

Lecture 05

SmartPhone Sensing

Birds-eye view

App option 1: localization

Basic
Activity Monitoring
& Localization

k-NN



Report 1

Advanced
Localization

problem: shadowing and fading

Bayesian
filters

a-trimmer
filters



Log normal
shadowing

Particle
filters

Report 2

Other Apps

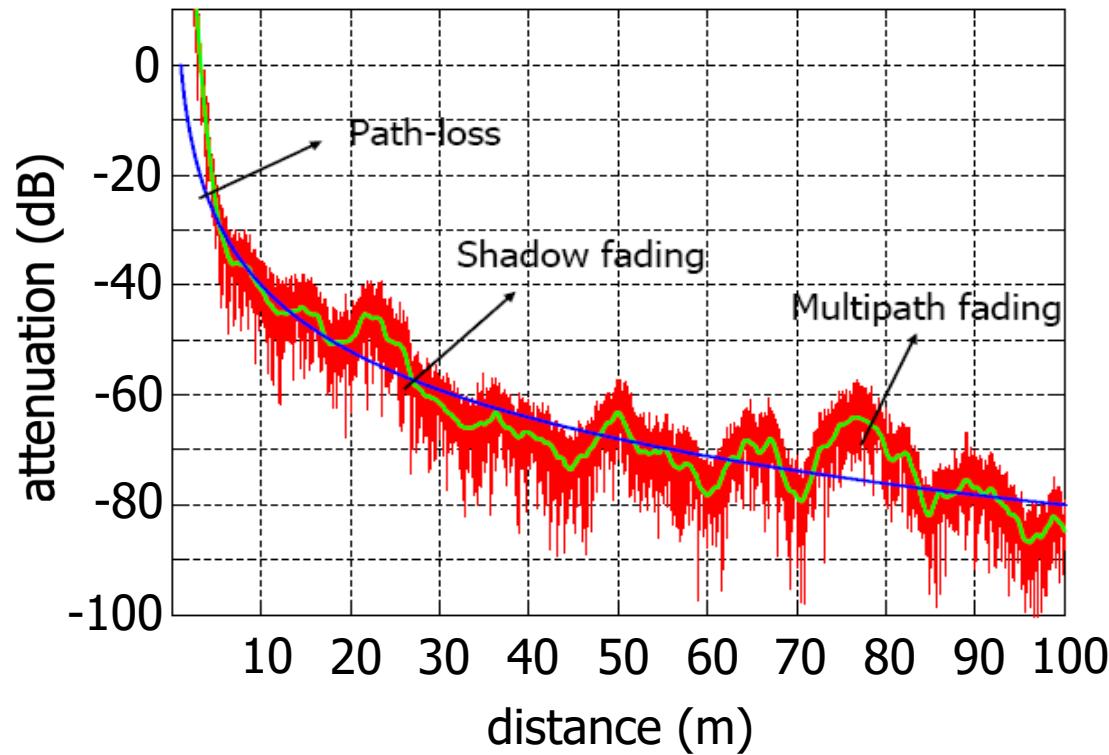
Shazam

may not
have time

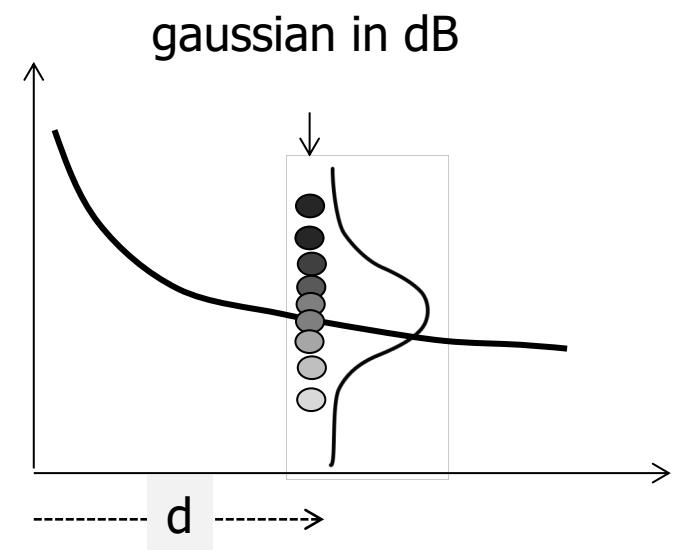
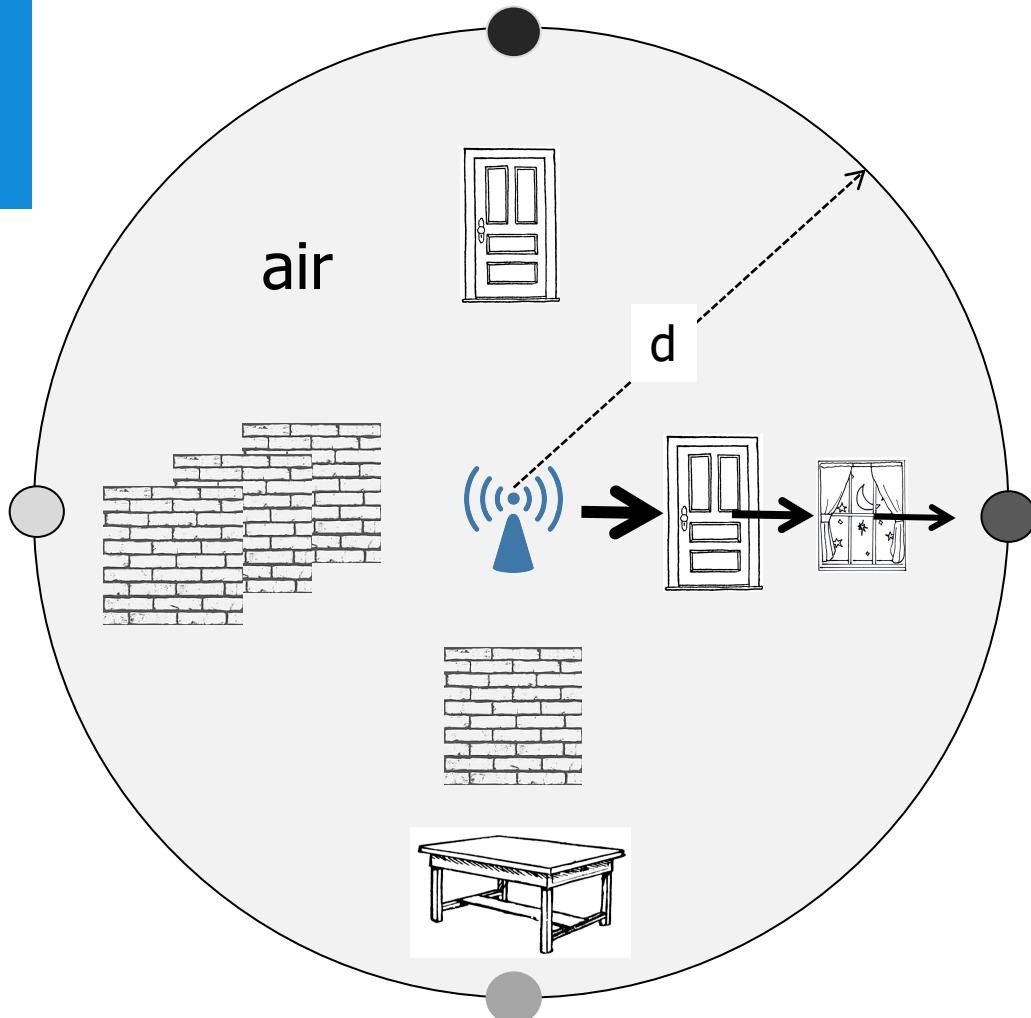


FADING

Shadow fading (green curve)

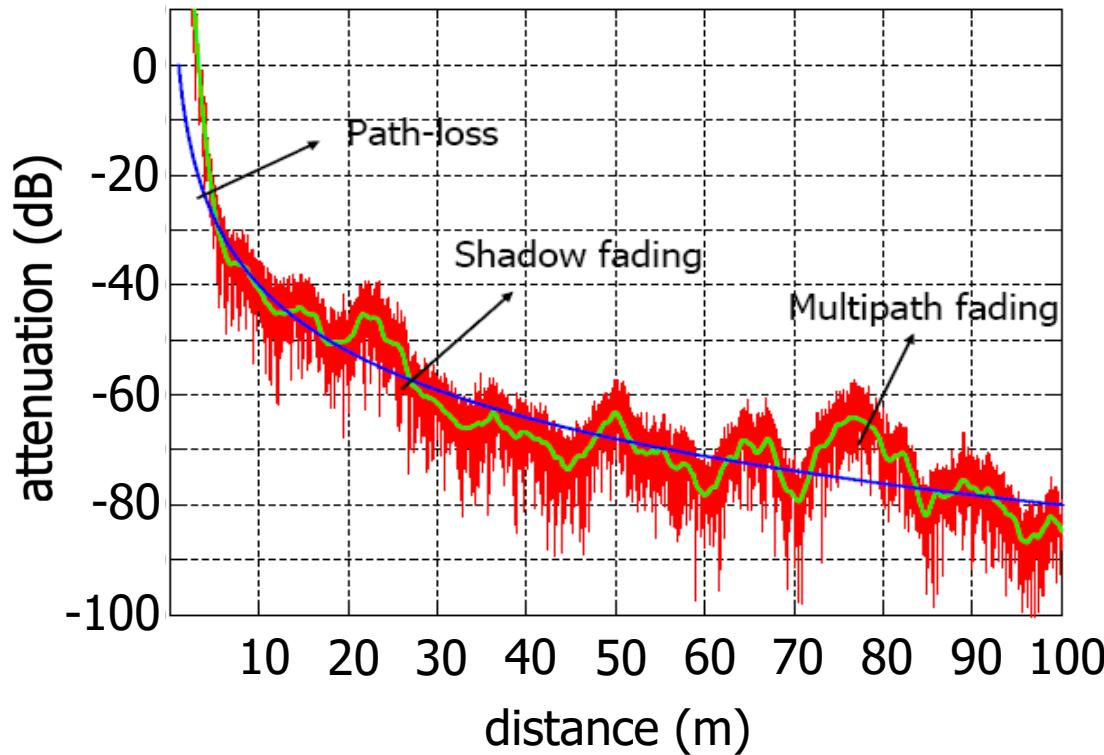


Large scale fading: absorption



why gaussian (normal)?

