Lecture 04

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

α-trimmer
filters

Log normal
shadowing

Particle filters

Report 2

Other Apps

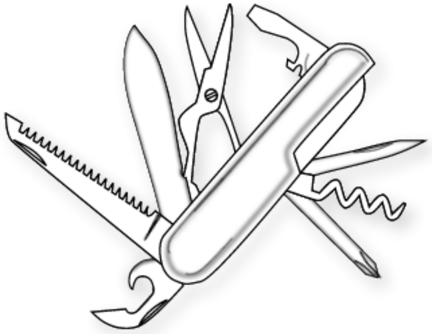
Shazam

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/scrwdrvr.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

Log normal shadowing model

TAMING RF SIGNALS

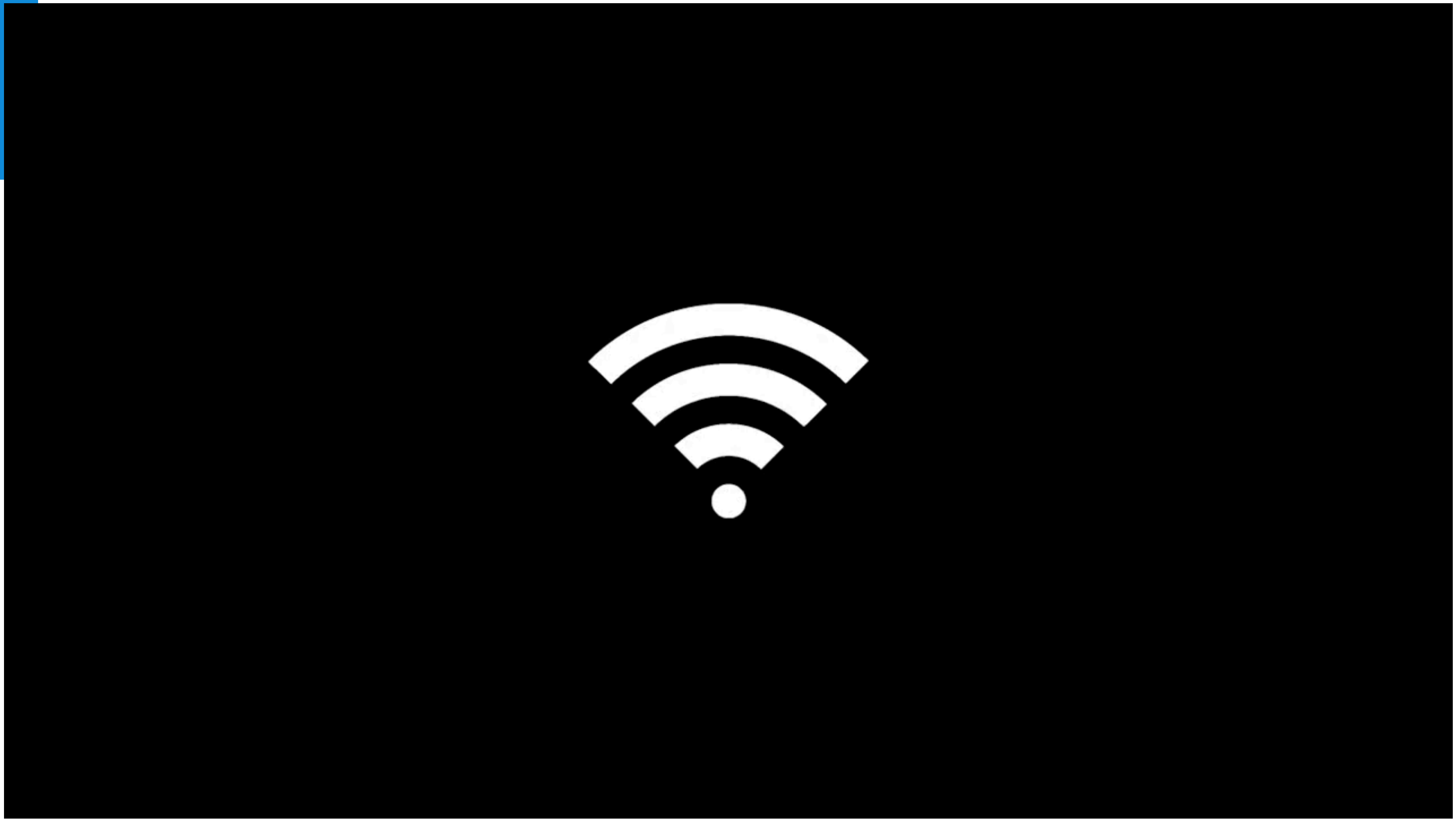
Log Normal Model

Understanding and taming radio signals

- Large-scale fading
- Small scale fading

Image taken from https://www.newscientist.com/blogs/nstv/2011/03/invisible-wi-fi-signals-caught-on-camera.html

