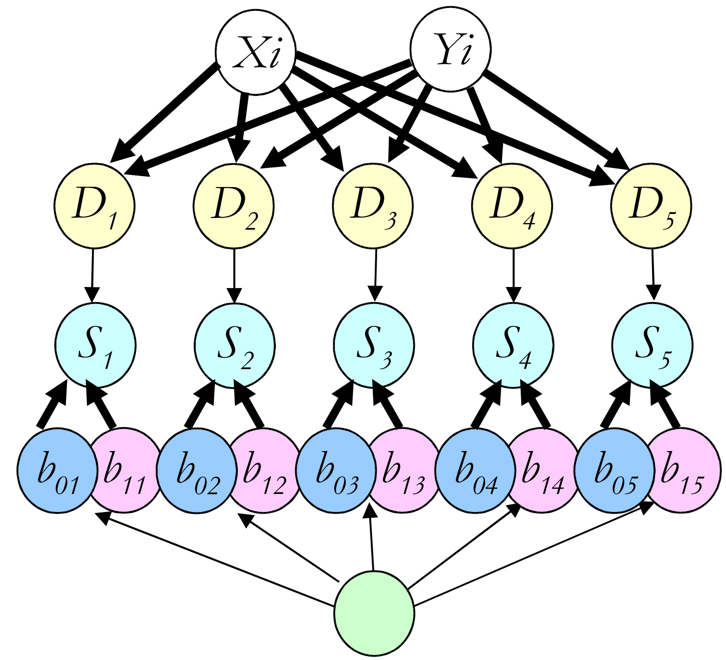
[(?,?),(-75,-55,-65,..)]

Output

- <u>Probability distributions for all the unknowns</u>
- Propagation constants
  - b0i, b1i for each Base Station
- **(x,y) for each (?,?)**

Model 3 (Zero Profiling)

- Same graph as M2 (Hierarchical) but with **<u>(unlabeled data)</u>**

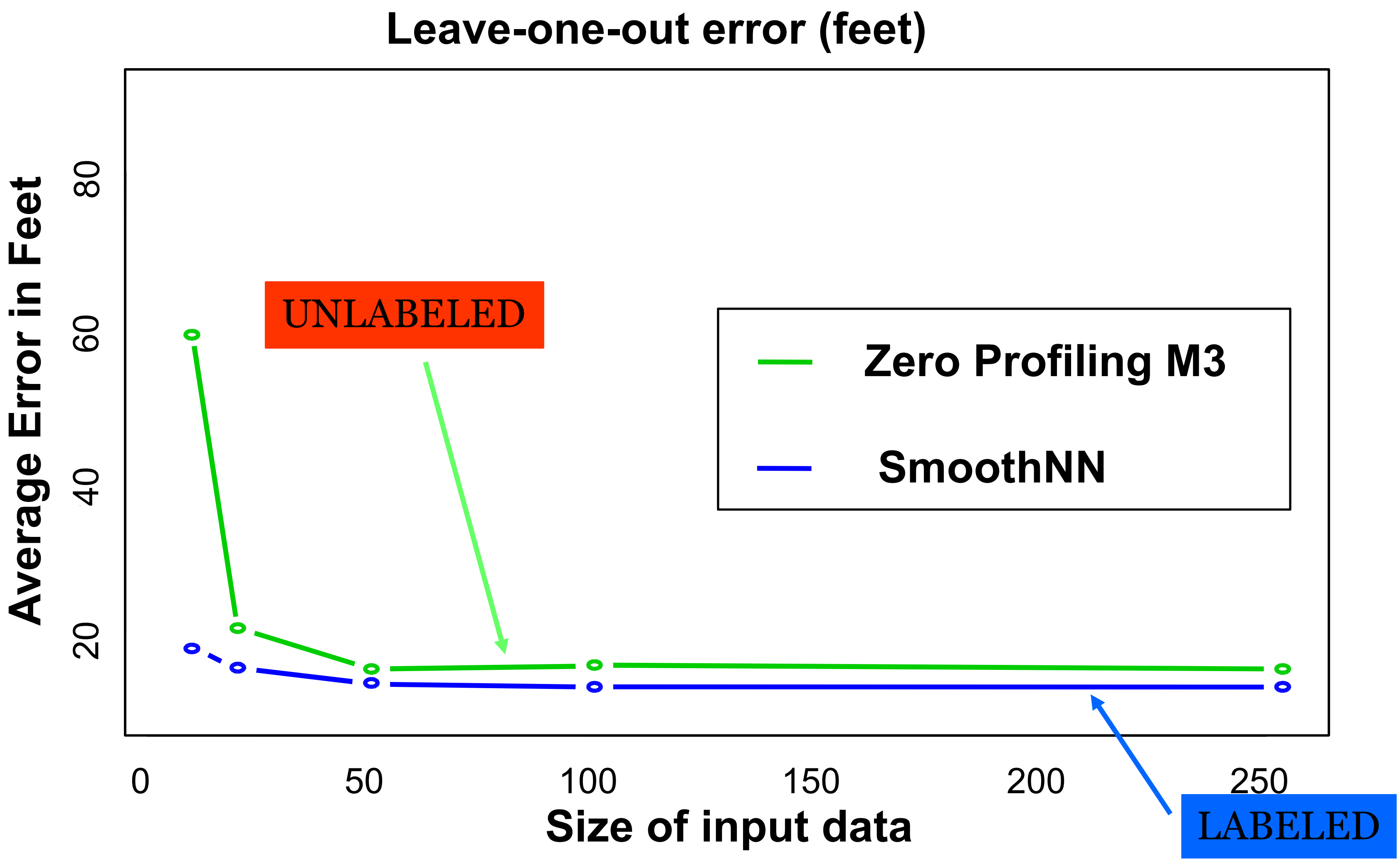


Why this works:

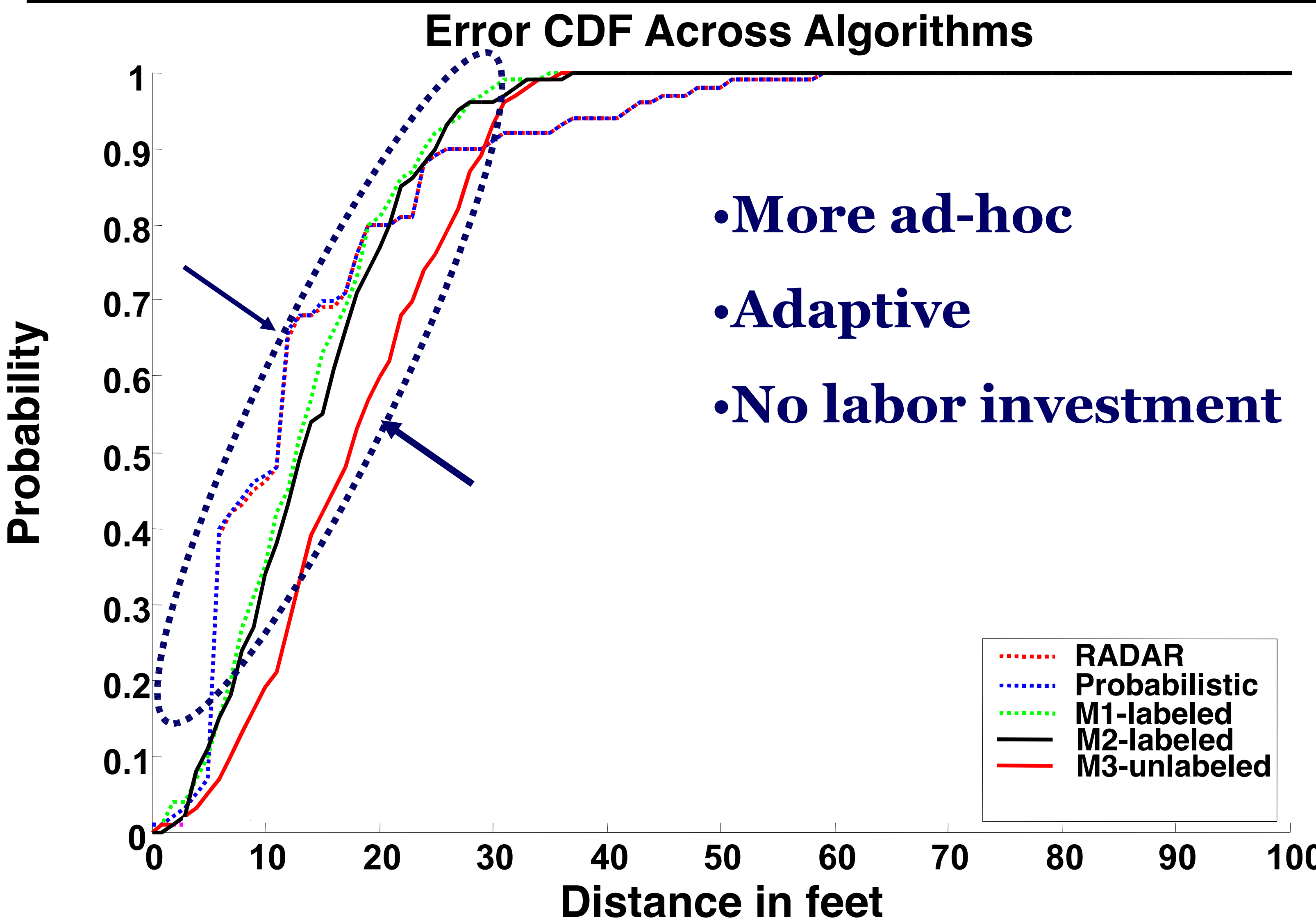
[1] Prior knowledge about distance-signal strength

[2] Prior knowledge that access points behave similarly

Results Close to SmoothNN



Comparison to previous work



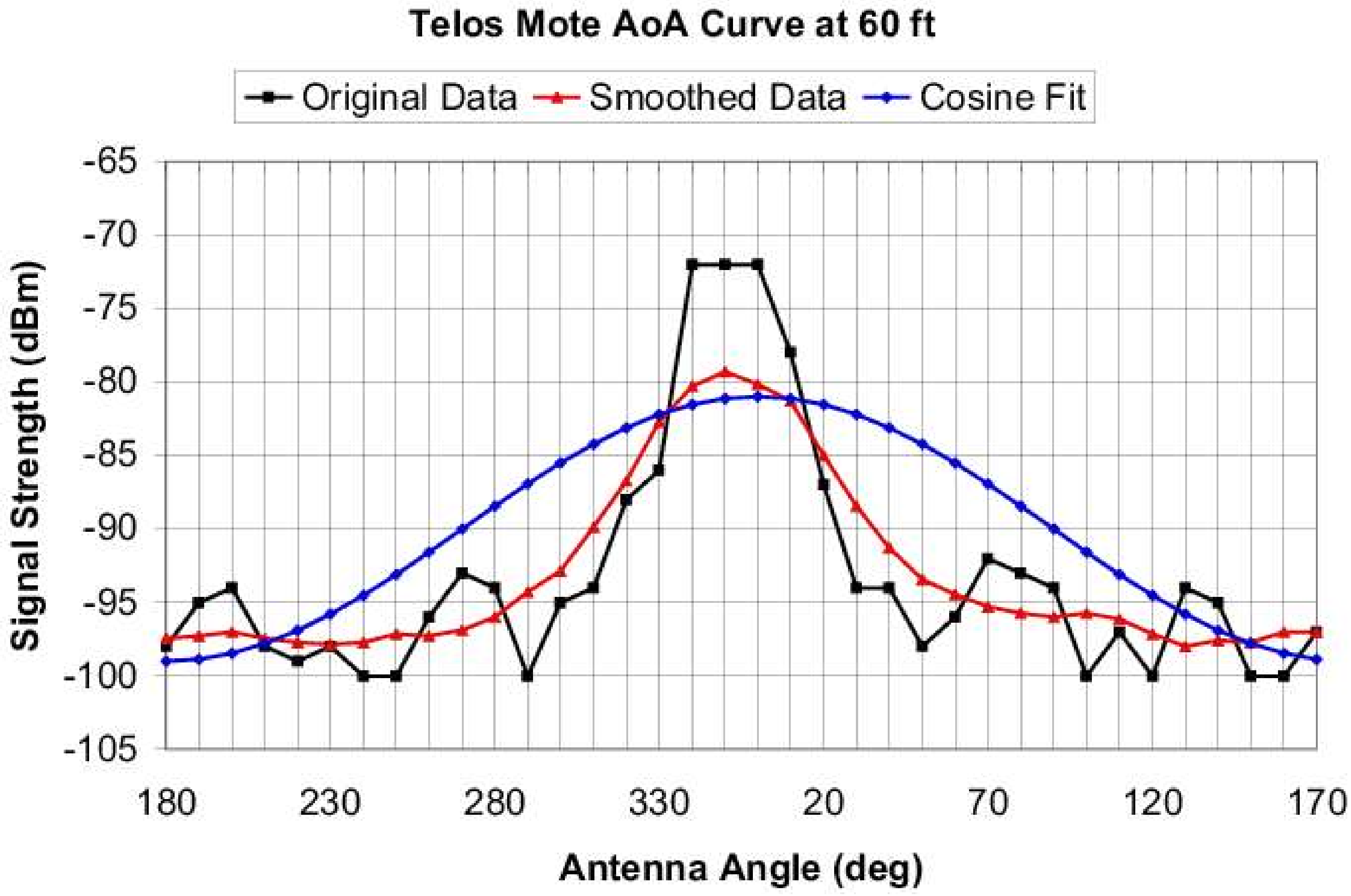
- More ad-hoc
- Adaptive
- No labor investment