Log normal shadowing model



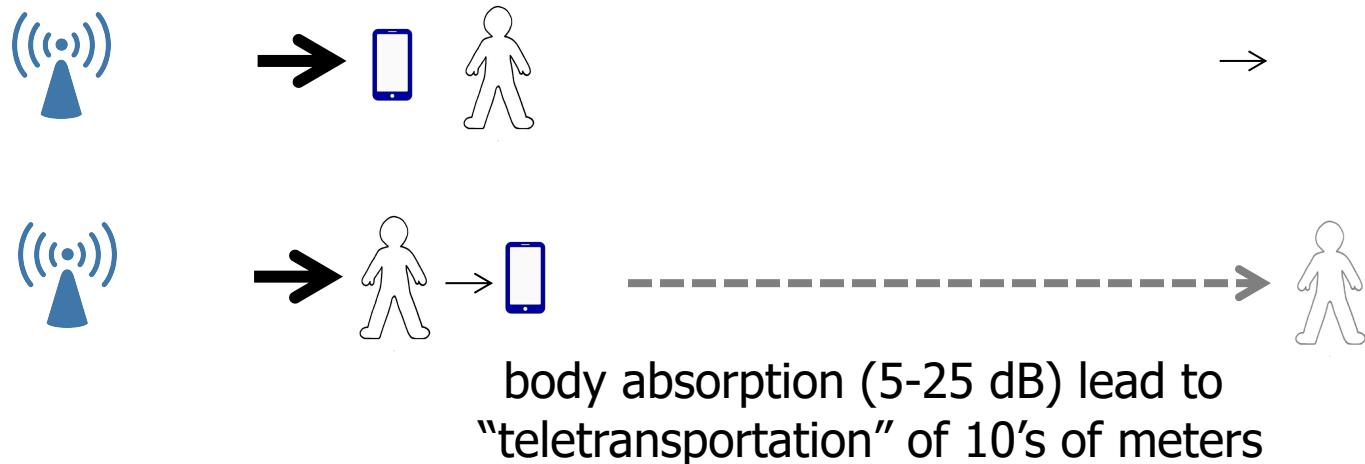
$$\begin{aligned} PL(dB) &= P_{Tx}(dBm) - P_{Rx}(dBm) \\ &= PL_0 + 10 \eta \log_{10}(d/d_0) + N(0, \sigma) \end{aligned}$$

this is an empirical model

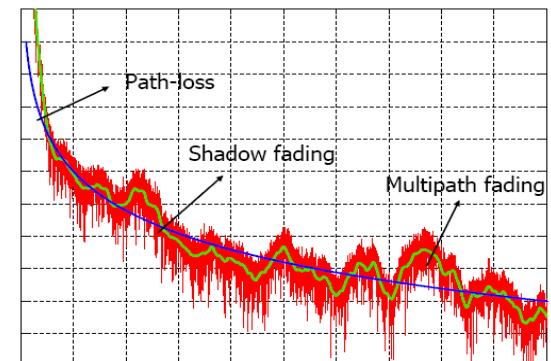
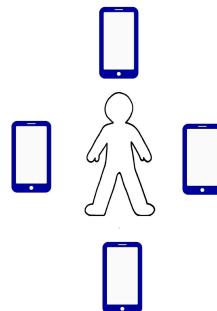
pros & cons of large scale fading

- You can't do much against large scale fading
 - tearing down a wall is not a daily option
- In a way, large scale fading is good
 - it helps in characterizing specific spaces,
 - localization in the aisle will be harder than in rooms.
- There is one absorption effect that causes problems, but that can be overcome to some extent
 - Body effects

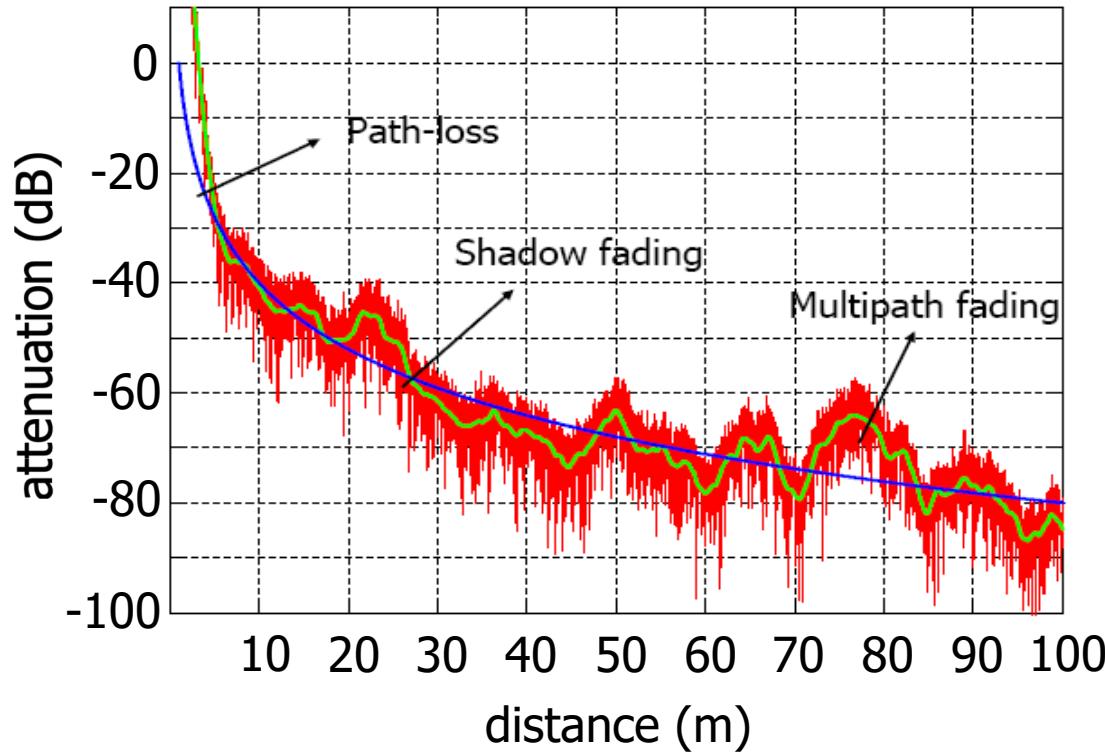
Teletransportation problem 1: Body effects



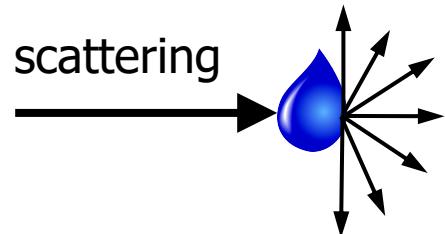
Solution (palliative): quadrant sampling



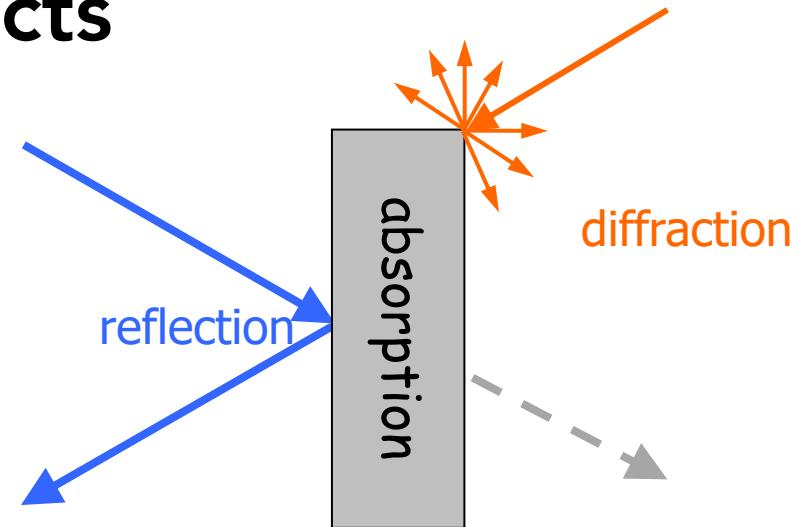
Multipath fading (red curve)



RF propagation effects

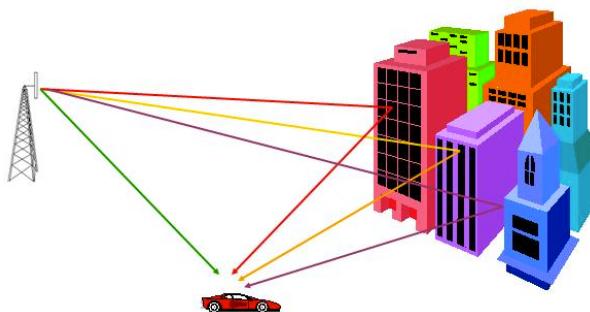


\sim size of wavelength



$>>$ size of wavelength

scattering, reflection and diffraction create multiple copies of the original signal



Wavelength and the size of objects



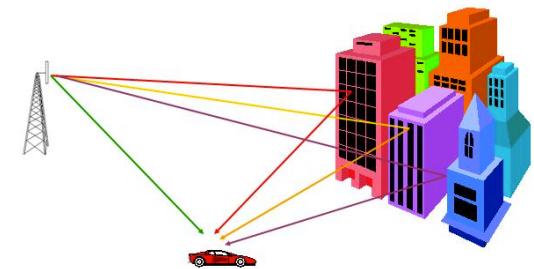
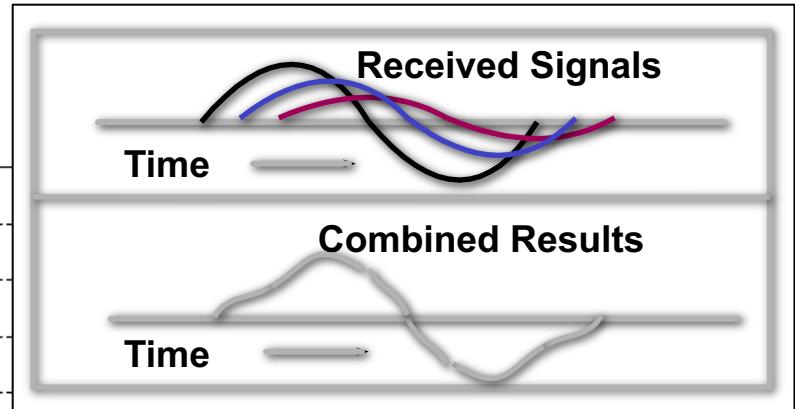
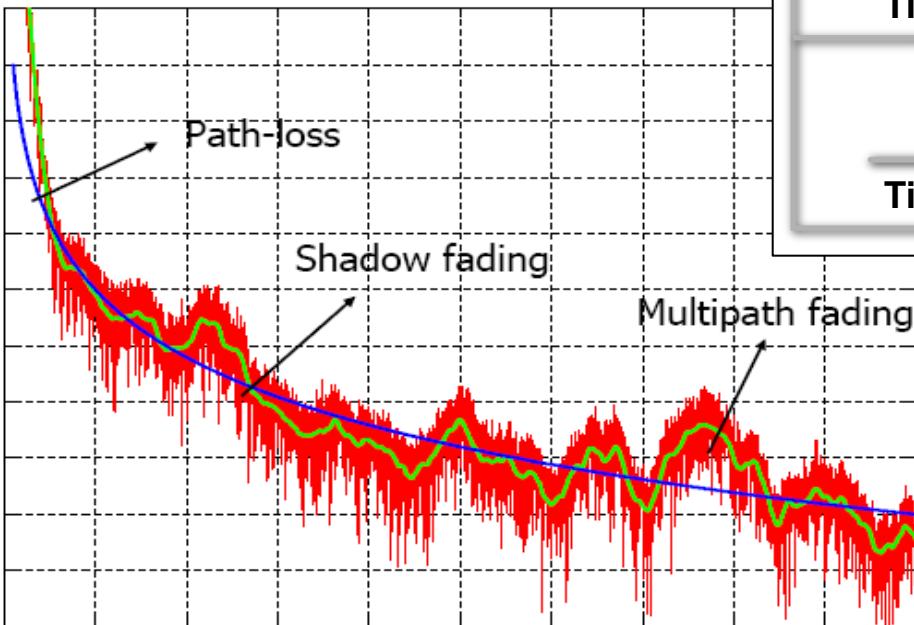
needle: negligible multipath effect



big rock: major multipath effect

The relationship between the size of object and the length of the wavelength is key