Immaterial WiFi

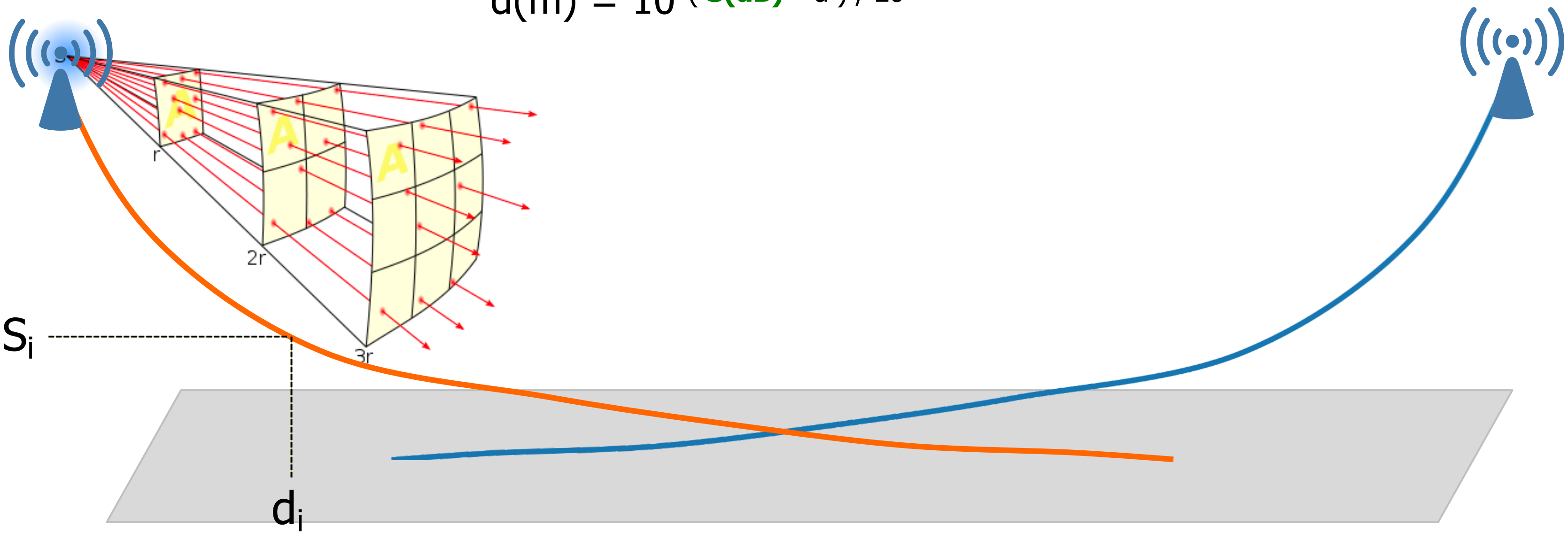


Problem definition: ideal RF localization

Path loss exponent

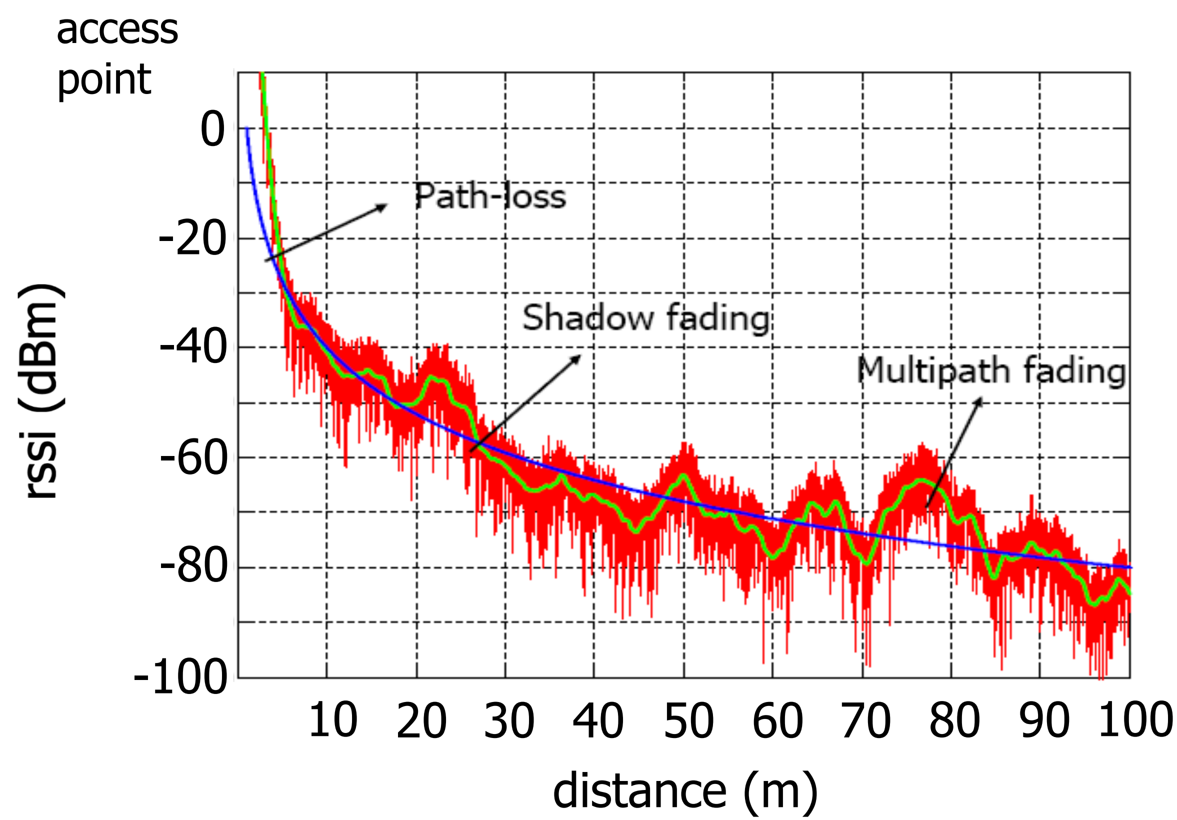
$$S(dB) = 20\log_{10}(d) + \overbrace{20\log_{10}(f) + 20\log_{10}(4pi/c)}^{\text{constant = a}}$$

$$d(m) = 10^{\,(\,\color{green}{\mathbf{S(dB)}}\, - \,a\,)\,/\,20}$$

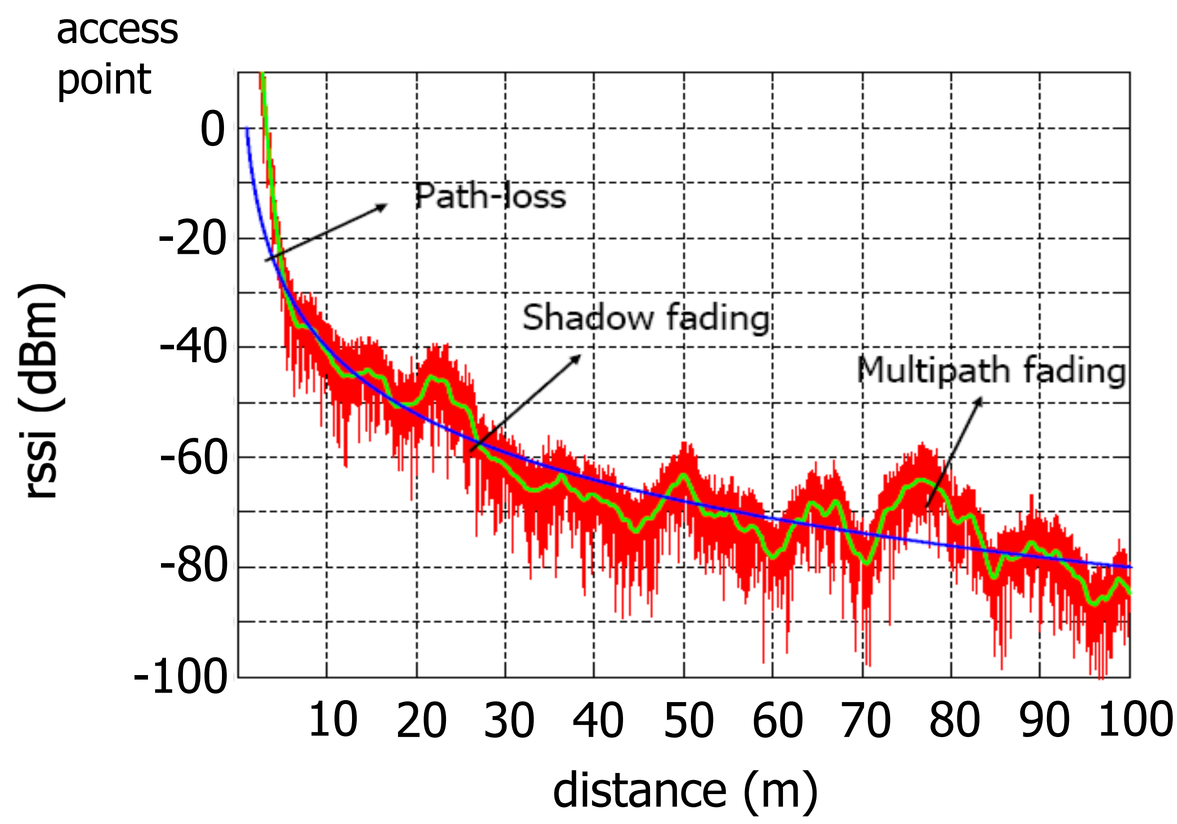


Localization with perfect RF signals is trivial, but there are no perfect signals in the wild.