Outline

- Motivations and Goals
- Experimental setup
- Bayesian background
- Distance-based Bayesian Models:
  - M1, M2, M3
  - Comparison to previous RSS work
- Angle & Distance model: A1
- Conclusions and Future Work

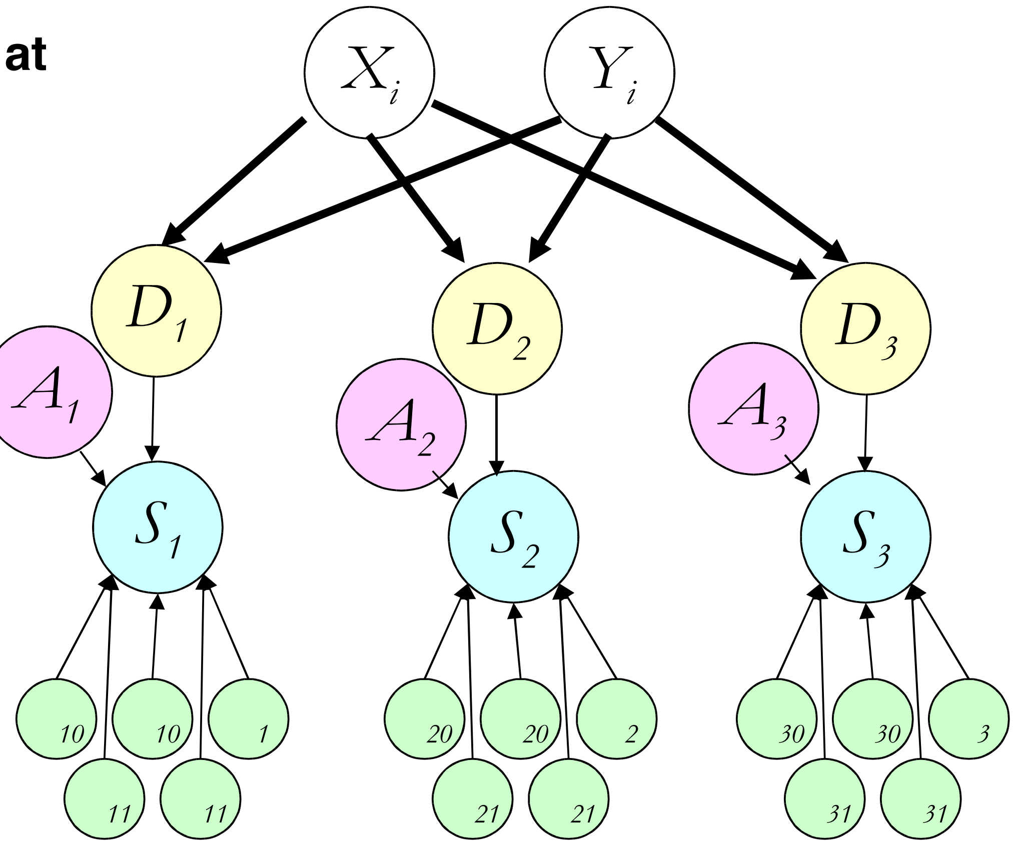
Augmenting the Base Station

Outdoor AoA Curve



Angle of Arrival Model (A1)

- **Use a directional Antenna at the Base station**



A_i is the angle of the directional Antenna i

Si is the signal strength given the distance and angle

Text representation of S_i

j = angle quantization
(e.g. every 10 deg)

Scaling by Angle
(% of peak)

Scaling by Distance
(vertical width)

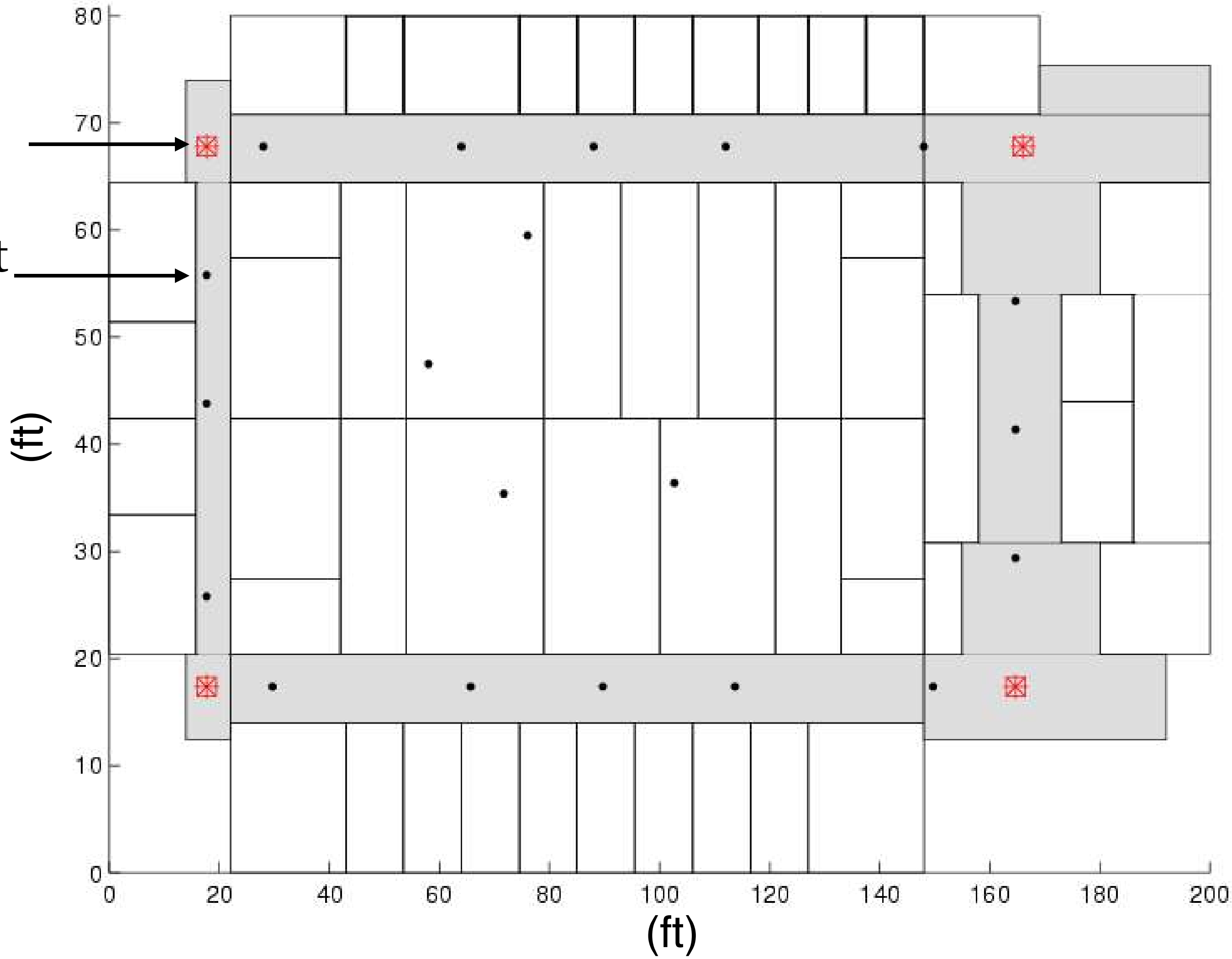
$$S_i[j] \sim N((\ _{i0}\ \ _{i1}\log D_i)(\cos(_3(a_i\ [j]\ ))(\ _{i2}\ \ _{i1} D_i),\ _i)$$