Multipath

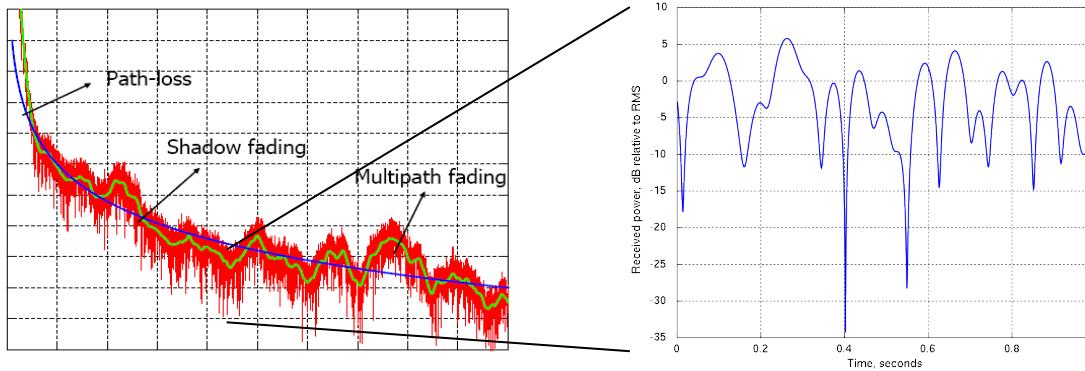


Propagation along multiple paths leads to self interference
Minor changes in environment can lead to dramatic changes in signal strength

Test small scale fading with your phone. Measure the rss signal at day & night

Teletransportation problem 2: small scale fading

- Measure “n” RSS samples



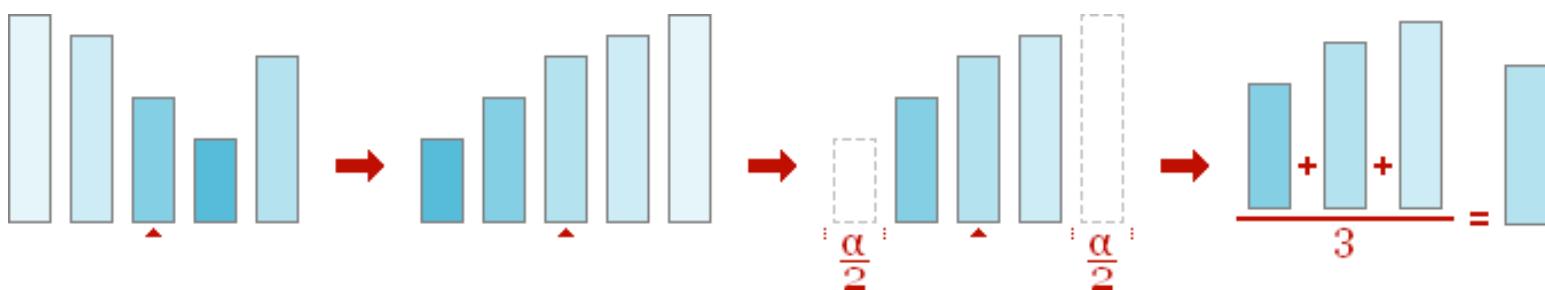
Rayleigh distribution
en.wikipedia.org/wiki/Rayleigh_fading

- How do we remove outliers?
- Will average-based filters work?
- [Read](#) (because you are sort of recreating this work):
“RADAR: an in-building RF-based user location and tracking system”, IEEE Infocom 2000

Alpha trimmer filters (1)

www.librow.com/articles/article-7

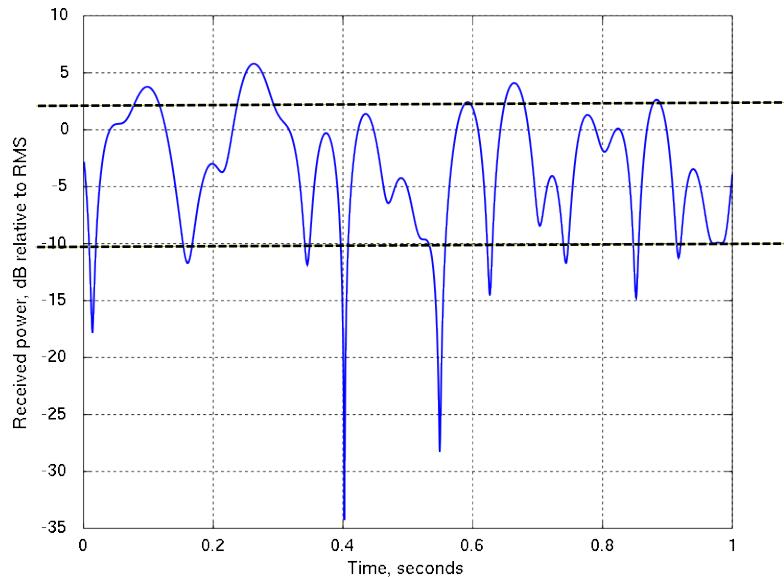
- Mean < alpha-trimmer < median
- Method:
 - Sort
 - Cut $\alpha/2$ at the head and tail
 - Average



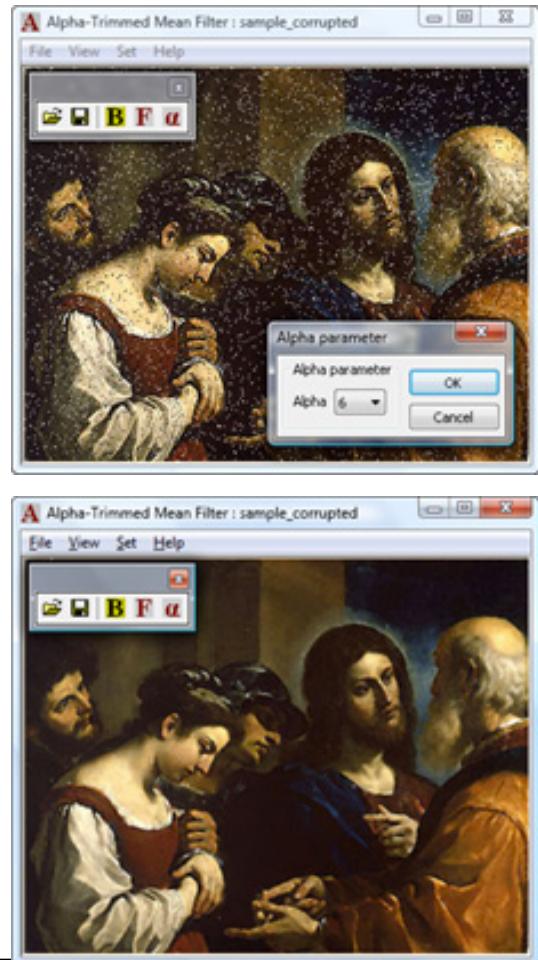
"Alpha-trimmed means and their relationship to median filters", IEEE Transactions on Acoustics, Speech and Signal Processing, 1984

Alpha trimmer filters (2)

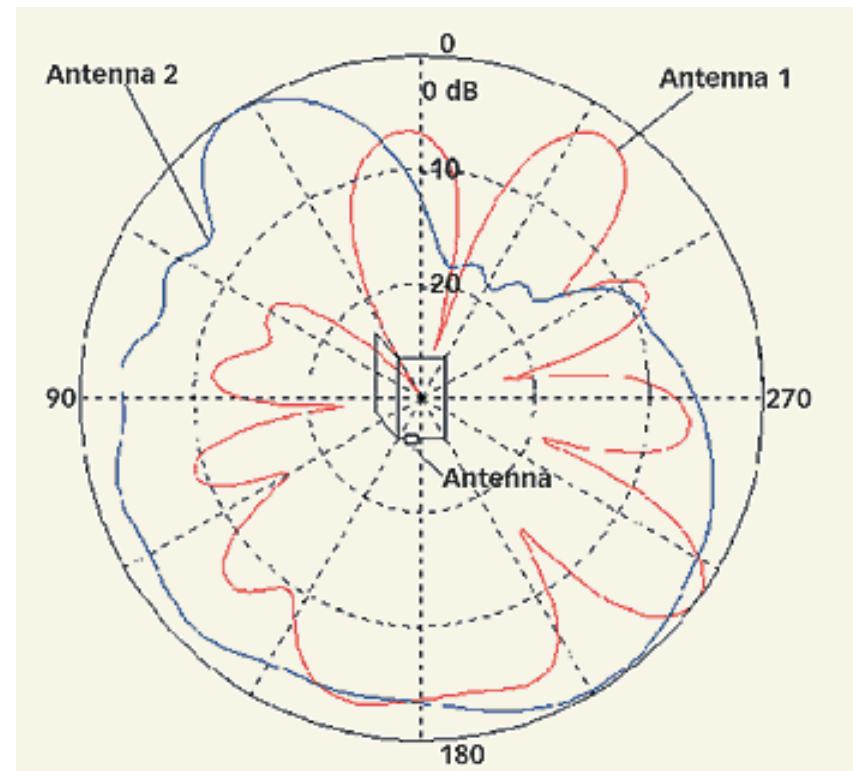
- $\alpha = 0$ -> mean, $\alpha \approx 0.5$ -> median
- $\alpha = 0.2$ should be ok