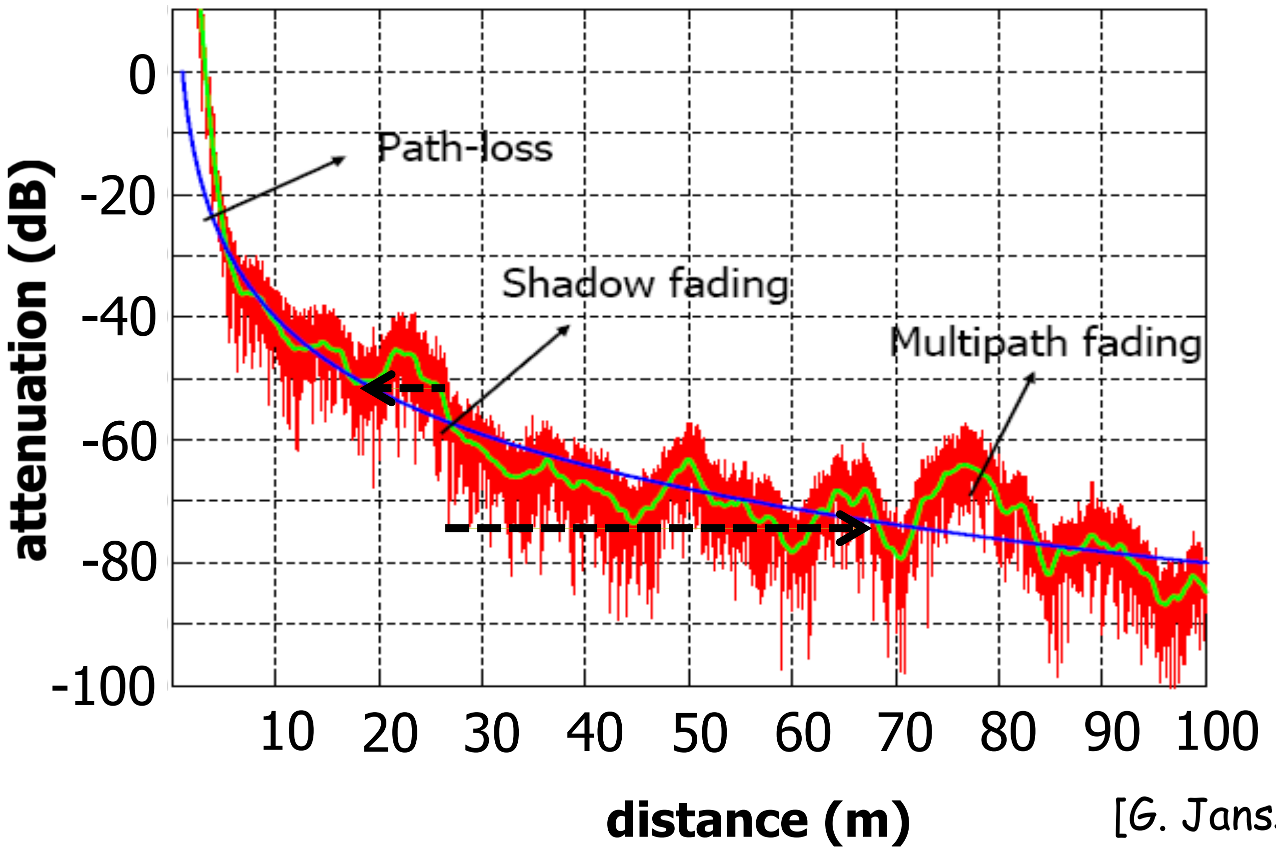
A user measures an rss value of -60 dBm, how far is the user from the access point? Use the blue curve as the training model.



A user measures an rss value of -60 dBm, how far is the user from the access point? Use the red curve as the training model.



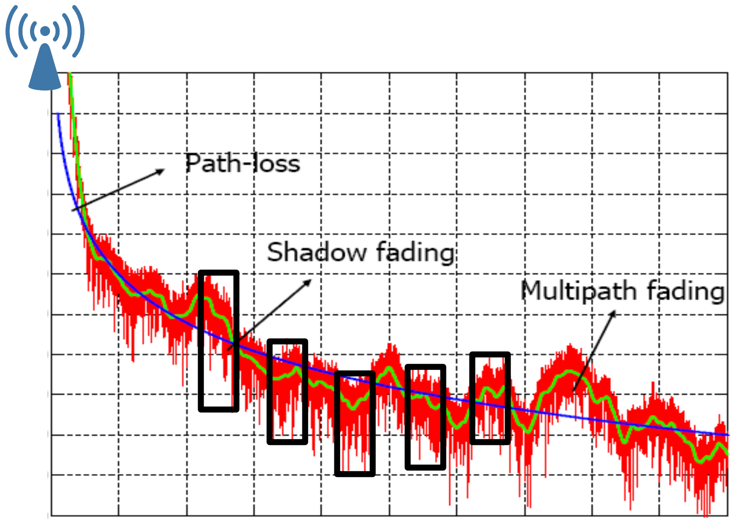
Problem definition: real RF localization



[G. Janssen, ET4358]

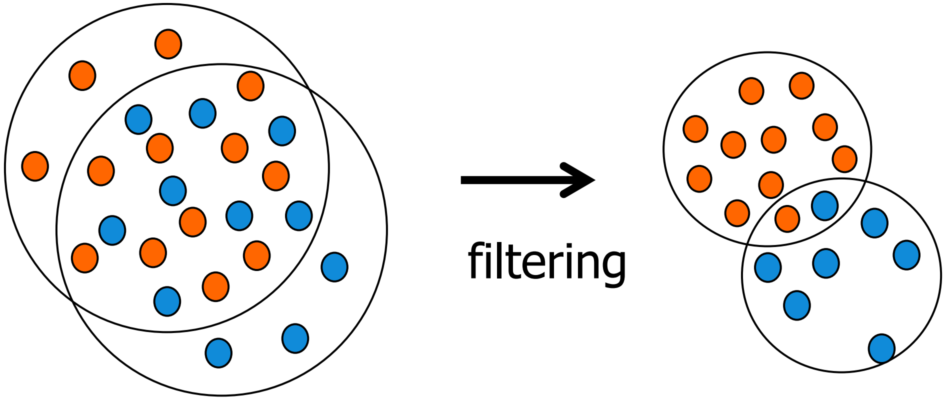
50m range!

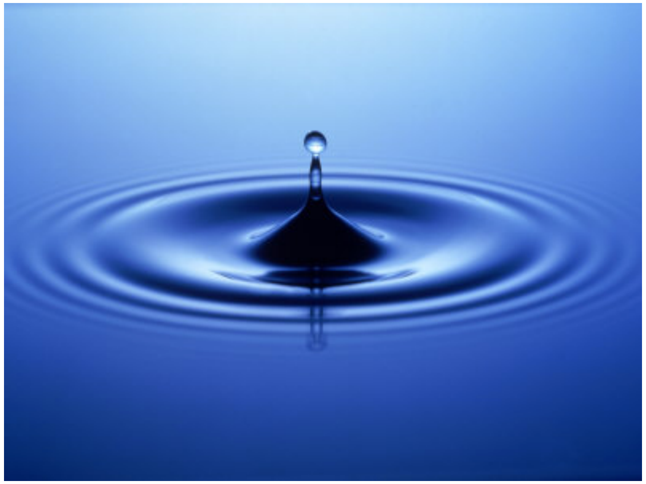
RF fingerprinting



Assuming K-NN,

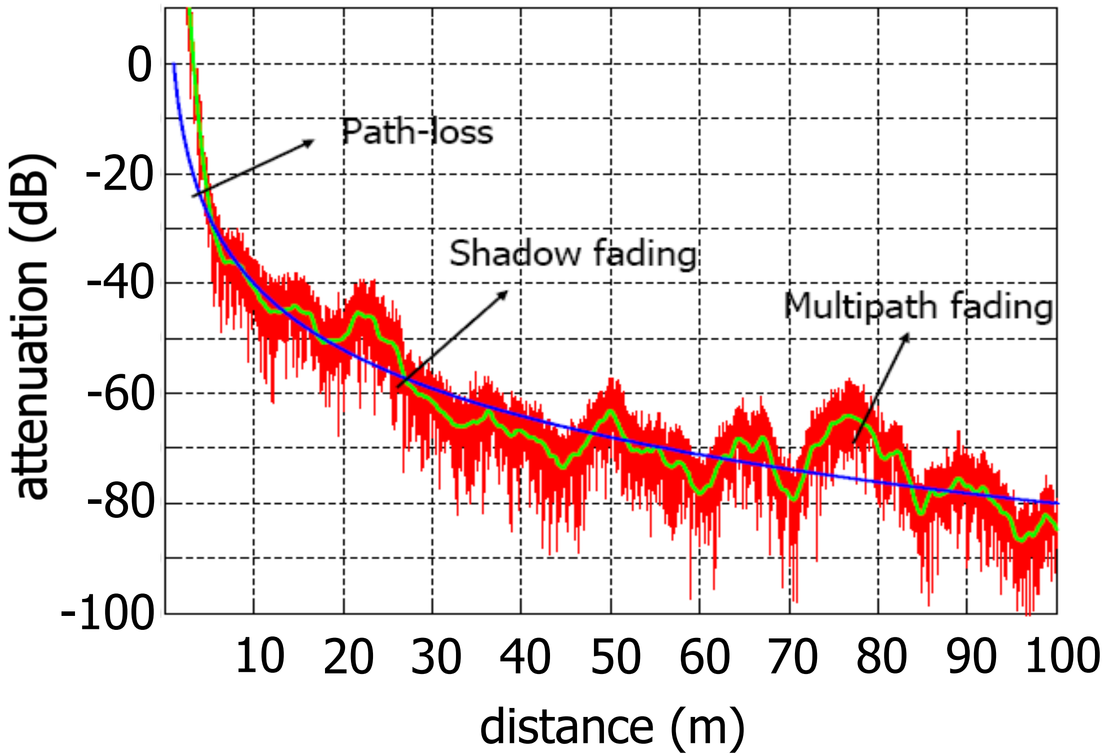
What problems do you think shadow and multipath fading will cause to your localization (classification) method?