Log-Linear
Signal-to-Distance
(baseline)

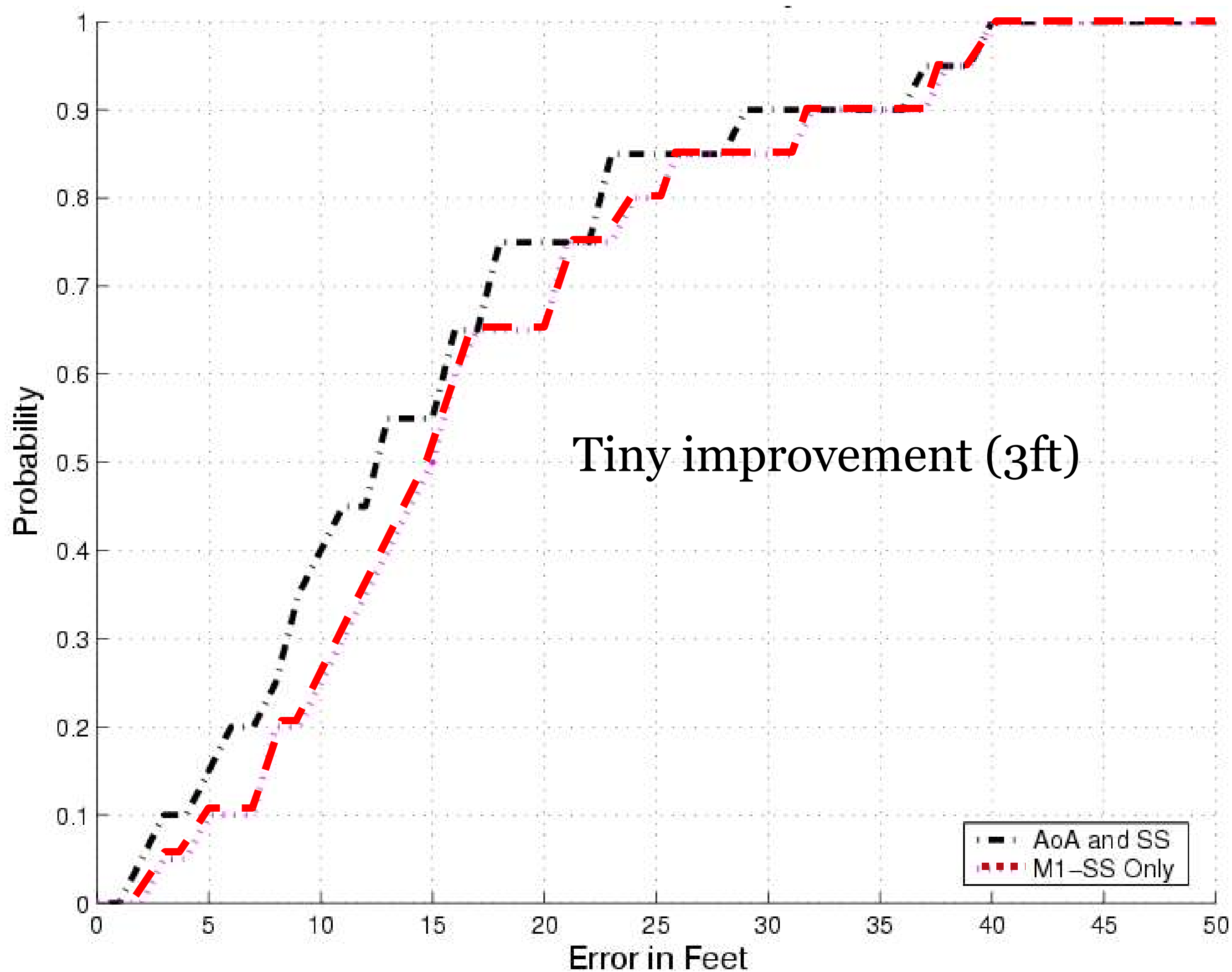
Experimental Set Up

Base station

Measurement point



A1 accuracy CDF compared to M1



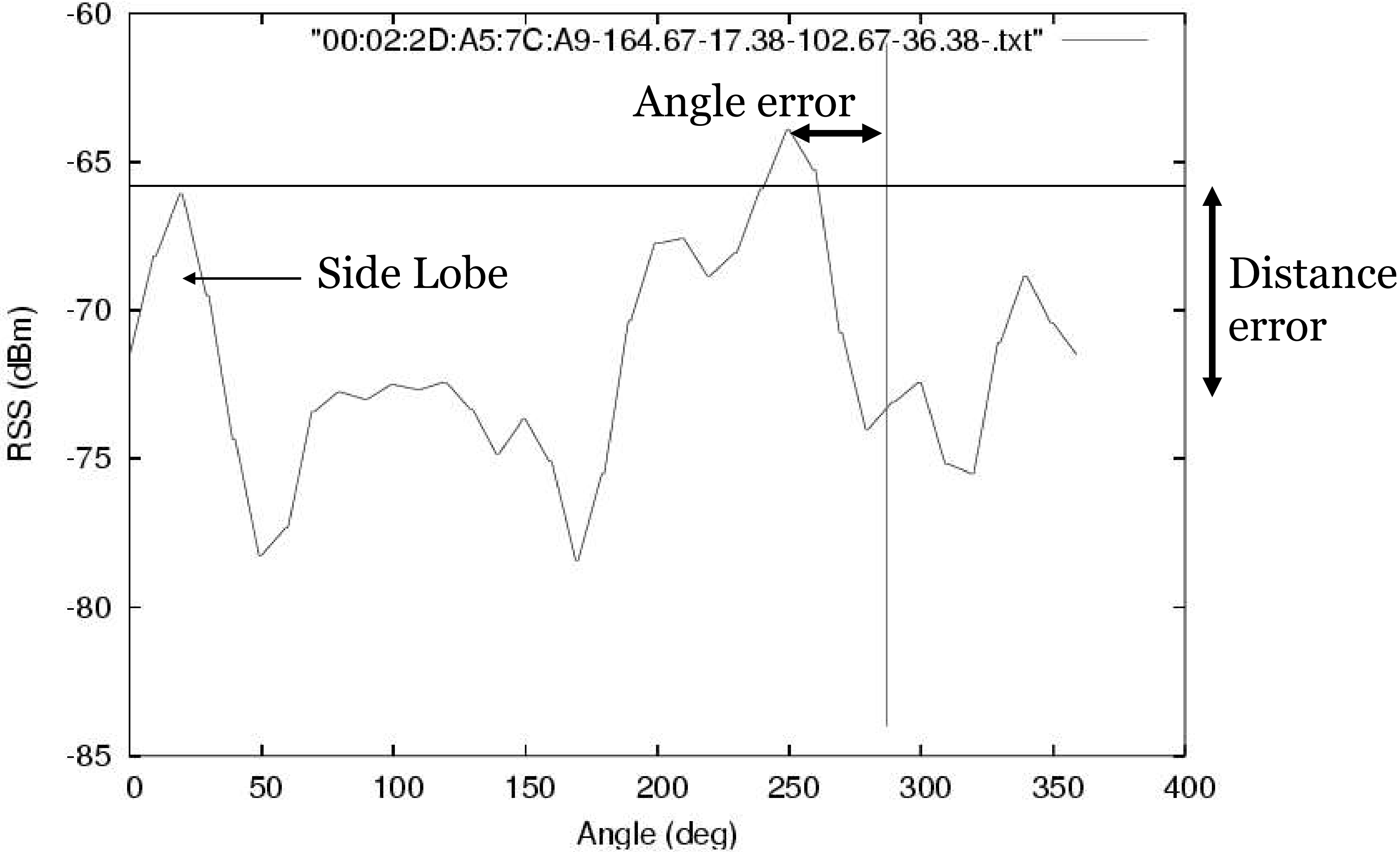
Finding the discrepancy

- Additional angle information provided tiny benefit to localization!
- Origins of performance?
- Strategy:
  - Characterize errors
  - Forward method:
    - Add errors to synthetic data
  - Backward method:
    - Subtract errors from measured curves
  - Observe accuracy as function of errors

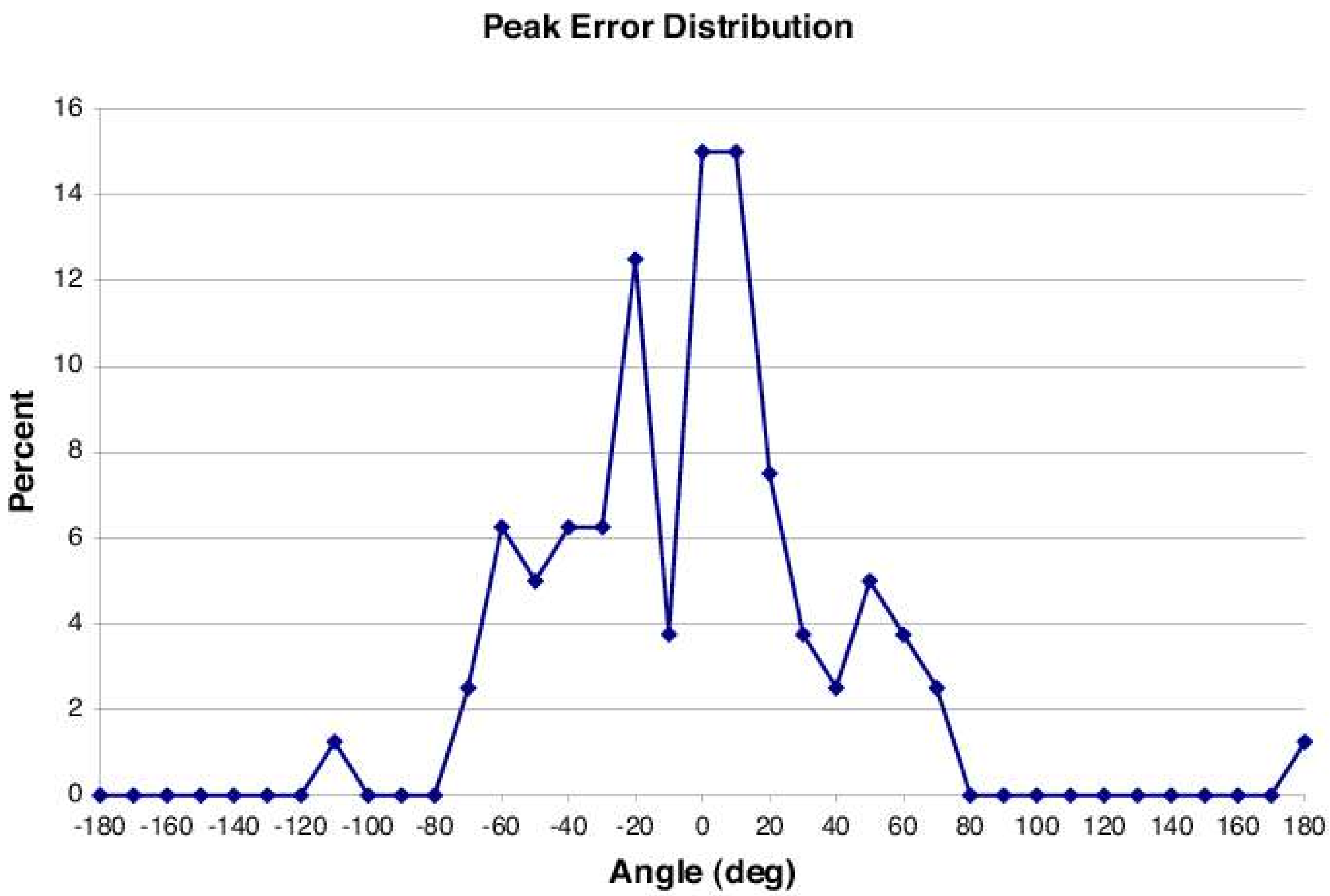
Types of Errors in AoA curve

- Angle error
  - Distance of AoA peak from the true angle
- Distance Error
  - Difference in predicted RSS-to-distance of curve average
- Lobe error
  - Percentage height of side lobe to the peak lobe