cut unlikely events



There are also antenna effects ... but we won't discuss those here

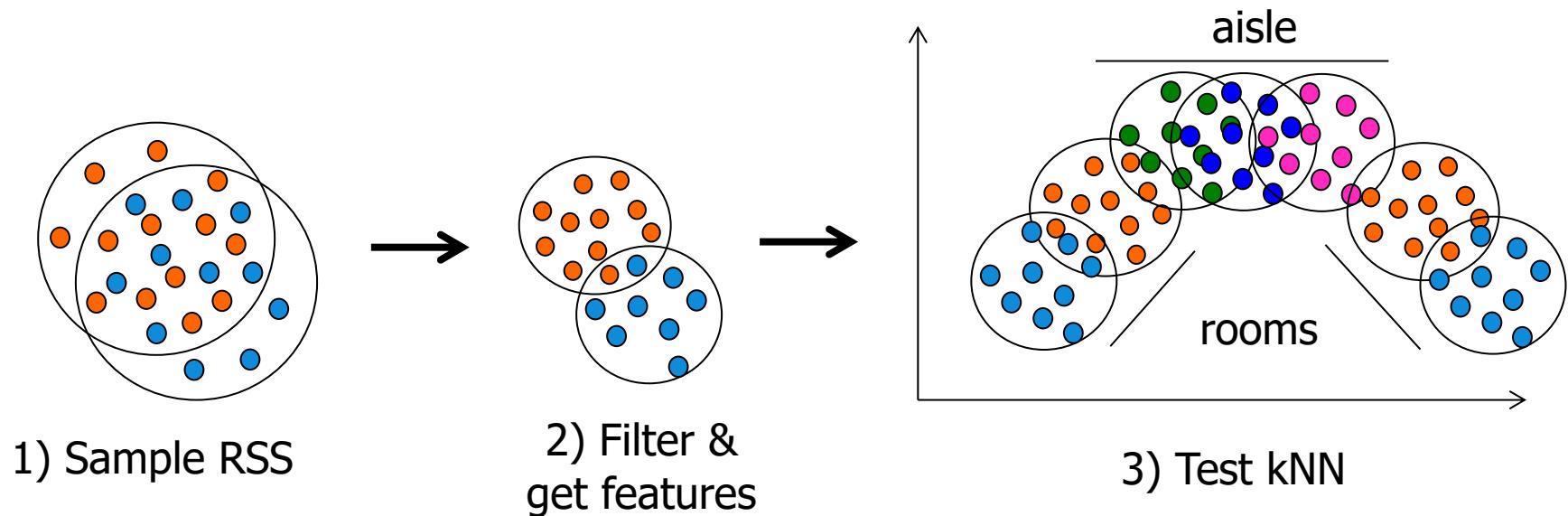
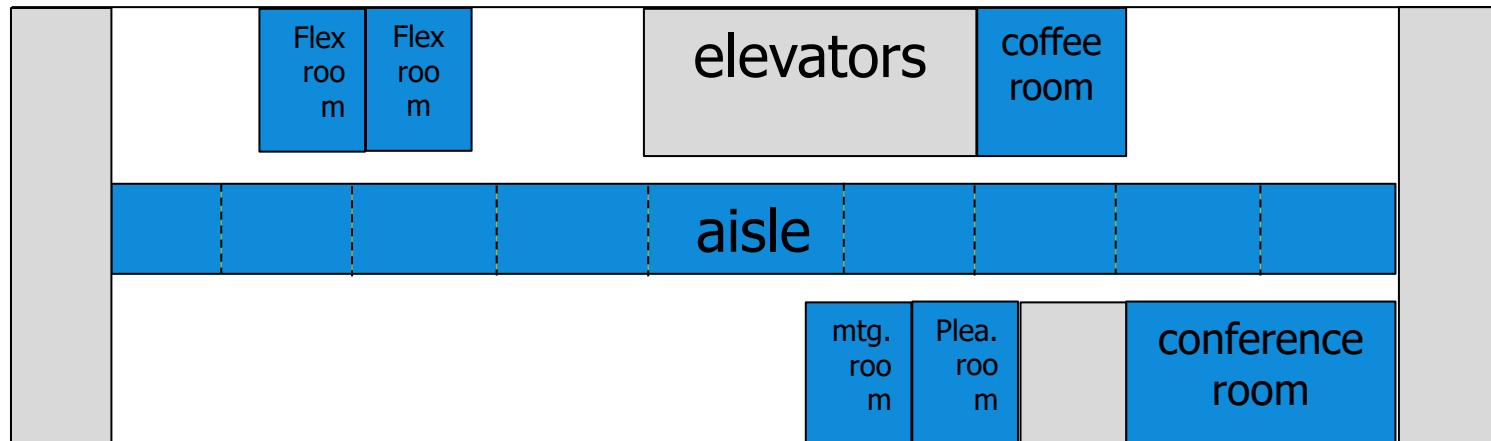


Distortion:

- metal objects
- electronics
- polarization

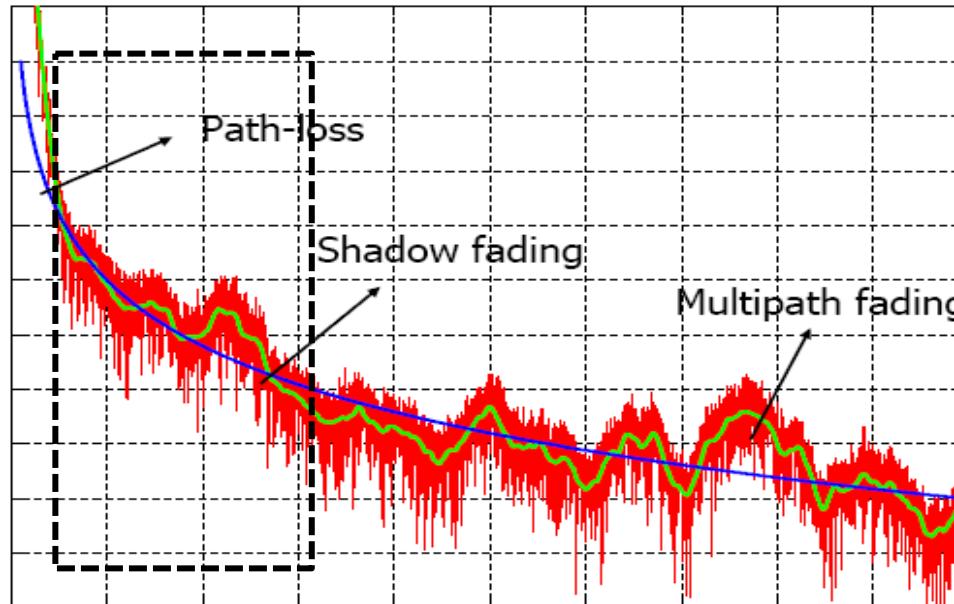
[<http://www.mwrf.com/>]

Revisiting kNN localization



Sort of good news

High density of Access points is on your side ...
less variability and steeper decay



A COOKBOOK FOR BAYESIAN FILTERS

A cookbook for Bayesian

- 1) Get running code to perform WiFi scans: SSID, MAC, RSSI
- 2) Gather RSSI data per cell
- 3) Clean SSID information (explained next)
- 4) Clean RSSI information (e.g. gaussian, alpha-trimmer)
- 5) Divide data into training and testing sets
- 6) First perform analysis of Bayesian Filters off-line
- 7) Construct confusion matrix (explained next)
- 8) Implement methods in App
- 9) Test it online in our floor
- 10) Add motion model (optional)

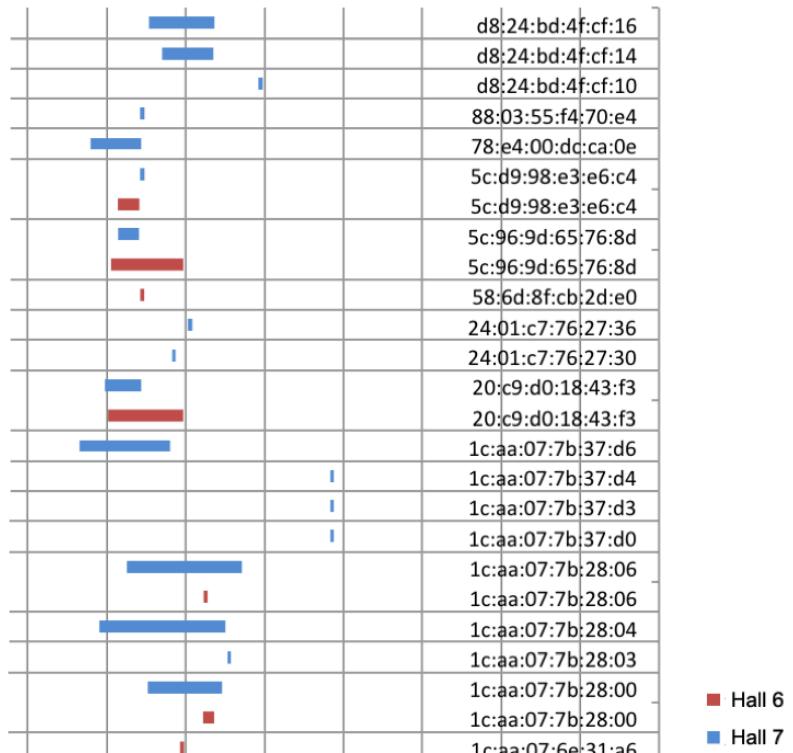
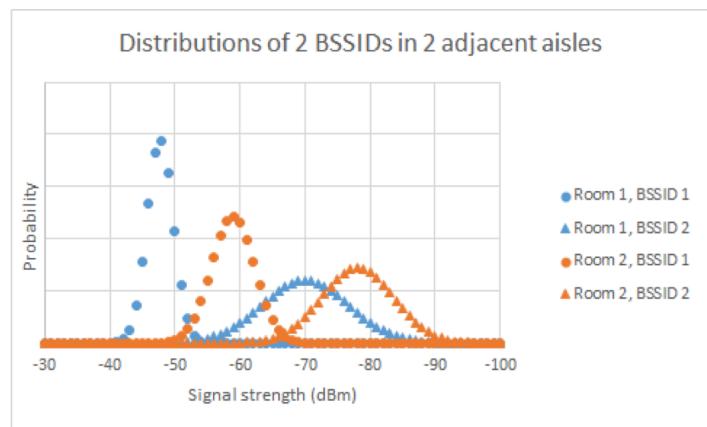
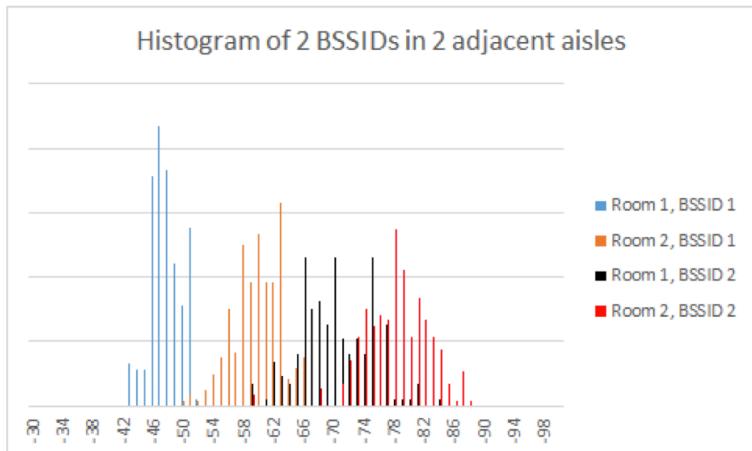
Clean SSID database

There may be:

- 1) **Temporary Access Points** (potentially a disastrous problem)
- 2) SSID's with many MAC addresses. (filter them out)

	Hall 1	Hall 2	Hall 3	Hall 4	Hall 5	Hall 6	Hall 7	Hall 8	Hall 9	Hall 10	Flex Room 1	Flex Room 2	mgt room	pleasure room	conference room 1	conference room 2	coffee room
same MAC: xx																	
00:0c:f6:6c:cf:xx	x	x	x	x	-	-	-	-	-	-	-	-	-	-	-	-	-
00:0c:f6:71:21:xx	-	-	-	-	-	-	-	-	-	-	x	-	-	-	-	-	-
00:0c:f6:c2:d1:xx	-	-	-	-	-	-	-	-	-	-	x	x	-	-	-	-	-
00:0e:a6:27:4d:xx	-	-	-	-	-	-	-	x	-	-	x	x	x	x	-	-	-
00:15:70:ad:99:xx	x	-	-	-	-	-	-	-	-	-	-	-	-	-	x	-	-
00:19:e3:fa:79:xx	-	-	-	-	-	-	-	-	-	-	x	-	-	-	-	-	-

Clean RSSI Data



- 1) Solve zero-probability problem (e.g. Gaussian or other)
 - 2) Filter RSSI if samples are too noisy (e.g. alpha trimmer)
 - 3) Remove Aps with very low samples