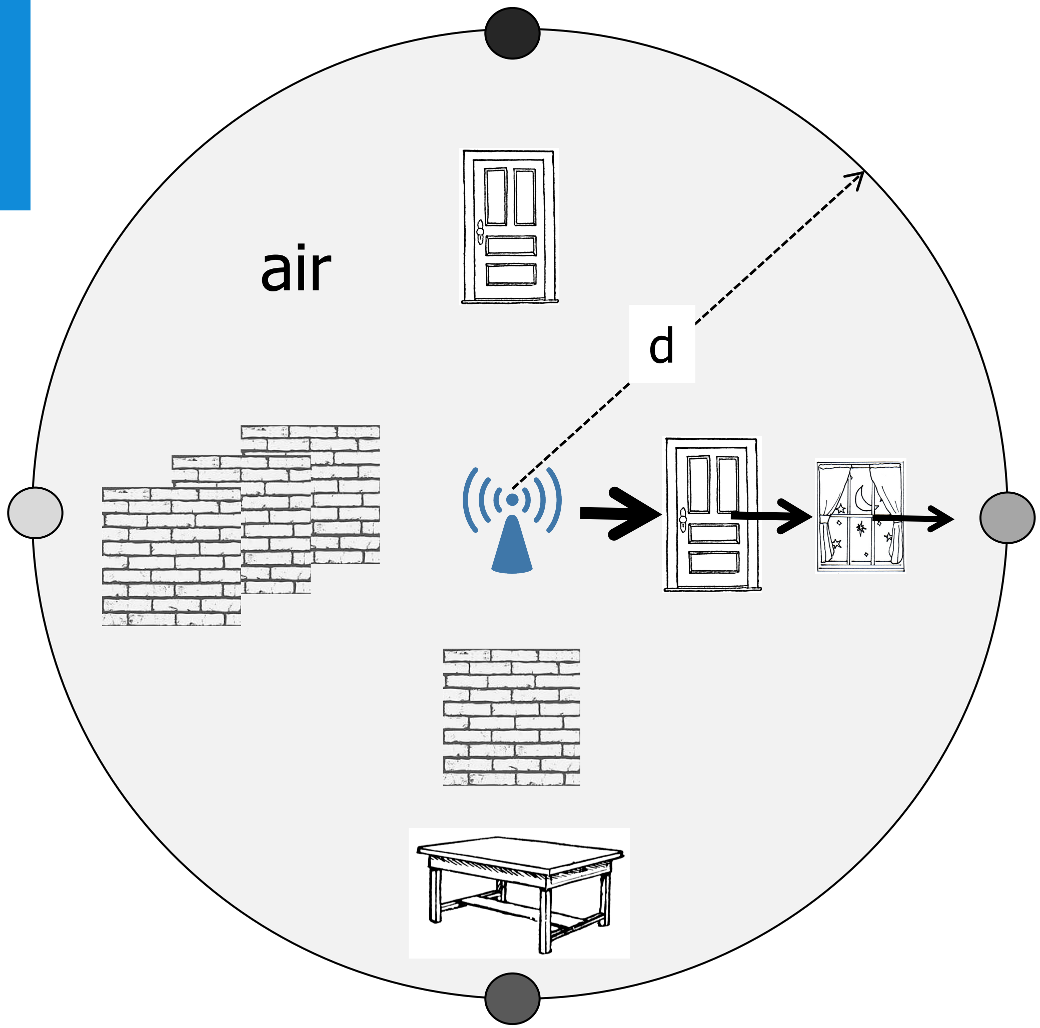


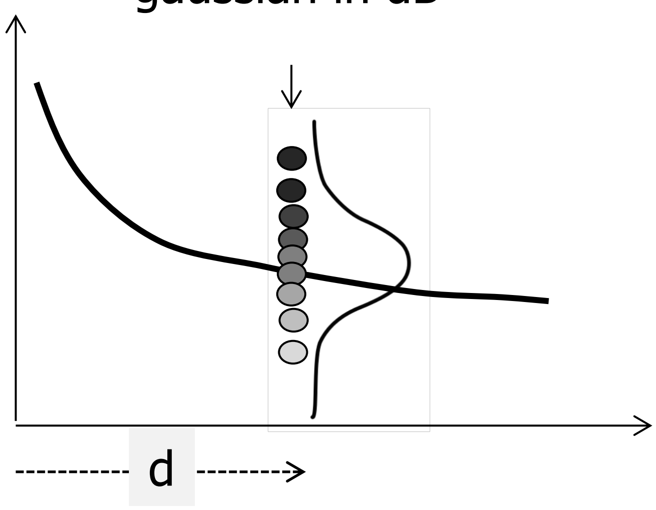
FADING

Shadow fading (green curve)



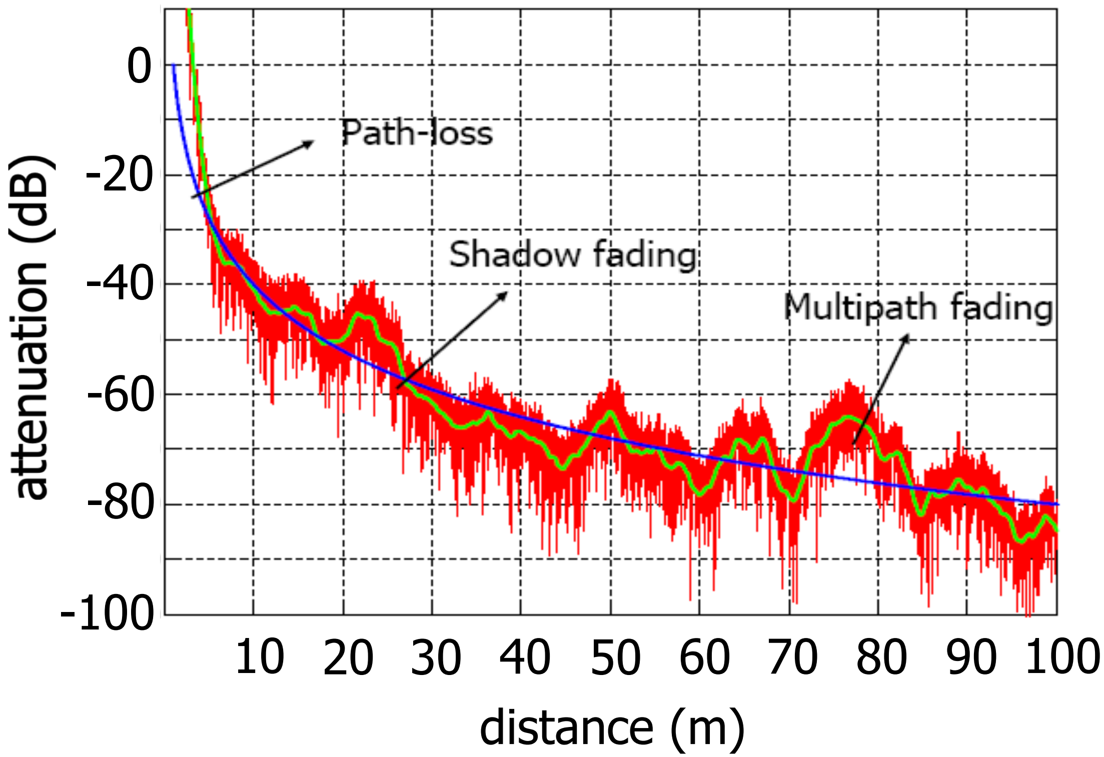
Large scale fading: absorption





why gausssian (normal)?