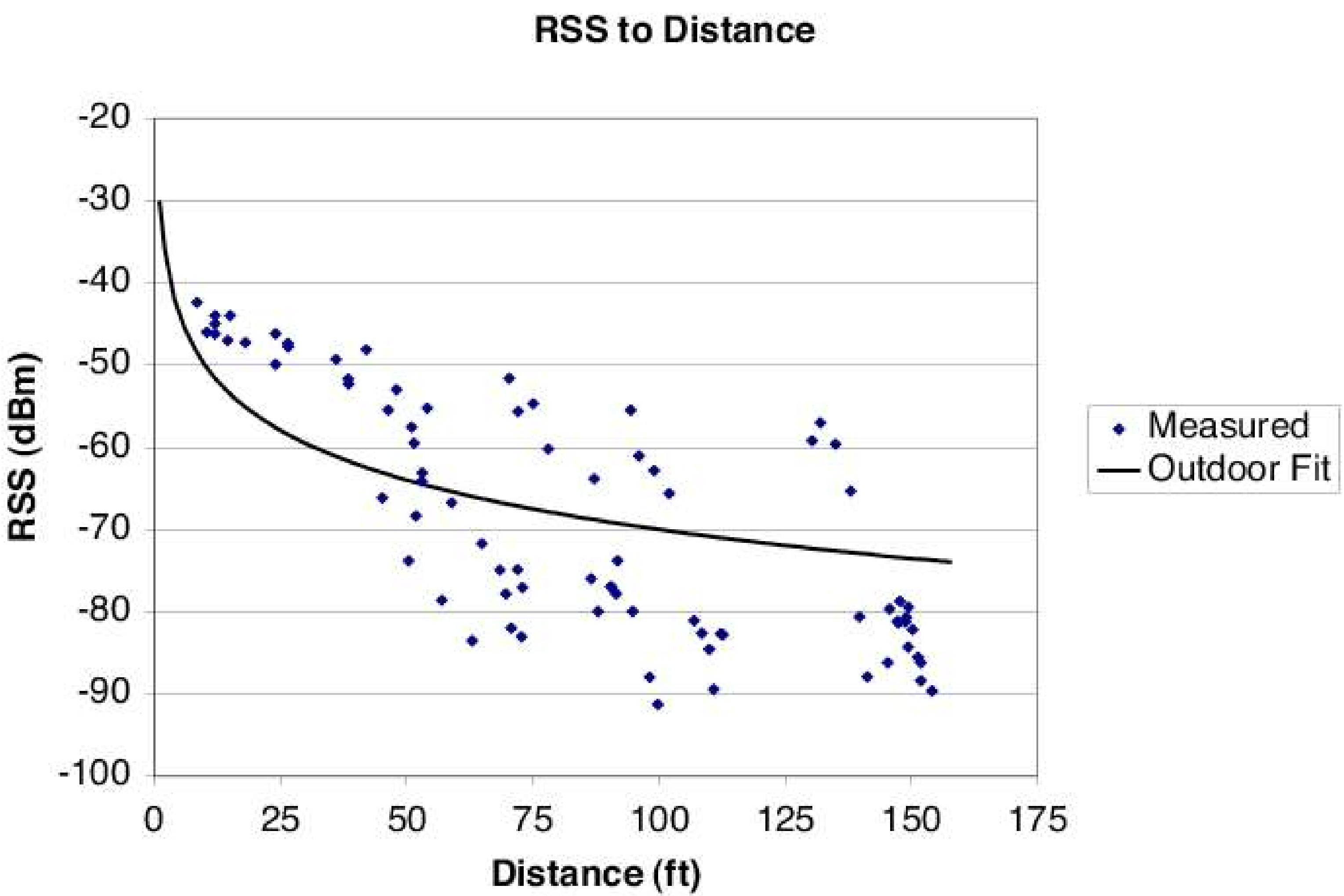
Example Errors



Angle Error Histogram



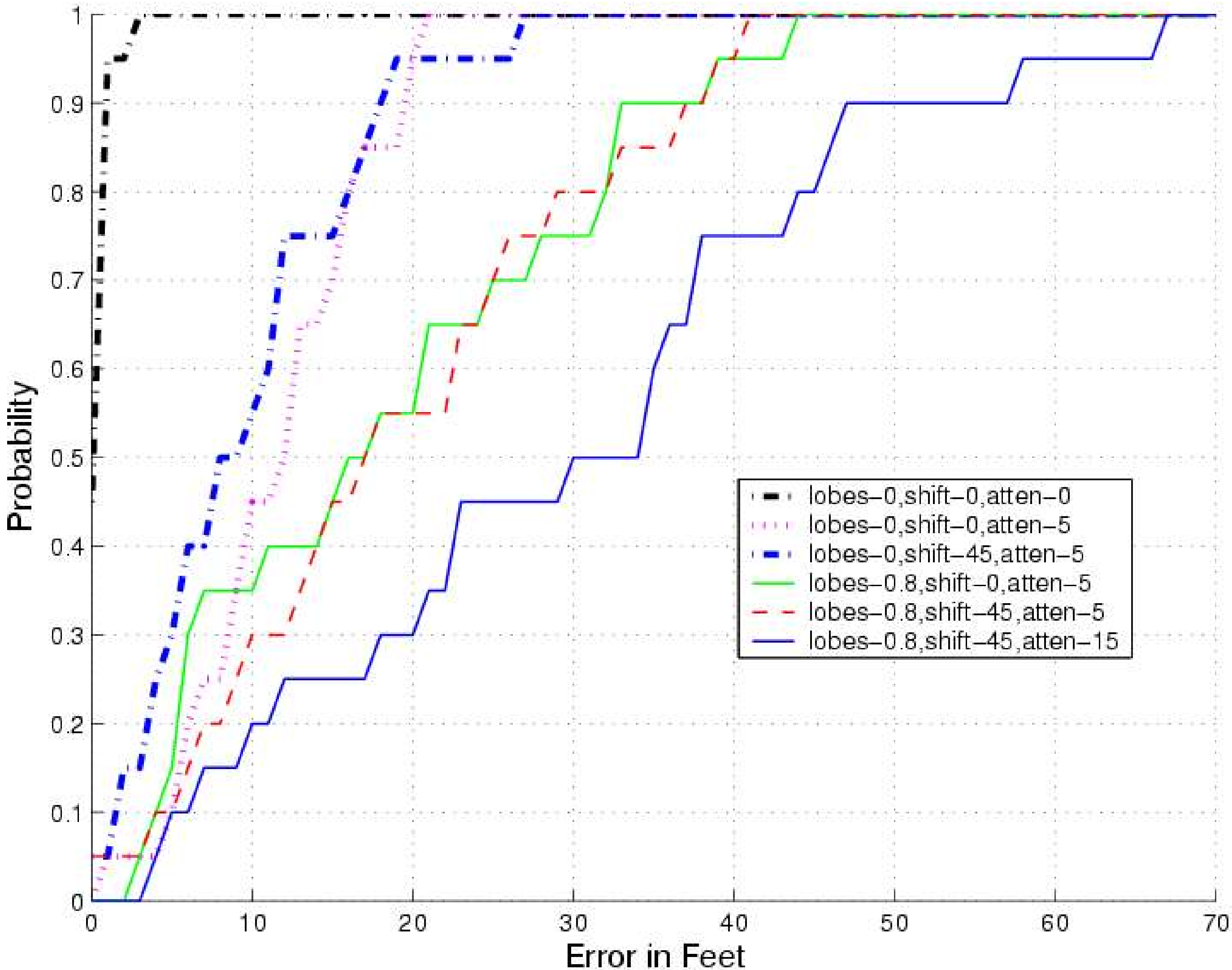
Distance Error Histogram



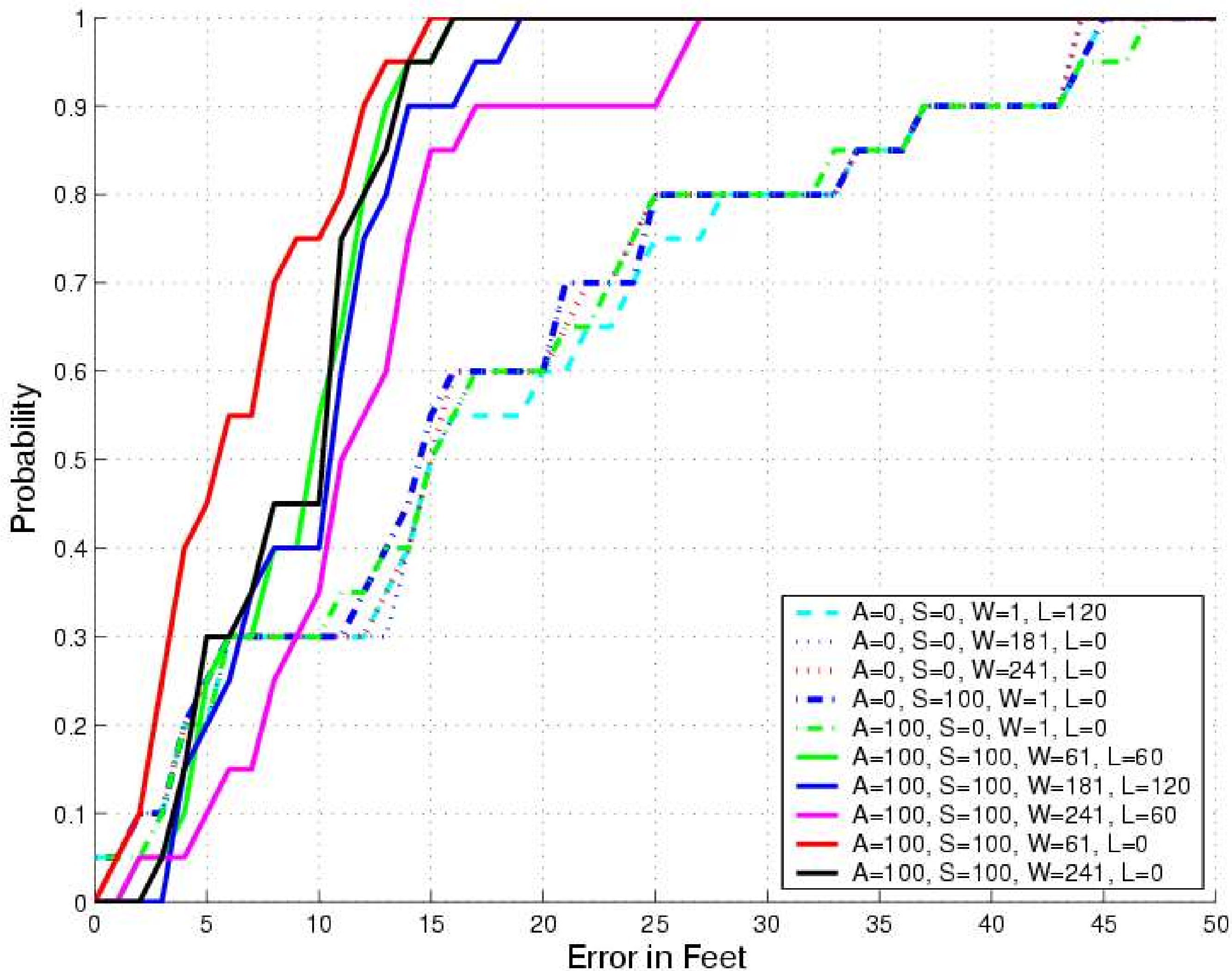
Sensitivity to Errors

- Synthetic: Perturb cosine curves
  - Add random shift in angle
  - Add random shift up/down to whole curve
  - Add 2 side lobes of % peak at random points
- Corrected: Subtract errors from measured curves
  - Shift as a % of there error toward the true angle
  - Correct whole height as a % toward true average
  - Smooth curve by averaging each point over a window (in degrees)

A1 accuracy on synthetic set



A1 accuracy on corrected set



A1: Summary

- Too sensitive to distance errors
  - Distance error dominate angle errors
- Future work:
  - Weight distance vs. angle?
  - Throw away distance information?
  - Sensitivity to base station placement?
    - Need a center base station?

Conclusions and Open Issues

- **First to use BGM**
- Considerable promise for localization
- Performance comparable to existing approaches
- Zero profiling!
  - Can we localize anything with a radio? How well?
- Can we scale the infrastructure?
  - Directional Antennas
  - High frequency clock
  - Cross traffic

Future Work using Bayesian Models

- Discount RSS to distance information in A1
- Indoor 802.15.4
- Variational approximations
  - No more sampling to solve variables
- Tracking
- Additional infrastructure
  - Time of Arrival (high frequency clocks)