Analyze a confusion matrix

	Hall 1	Hall 2	Hall 3	Hall 4	Hall 5	Hall 6	Hall 7	Hall 8	Hall 9	Hall 10	Flex 1	Flex 2	Mgt	Pl.	Conf 1	Conf 2	Coffee
Hall 1	0.99	0.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hall 2	0.28	0.72	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hall 3	0	0.04	0.96	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hall 4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Hall 5	0	0	0	0.06	0.94	0	0	0	0	0	0	0	0	0	0	0	0
Hall 6	0	0	0	0.01	0	0.97	0.02	0	0	0	0	0	0	0	0	0	0
Hall 7	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Hall 8	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Hall 9	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Hall 10	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Flex 1	0	0	0	0	0	0	0	0	0	0	0	0.95	0.05	0	0	0	0
Flex 2	0	0	0	0	0	0	0	0	0	0	0	0.08	0.92	0	0	0	0
Mgt.	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pl.	0	0	0	0	0	0	0	0	0	0	0	0	0.99	0	0.01	0	0
Conf 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0.5	0
Conf 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0.6	0	0
Coffee	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Birds-eye view

App option 1: localization

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k-NN



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problem: shadowing and fading ✓

Bayesian
filters

a-trimmer
filters



Log normal
shadowing

Particle
filters

Report 2

Other Apps

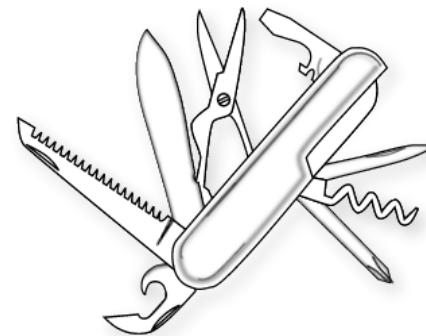
Shazam

may not
have time

Why these tools?

- k-NN
- Bayesian Inference
- Particle Filters
- Log normal shadowing model

combinations of these tools have revolutionized
indoor localization in the last 15 years



Images taken from:

<http://school.discoveryeducation.com/clipart/clip/scrwdrv.html>

<http://clipartist.net/svg/food-swiss-army-knife-black-white-line-art-svg/>

Papers

2000: k-NN

- RADAR: an in-building RF-based user location and tracking system
 - <http://www.itu.dk/people/bardram/teaching/material/radar.pdf>

2004: Bayesian

The Horus WLAN Location Determination System

- http://www.cs.umd.edu/~moustafa/papers/horus_usenix.pdf

→ Practical Robust Localization over Large-Scale 802.11 Wireless Networks

- <http://www.kavrakilab.rice.edu/sites/default/files/mobicom2004.pdf>

2010: Log normal shadowing

Indoor Localization Without the Pain

- <http://research.microsoft.com/pubs/135721/ez-mobicom.pdf>

2012: Particle filters

→ Zee: Zero-Effort Crowdsourcing for Indoor Localization

- <http://research.microsoft.com/pubs/166309/com273-chintalapudi.pdf>

Pointers

- Parts of this lecture are based on content from
 - "Artificial Intelligence for Robotics"
 - <https://www.udacity.com/course/cs373>
 - This is an *excellent* course from Udacity.
 - "A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking"
 - <http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=00978374>

Pointers for bayesian inference and particle filters

- A great Udacity course, take it! (has python code)<https://www.udacity.com/course/cs373>
- A video on particle filters without equations (has matlab code)
<https://www.youtube.com/watch?v=aUkBa1zMKv4>
- A tutorial on particle filters (slides, math)http://web.mit.edu/16.412j/www/html/Advanced%20lectures/Slides/Hsaio_plinval_miller_ParticleFiltersPrint.pdf
- A tutorial on particle filters (paper, math)<http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=00978374>
- A tutorial on particle filters (paper, math)<http://dip.sun.ac.za/~herbst/MachineLearning/ExtraNotes/ParticleFilters.pdf>

Birds-eye view

App option 1: localization

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Report 1

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may not
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Continuous case

PARTICLE FILTERS FOR LOCALIZATION

WiFi-based Localization Story

Steps

- Step 1: Radio Map training
- Step 2: Localization testing

Development

- 2000: k-NN deterministic & painful
- 2004: Bayesian probabilistic & a bit less painful
- 2010: Log normal shadowing probabilistic & less painful
- 2012: Particle filters probabilistic & no pain

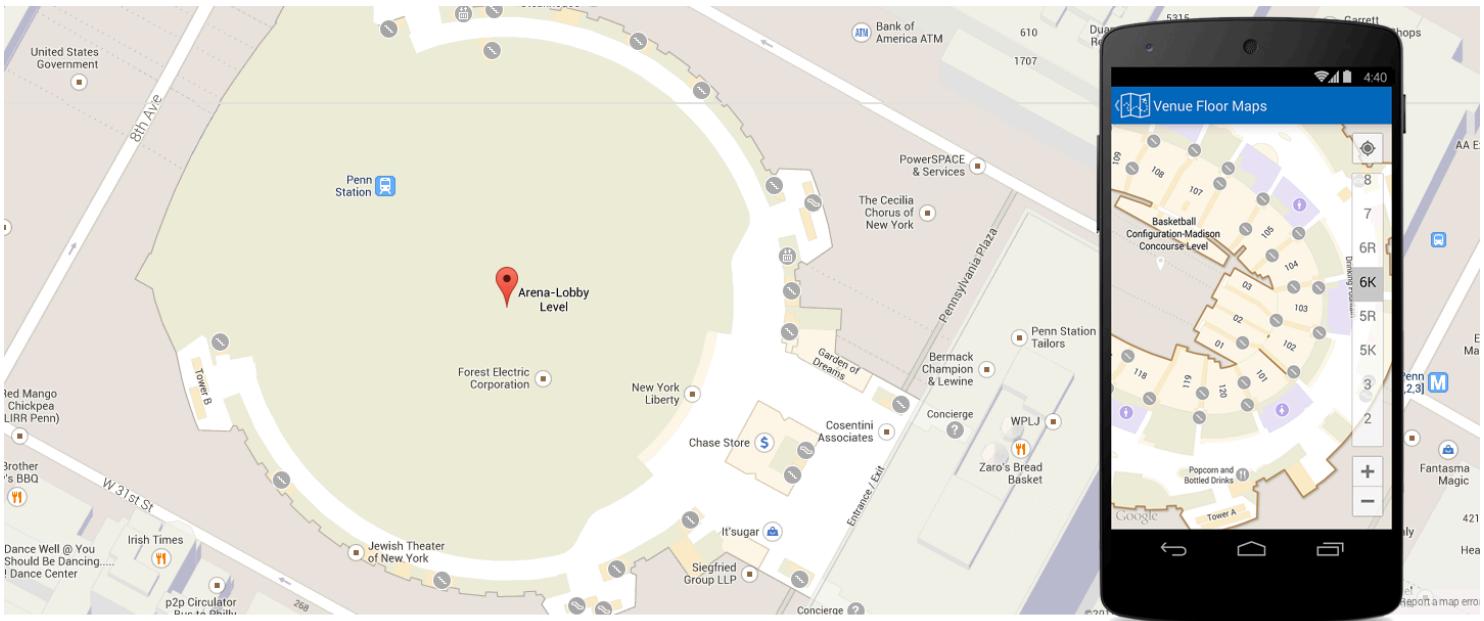
But I hate training!

Imagine training a building
with 100 floors and 10K
offices

Solution

GET A MAP!

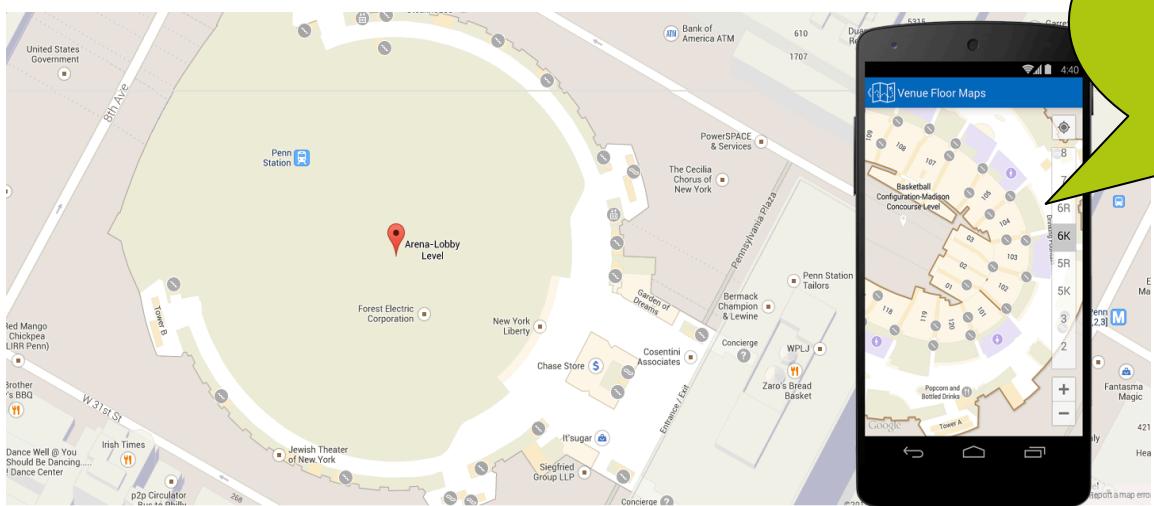
Indoor maps (google)



Assuming existence of indoor maps is not unreasonable

- an up-and-coming trend. Four steps to upload your map
- allow you to minimize the cumbersome training process