Log normal shadowing model



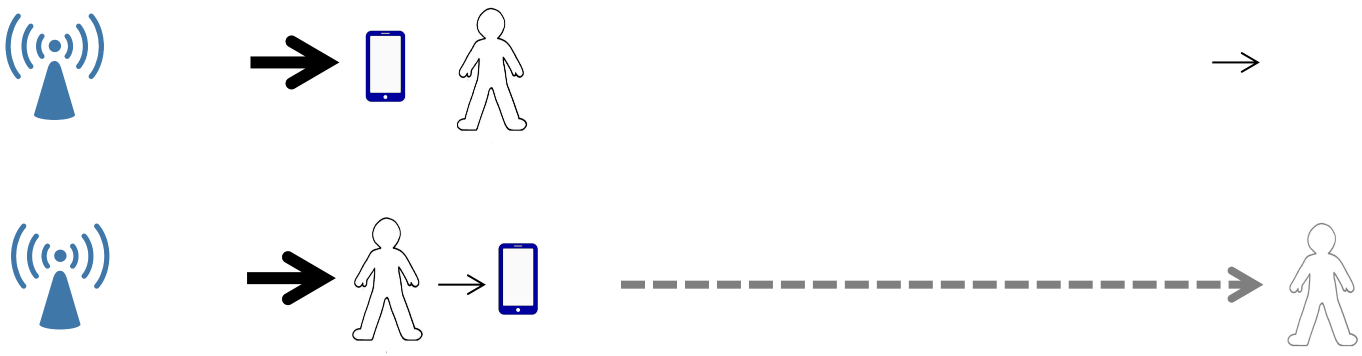
$$PL(dB) = P_{Tx}(dBm) - P_{Rx}(dBm)$$
$$= PL_0 + 10\,\eta\log_{10}(d/d_0) + N(0,\sigma)$$

this is an empirical model

pros & cons of large scale fading

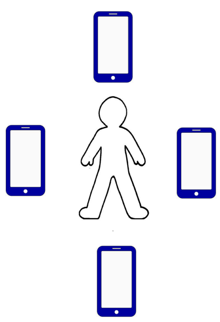
- You can't do much against large scale fading
  - tearing down a wall is not a daily option
- In a way, large scale fading is good
  - it helps in characterizing specific spaces,
  - localization in the aisle will be harder than in rooms.
- There is one absorption effect that causes problems, but that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

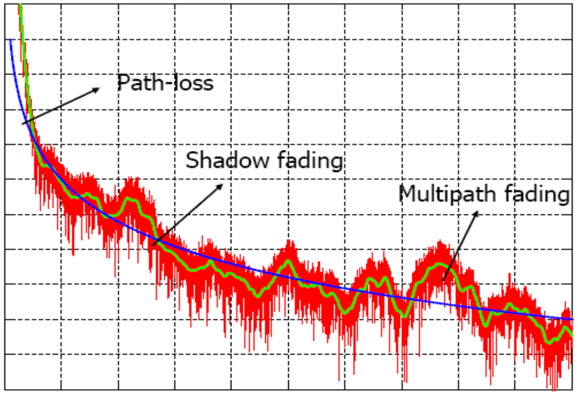
Teletransportation problem 1: Body effects



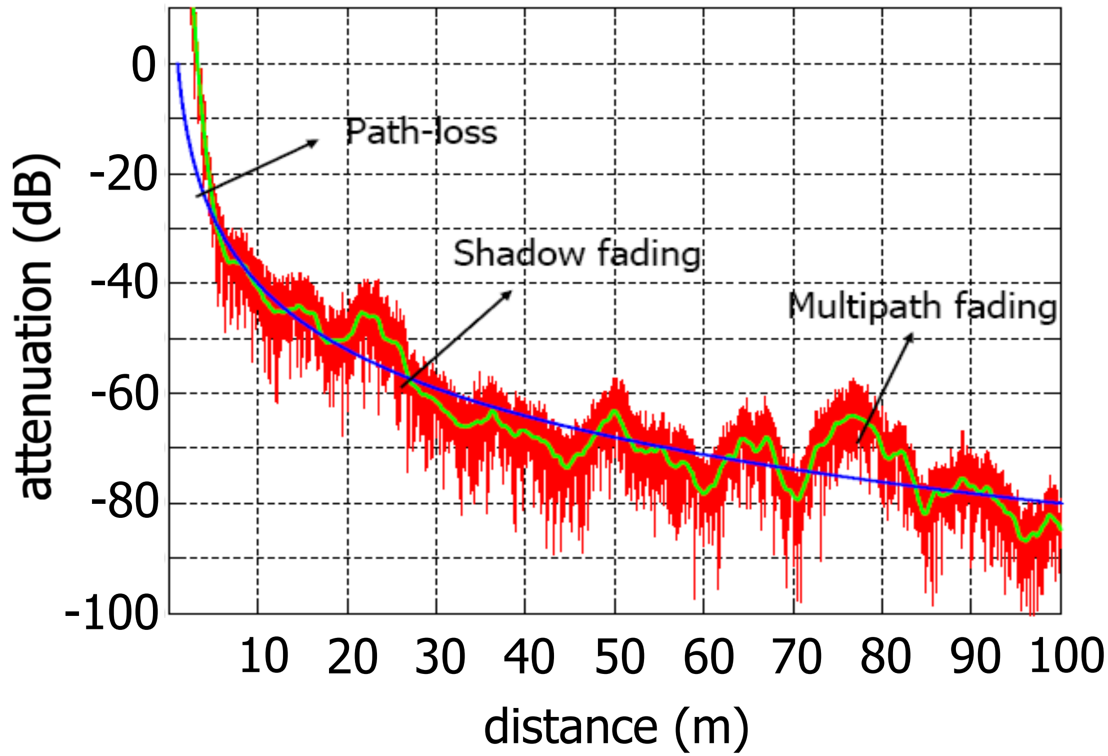
body absorption (5-25 dB) lead to
“teletransportation” of 10’s of meters

Solution (palliative): quadrant sampling

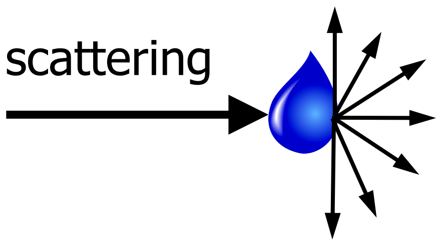


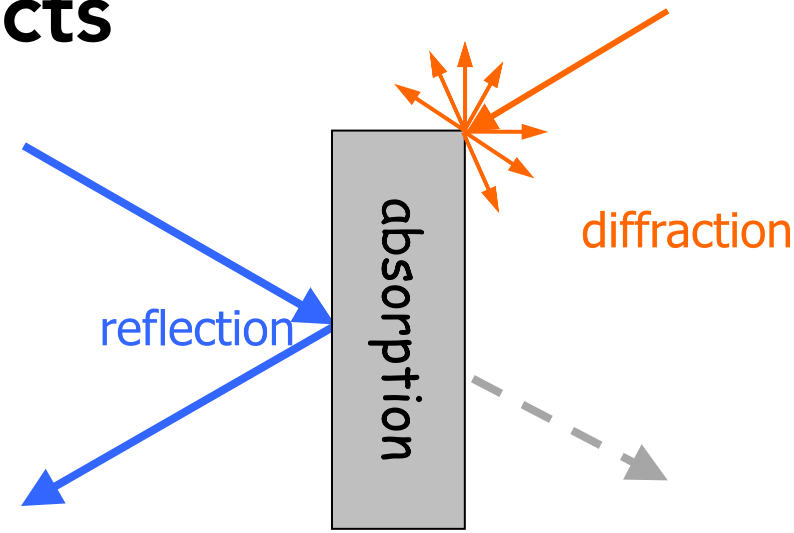


Multipath fading (red curve)