References

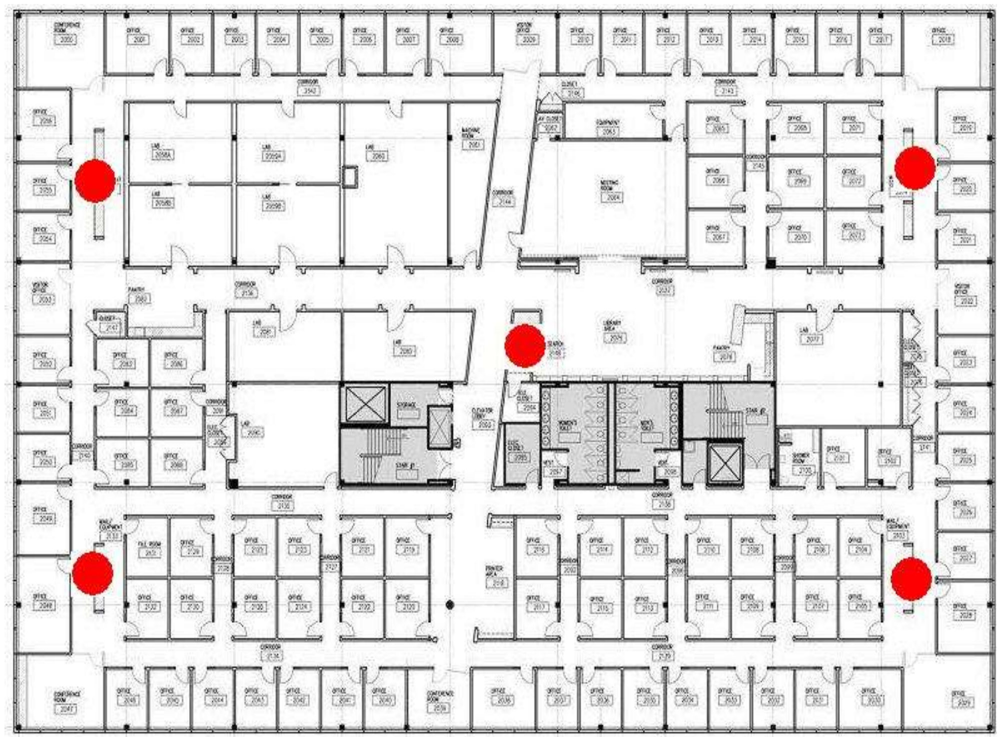
- D. Madigan , E. Elnahrawy ,R. P. Martin ,W. H. Ju ,P. Krishnan ,A. S. Krishnakumar, Bayesian Indoor Positioning Systems ,In Proceedings of the 24th joint conference of the IEEE Computer and Communication Societies (INFOCOM 2005), March 2004

- E. Elnahrawy ,X. Li ,R. P. Martin, Using Area-based Presentations and Metrics for Localization Systems in Wireless LANs ,4th IEEE Workshop on Wireless Local Networks, November 2004.

- E. Elnahrawy ,X. Li ,R. P. Martin, The Limits of Localization Using Signal Strength: A Comparative Study In Proceedings of the IEEE Conference on Sensor and Ad Hoc Communication Networks (SECON), October, 2004.

Experimental Setup

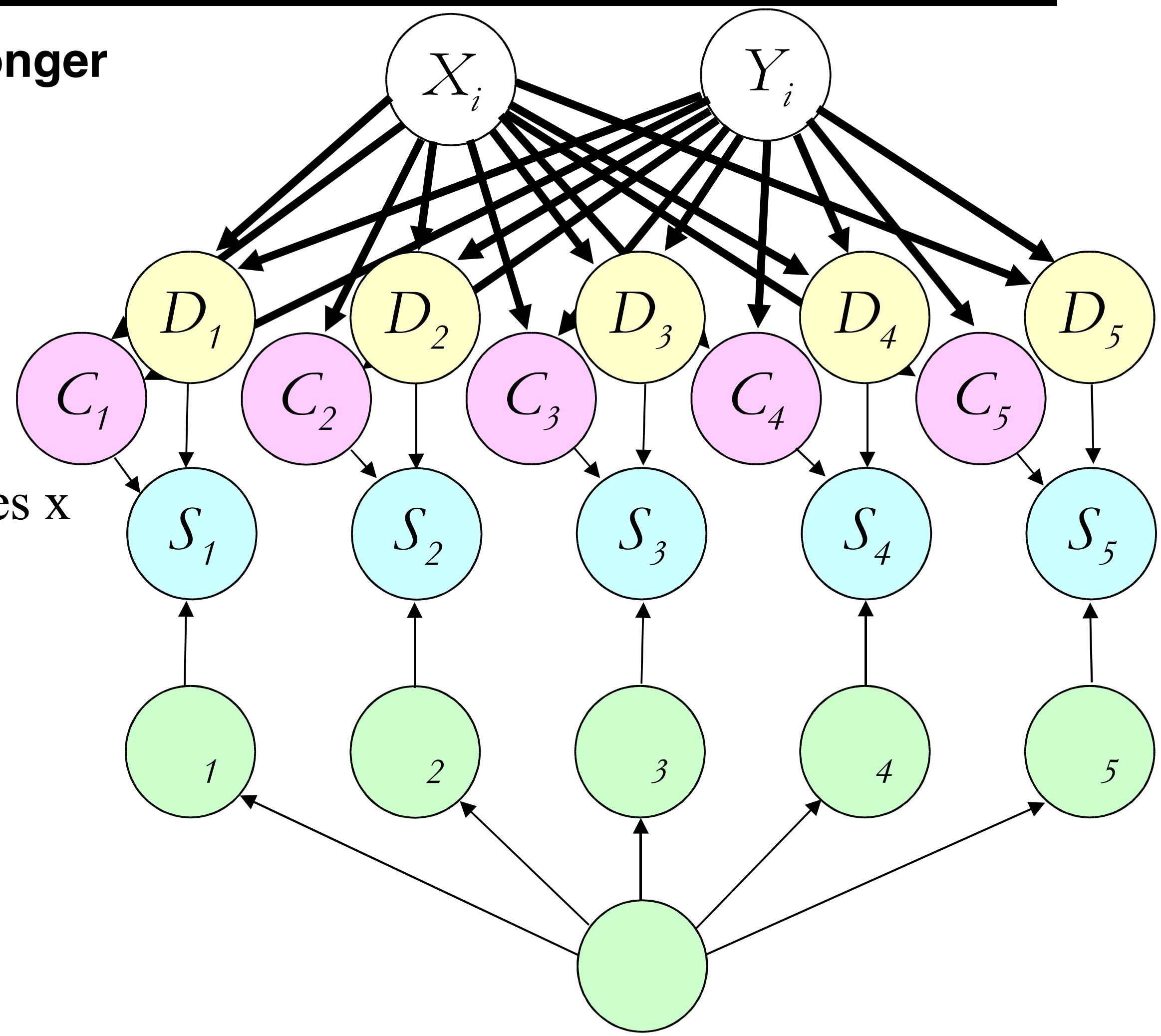
- 3 Office buildings
  - BR, CA Up, CA Down
- 802.11b
- Different sessions, days
- All give similar performance
- Use BR as example



BR: 5 access points, 225 ft x 175 ft, 254 measurements

Corridor Effects

- **Observation: RSS is stronger along corridors**
- **Add this to the M2**



Variable c =1 if the point shares x or y with the AP

No improvements

Informative Prior distributions