Indoor maps



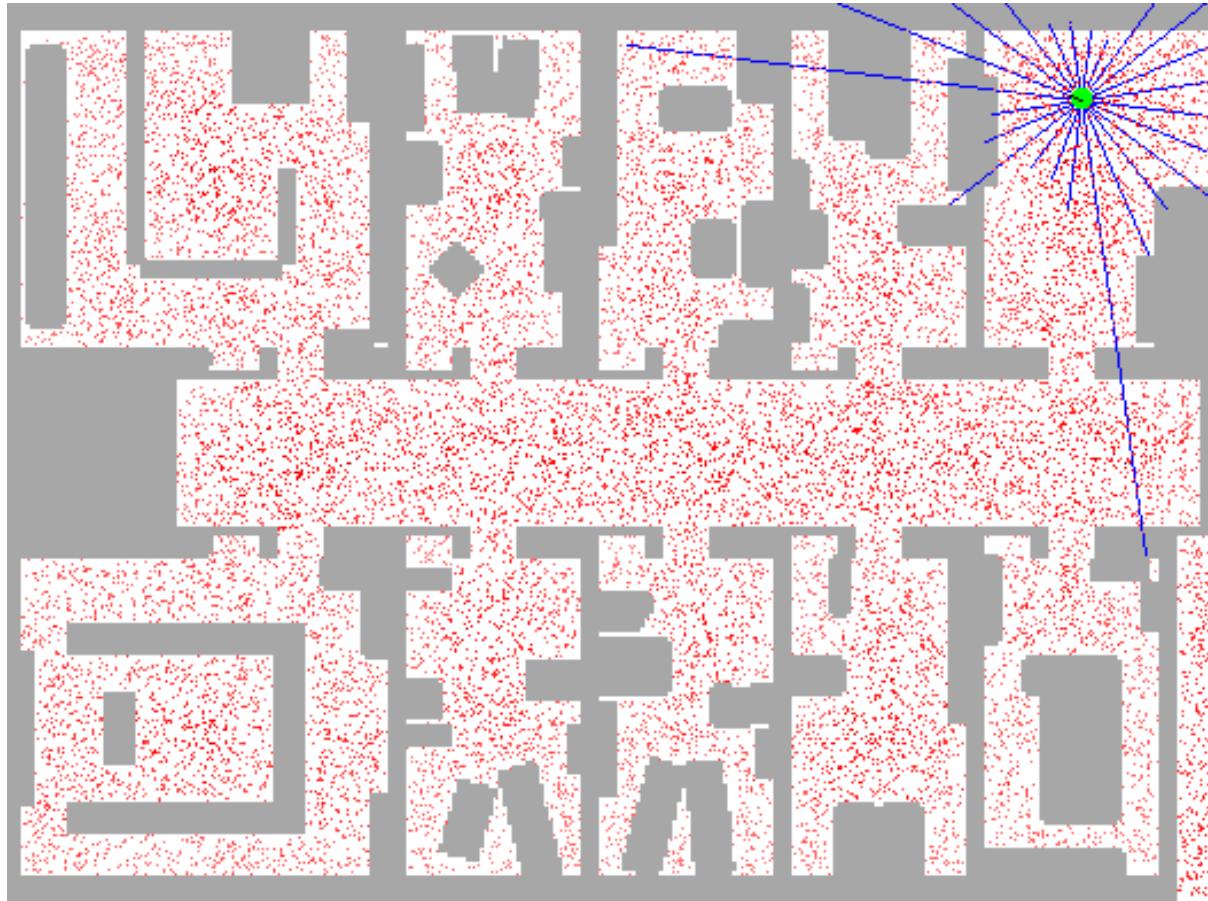
Where am I?

**WALK and you will
find where you are.**

This Lecture has 3 parts

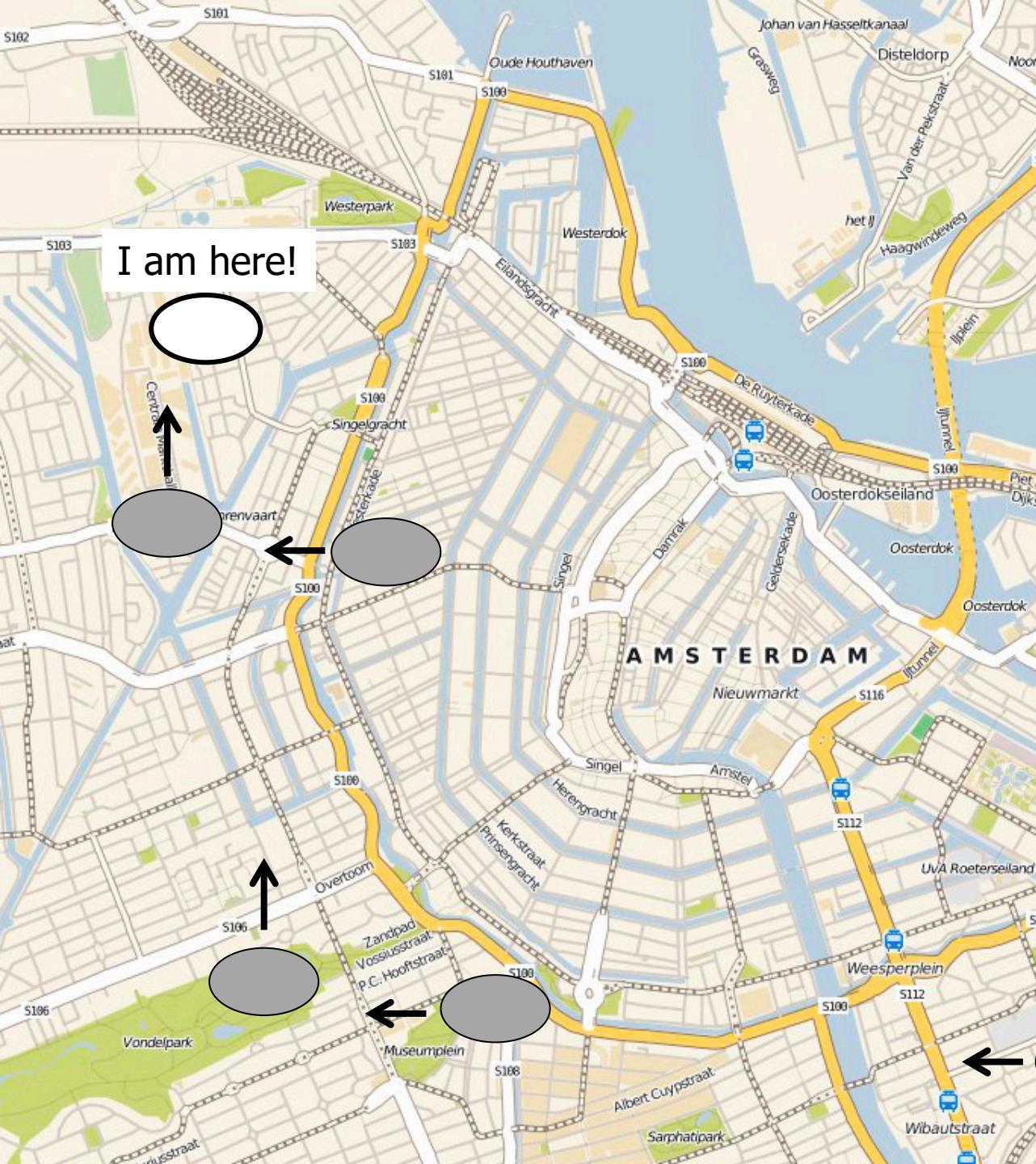
- 1) Particle Filters
- 2) Motion model: distance and direction
- 3) Building RSSI database for “free”

Now, a real evaluation of particle filters



movie link: <http://robots.stanford.edu/movies/sca80a0.avi>

Where am I?



I am here!

Step 0: Clueless

I could be anywhere

Step 1: Sense

I can see a **tall building**

Step 2: Move

oops!

Step 3: Sense (again)

I can see a **super market**

Step 4: Move (again)

oops!

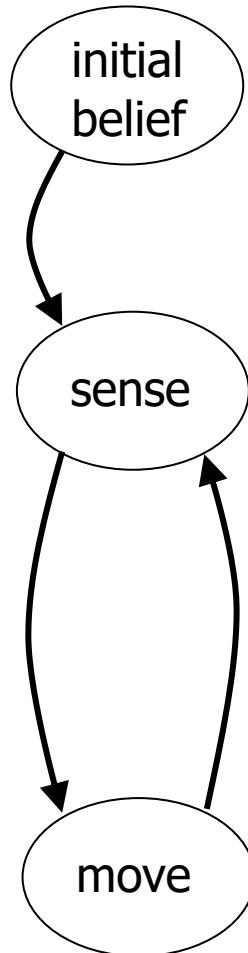
Step 5: Sense (again)

I can see a "**coffee shop**"

I know where I am!



You may have not realized it, but you already know the gist of Particle (and Bayesian) filters! Below, \mathcal{X} represents location and \mathcal{Z} measurements



current pdf
(posterior)

$p(\mathcal{X}_k | \mathcal{Z}_{1:k}) = \frac{p(\mathcal{Z}_k | \mathcal{X}_k) p(\mathcal{X}_k | \mathcal{Z}_{1:k-1})}{p(\mathcal{Z}_k | \mathcal{Z}_{1:k-1})}$

perception model
(sense)

pdf from last time step
(prior)

$$p(\mathcal{X}_k | \mathcal{Z}_{1:k}) = \frac{p(\mathcal{Z}_k | \mathcal{X}_k) p(\mathcal{X}_k | \mathcal{Z}_{1:k-1})}{p(\mathcal{Z}_k | \mathcal{Z}_{1:k-1})}$$

normalization

current pdf
(posterior)

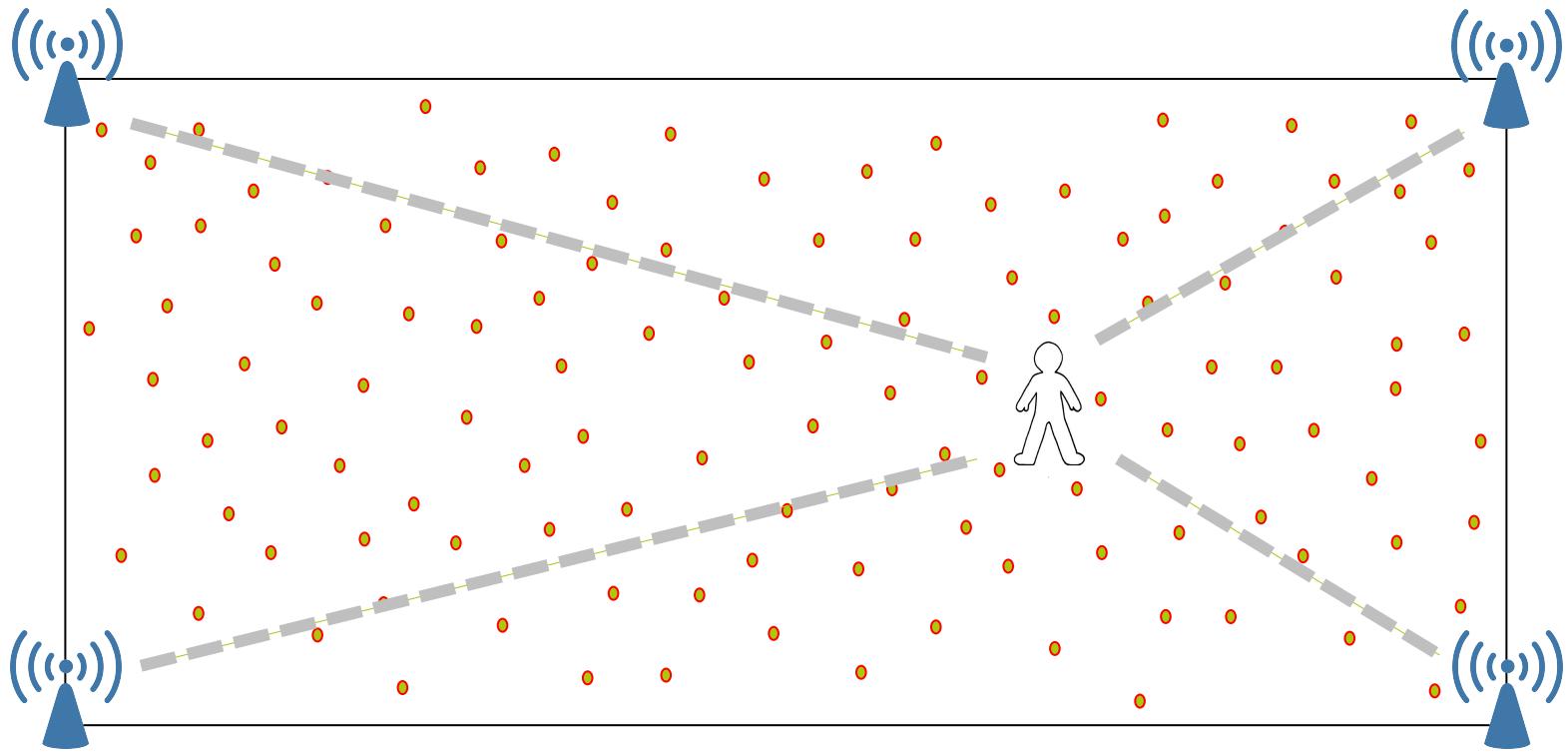
$p(\mathcal{X}_k | \mathcal{Z}_{1:k-1}) = \int p(\mathcal{X}_k | \mathcal{X}_{k-1}) p(\mathcal{X}_{k-1} | \mathcal{Z}_{1:k-1}) d\mathcal{X}_{k-1}$

motion model
(move)

pdf from last time step
(prior)

Paper: "A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking", IEEE Trans. Signal Processing, 2002.