RF propagation effects

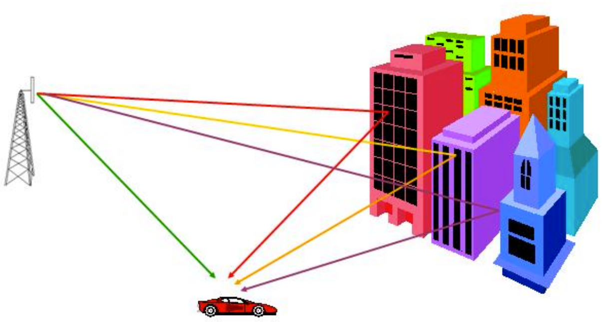




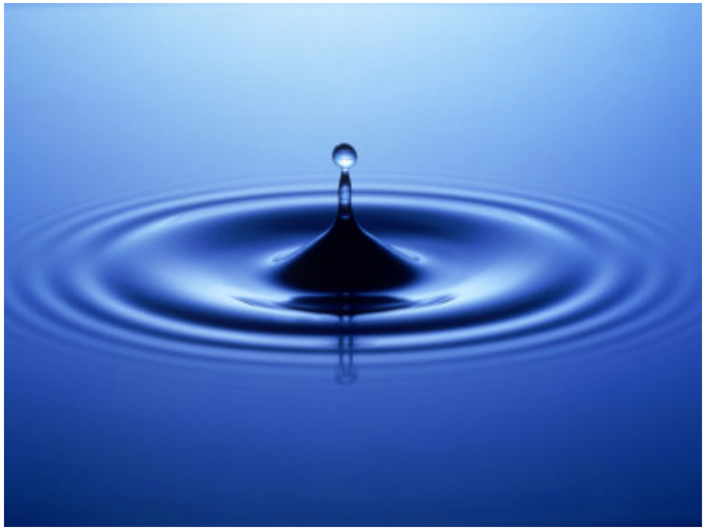
~ size of wavelength

>> size of wavelength

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



Wavelength and the size of objects

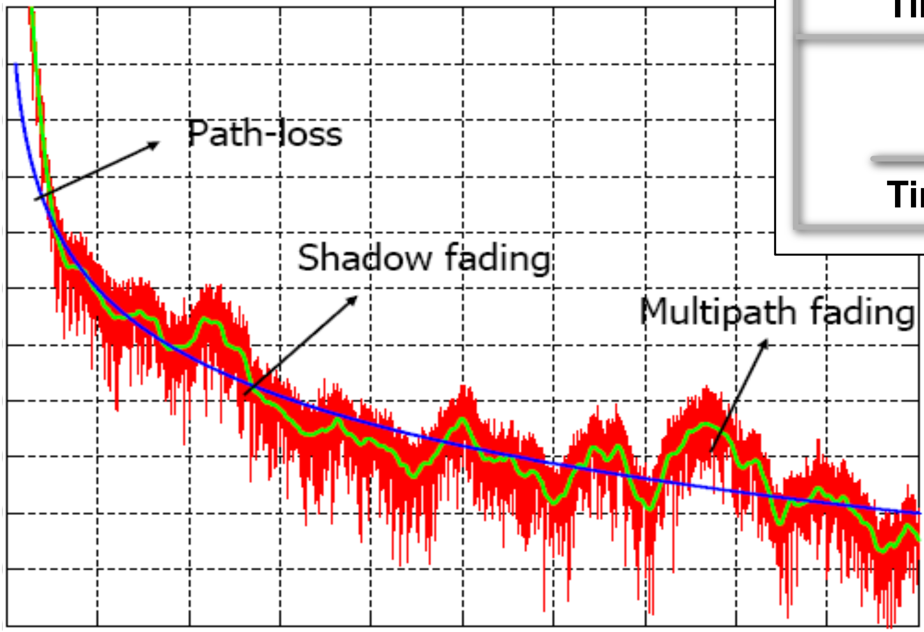


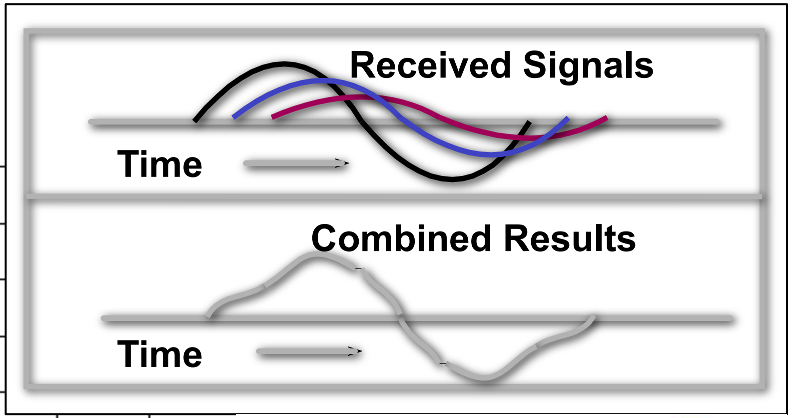
needle: negligible multipath effect

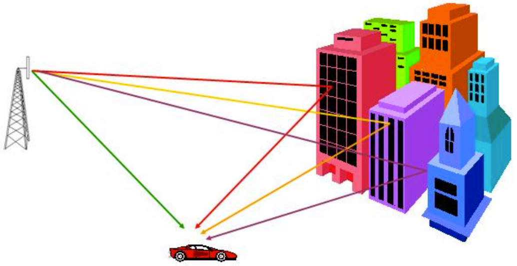
big rock: major multipath effect

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

Multipath





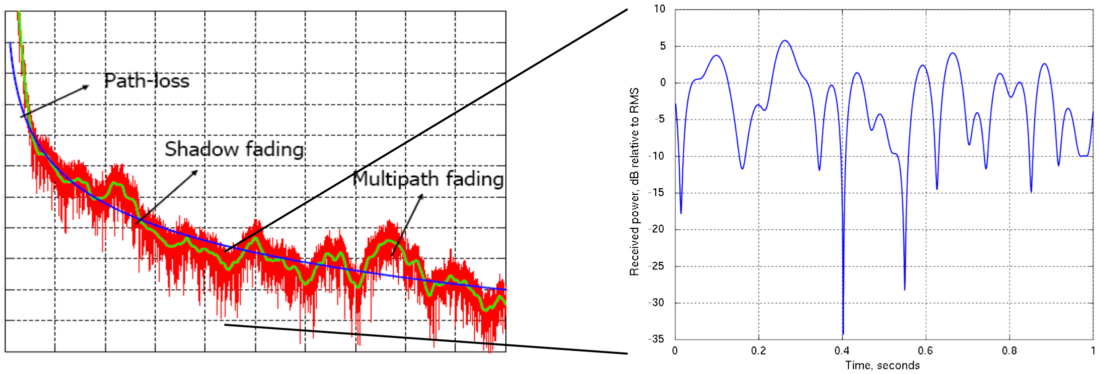


Propagation along multiple paths leads to self interference
Minor changes in environment can lead to dramatic changes in signal strength

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

Teletransportation problem 2: small scale fading

- Measure "n" RSS samples
  - 1 sample per second for 2 minutes should be ok.

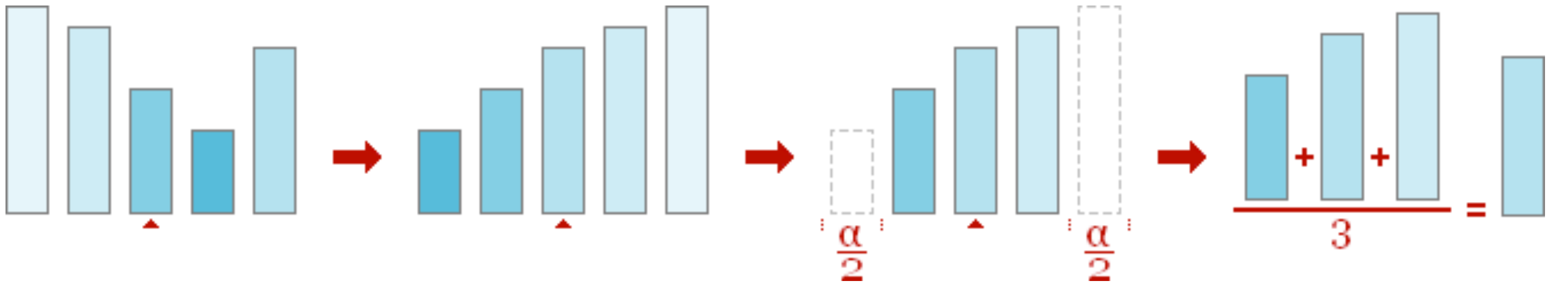


Rayleigh distribution
en.wikipedia.org/wiki/Rayleigh_fading

- 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)

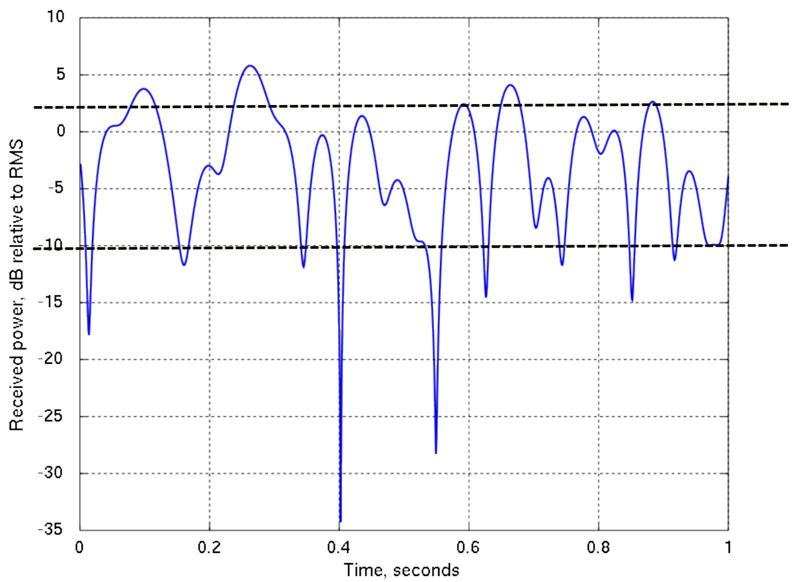
- Mean < alpha-trimmer < median
- Method:
  - Sort
  - Cut α/2 at the head and tail
  - Average



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

Alpha trimmer filters (2)

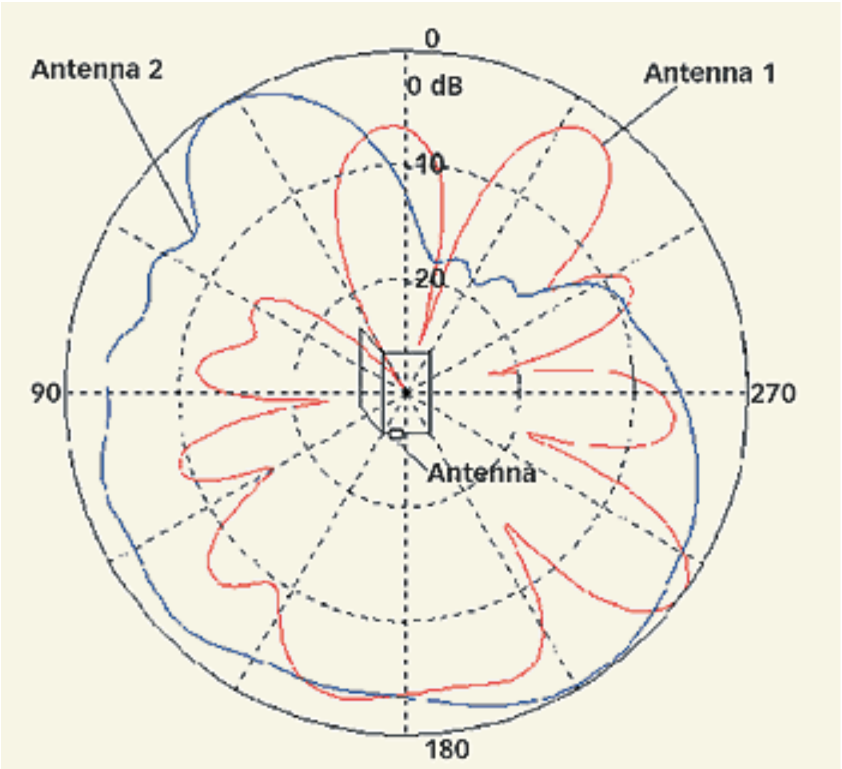
- α = 0 -> mean, α≈ 0.5 -> median
- α = 0.2 should be ok



cut unlikely events

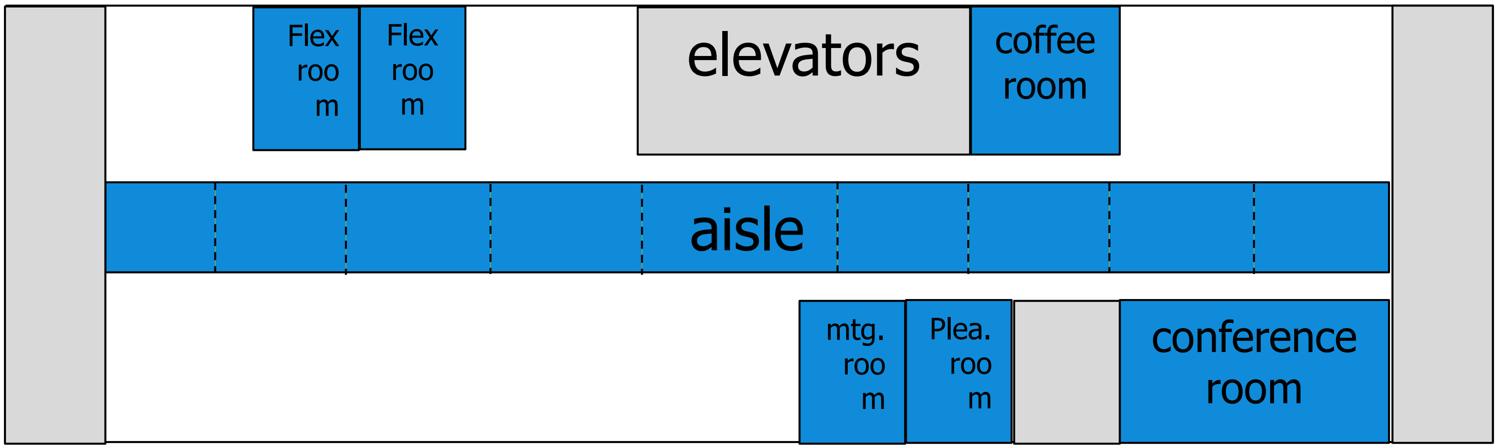
There are also antenna effects … but we won't discuss those here

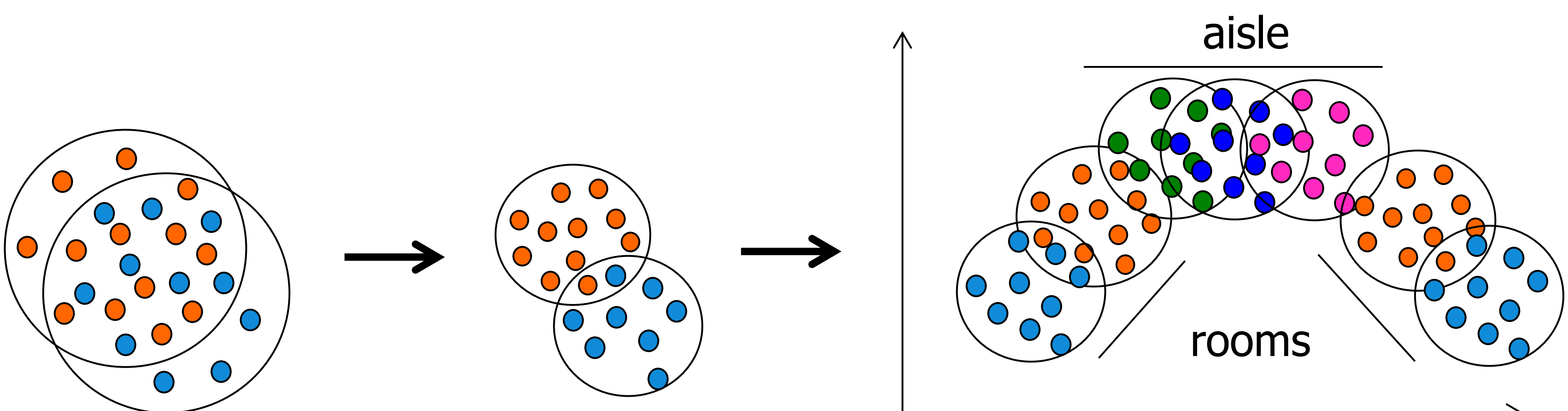
Distortion:
- metal objects
- electronics
- polarization