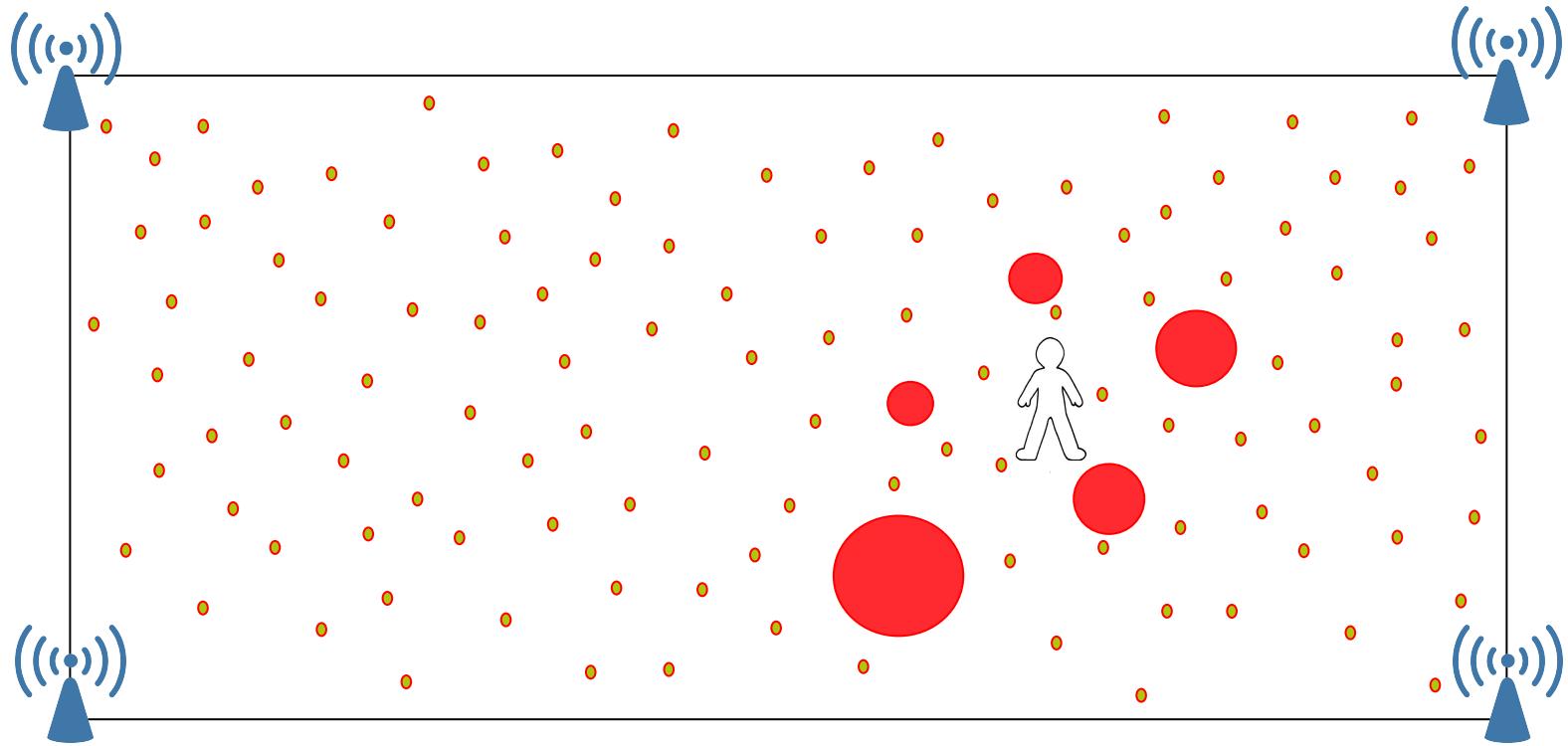
Initial distribution of particles



N particles (N is large). Every particle has three parameters:
x coordinate, y coordinate and direction of movement (angle)



Importance weight

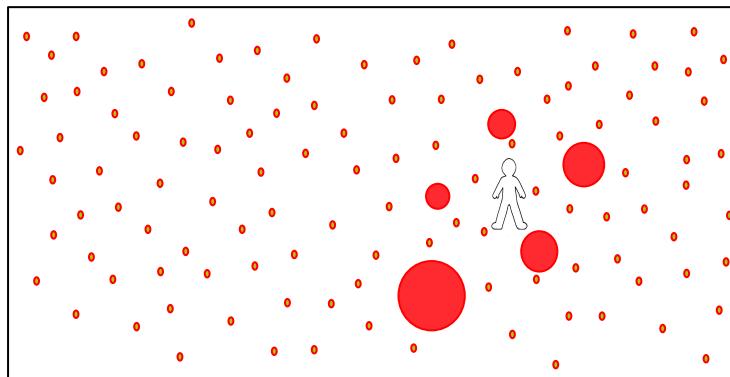


particles will have different weights depending on their likelihood of being the 'right guess'

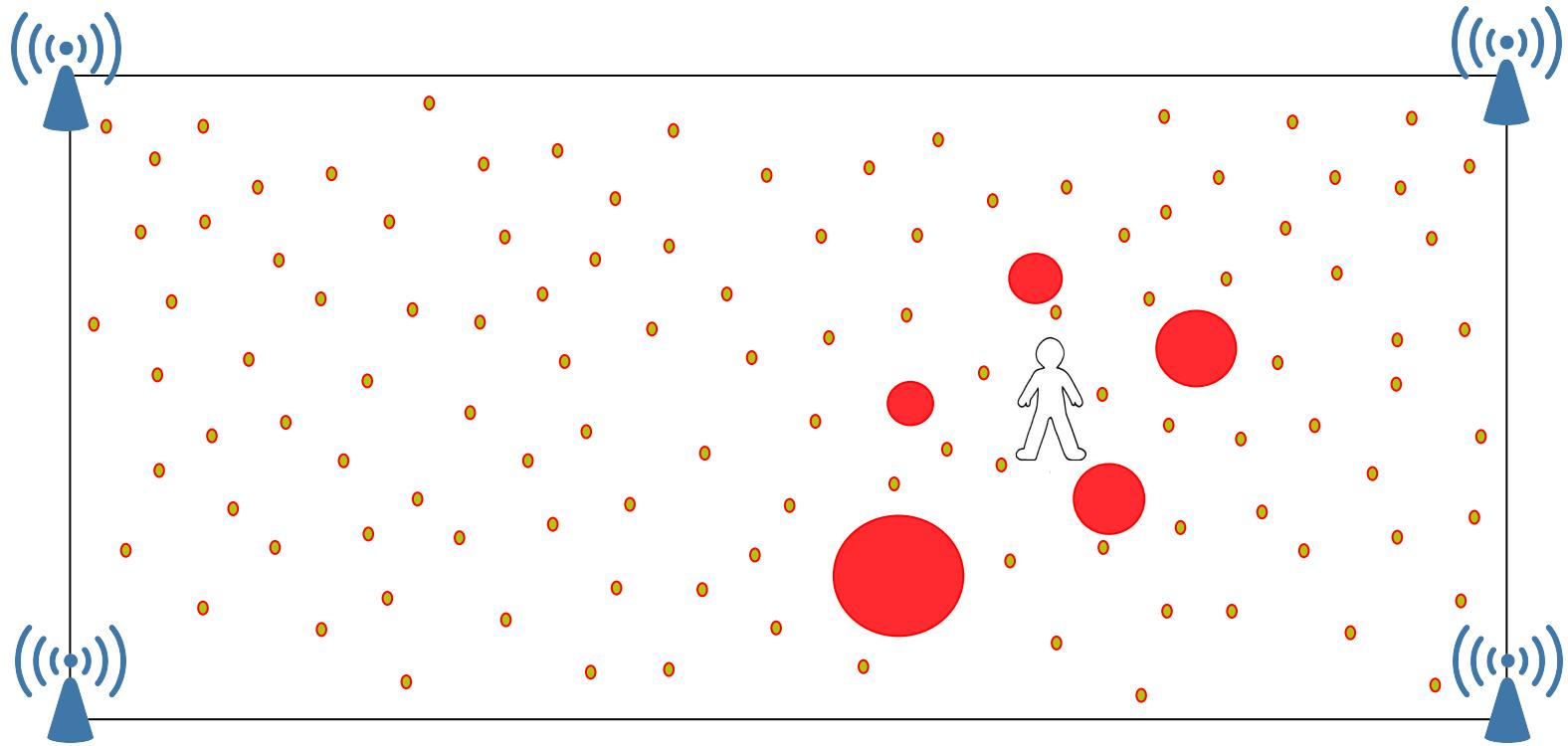
Resampling

- Each particle i will have a likelihood p_i
- The higher p_i , the higher the likelihood that the particle is in the correct location (sensing)
- The weight of each particle will be

$$w_i = \frac{p_i}{\sum p_i}$$

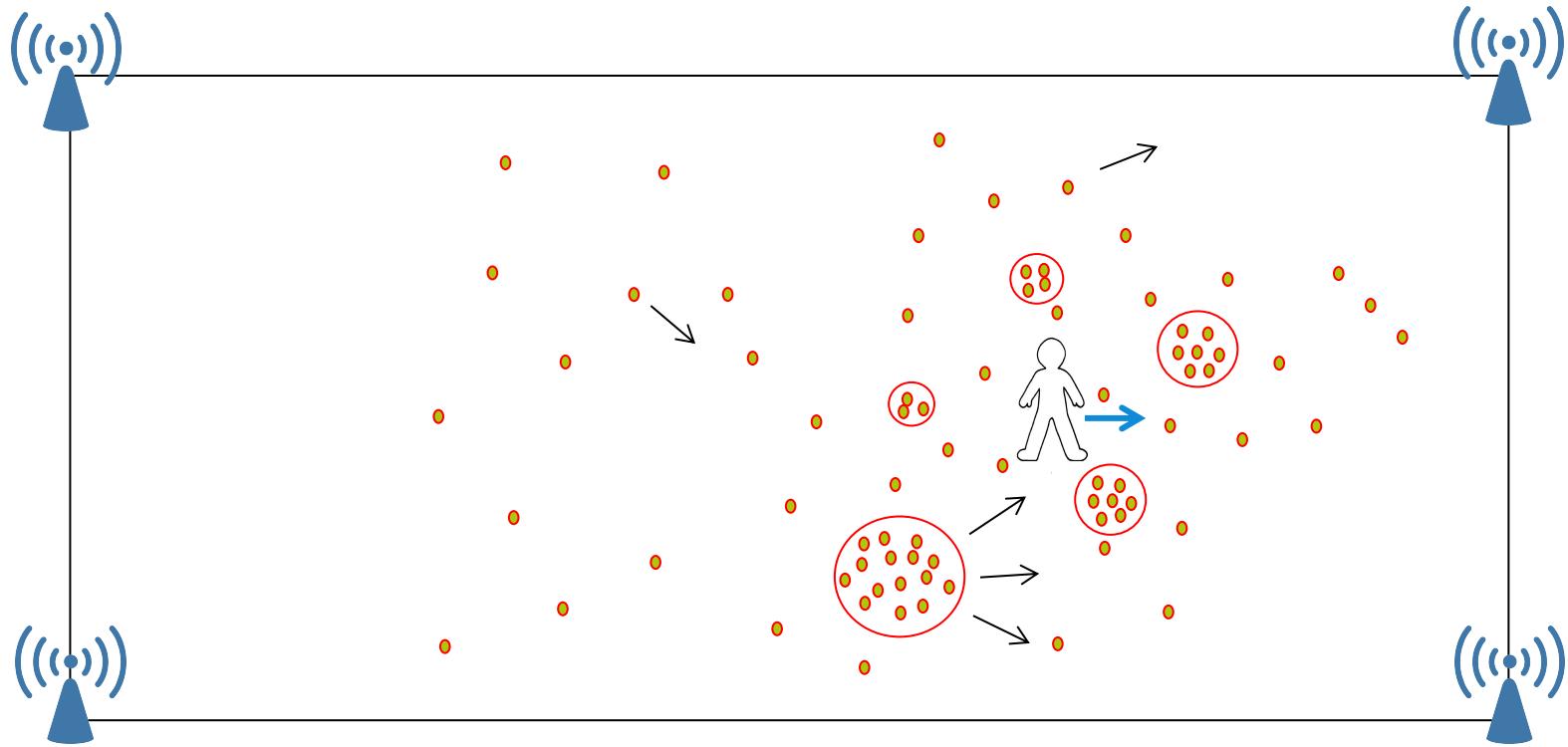


Resampling (1)



Re-deploying the troops: the higher the weight the more particles will be chosen on that specific position.

Resampling (2)



particles with the same coordinates (inside big circles) have different directions (paths) according to the motion model

Resampling

- Each particle i will have a likelihood p_i
- The weight of each particle will be

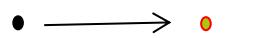
$$w_i = \frac{p_i}{\sum p_i}$$

- Obtain N new particles from the original set.
 - The resampling is done with replacement.
 - Particles with high weight may have multiple copies
 - Particles with low weight may disappear.

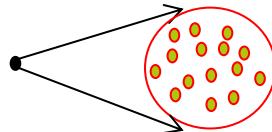
Move

The accuracy of the motion model is very important

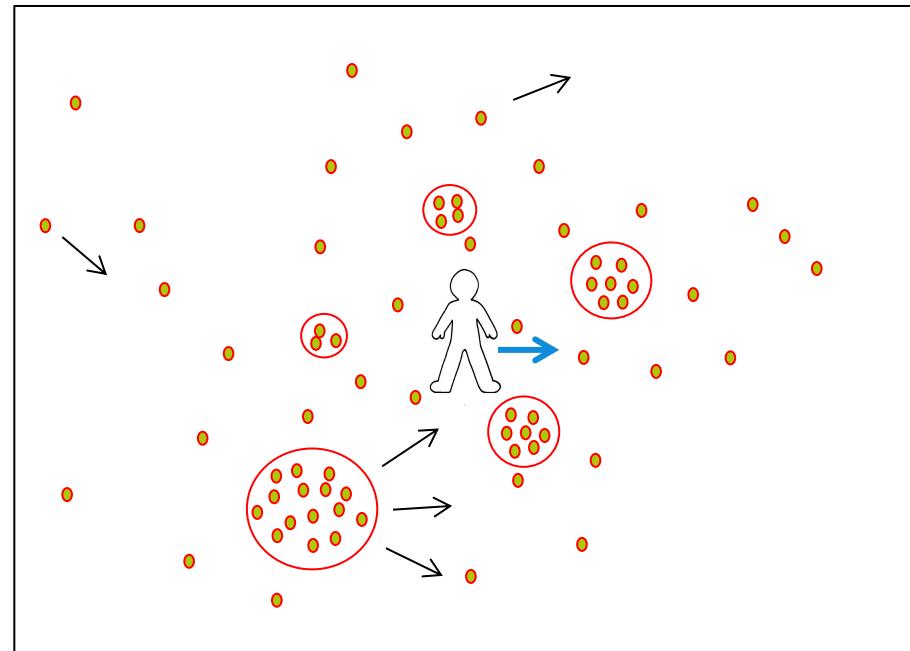
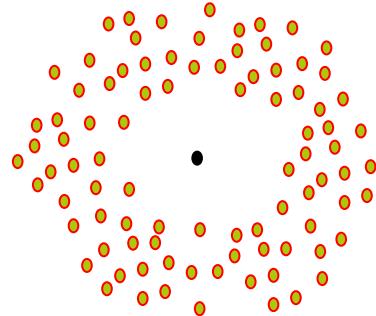
perfect



good



bad



Each resampled particle moves according to the motion model.
The more accurate the model is, the better

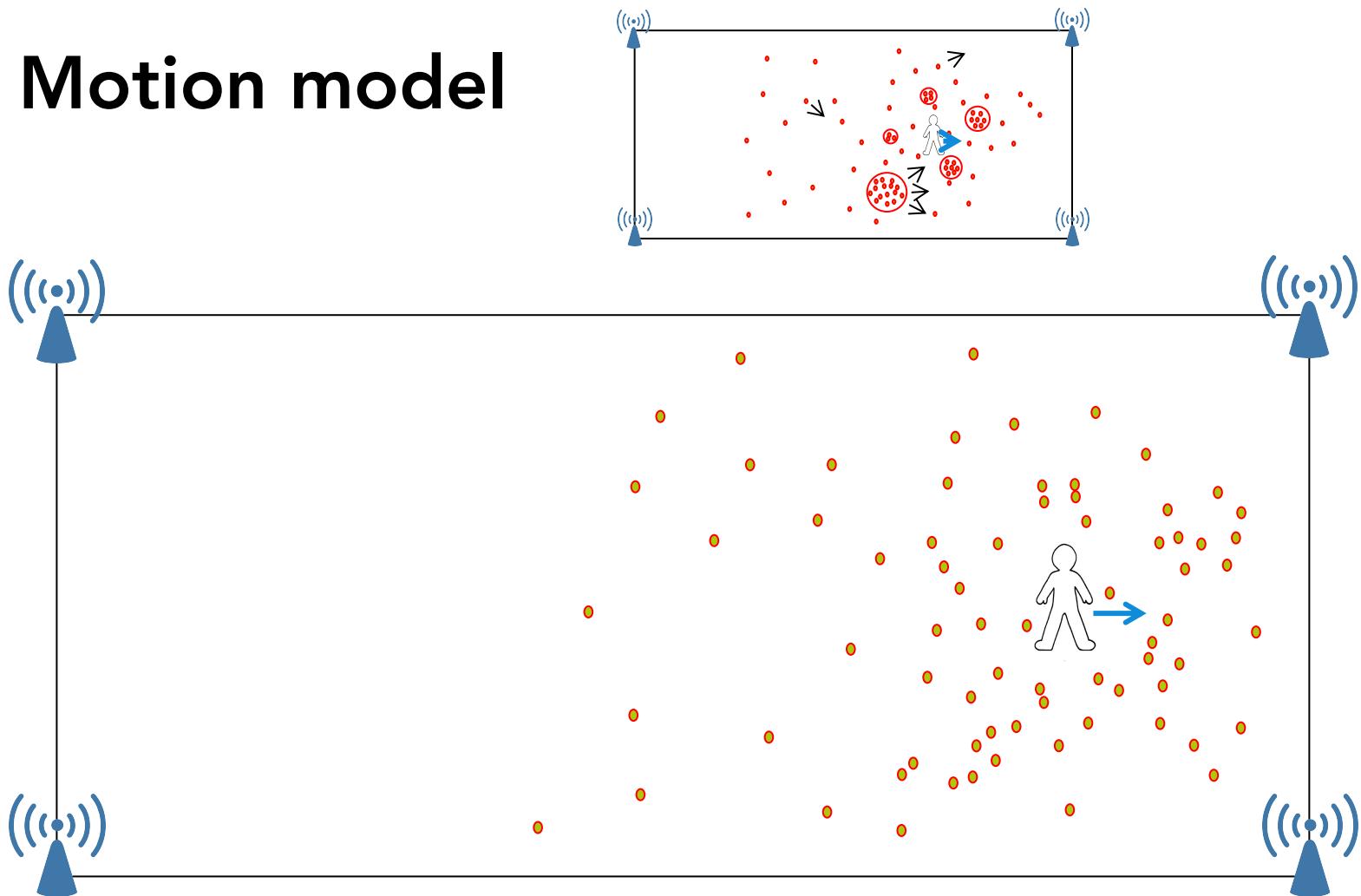
Resampling

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- Obtain N new particles from the original set.
 - The resampling is done with replacement.
 - Particles with high weight may have multiple copies
 - Particles with low weight may disappear.
- The new particles will have different destinations according to the mobility model

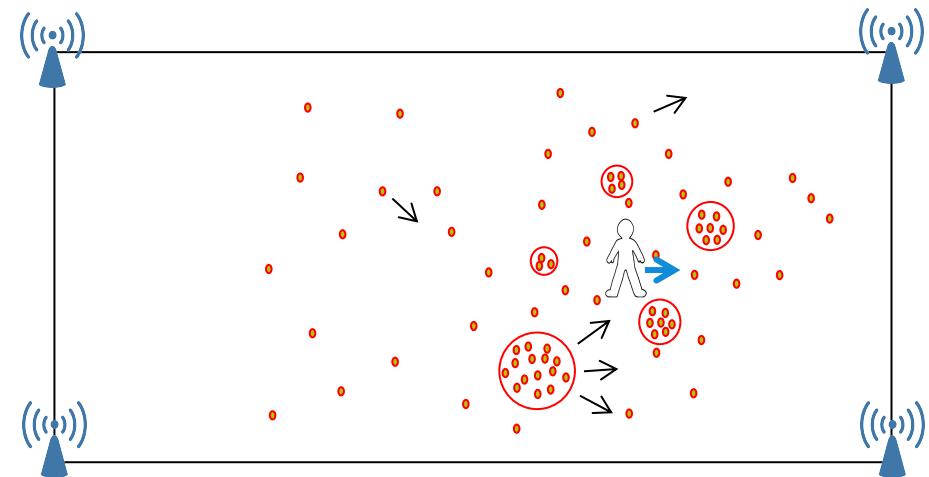
Motion model



After moving each particle, repeat the *importance weight* and *resampling* steps.
In time only the most likelihood options will remain (survival of the fittest)

Why do I need to resample?

- Why not just keep weights?



Why do I need to resample?

- Why not just keep weights?
 - Particle depletion
 - Density of particles should represent the pdf
 - Areas with high probability in posterior not represented well.
 - You won't be able to recover fast from errors