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

Revisting kNN localization





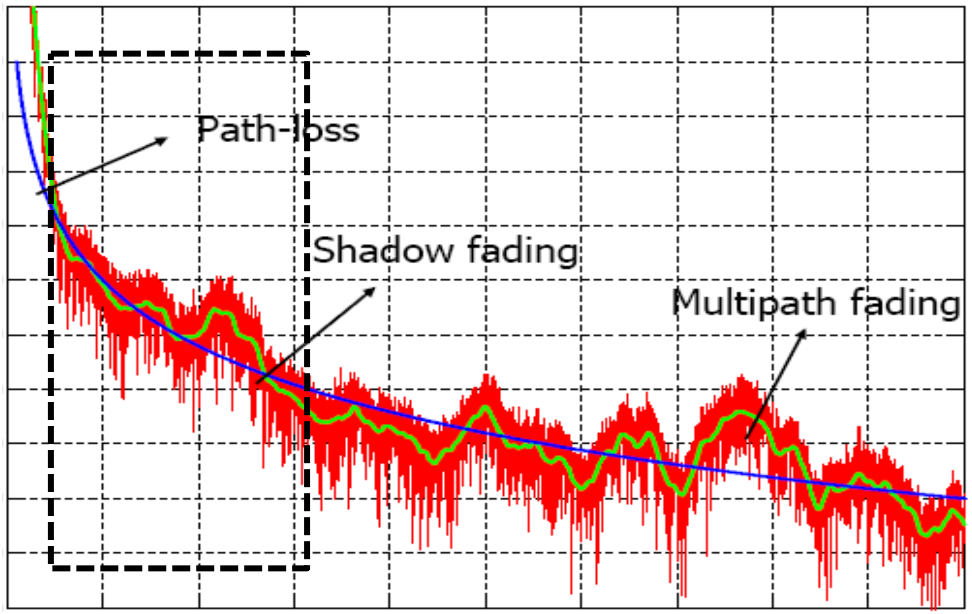
1) Sample RSS

2) Filter & get features

3) Test kNN

Sort of good news

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



Suggestions for localization part

- Recall RF signals are naughty
  - Body effects: quadrant sampling
  - Multipath effects: alpha trimmer

- This fingerprinting method is still very susceptible to changes in environment.
  - What if somebody moved a desk after training.

Pointers

- Alpha trimmer filter
  - http://www.librow.com/articles/article-7
- Fading (Wikipedia)

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 in online in our floor
10) Add motion model

Cell distributions

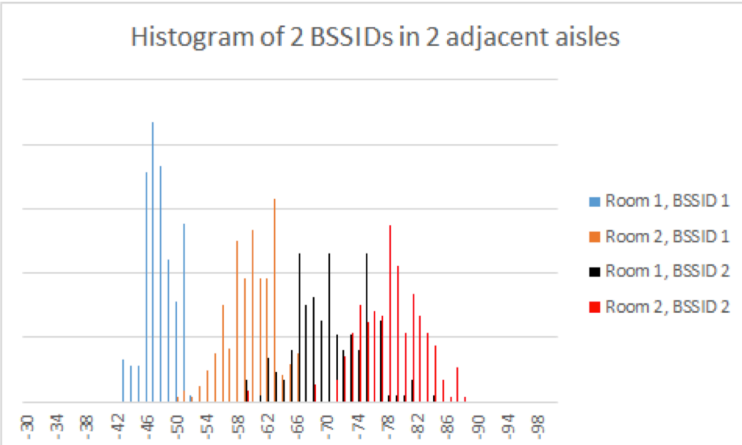
- The aisle will be divided in cells
- We will notify you about the times when we will open all the rooms for you to gather data

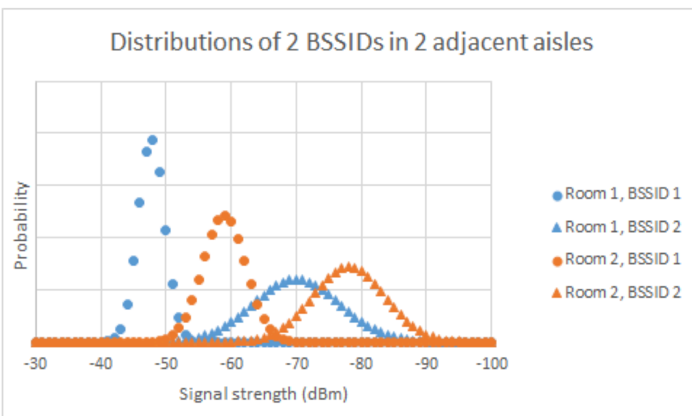
Clean SSID database

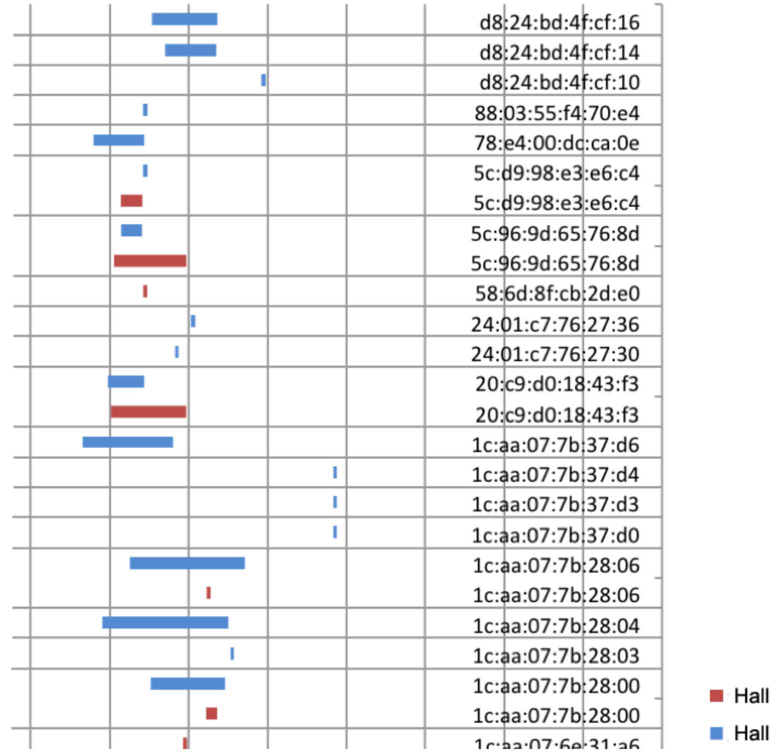
There may be:
1) Temporary Access Points (potentially a disastrous problem)
2) SSID's with many MAC addresses.
Filter them out.

	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
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	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	1	0	0	0	0	0	0	0	0	0	0
Hall 8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Hall 9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Hall 10	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Flex 1	0	0	0	0	0	0	0	0	0	0	0.95	0.05	0	0	0	0	0
Flex 2	0	0	0	0	0	0	0	0	0	0	0.08	0.92	0	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	0.99	0	0.01	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	0.4	0.6	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

Basic Activity Monitoring & Localization

k-NN

Report 1

Advanced Localization

problem: shadowing and fading

Bayesian filters

α-trimmer filters

Log normal shadowing

Particle filters

Report 2

Other Apps

Shazam

may not have time

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

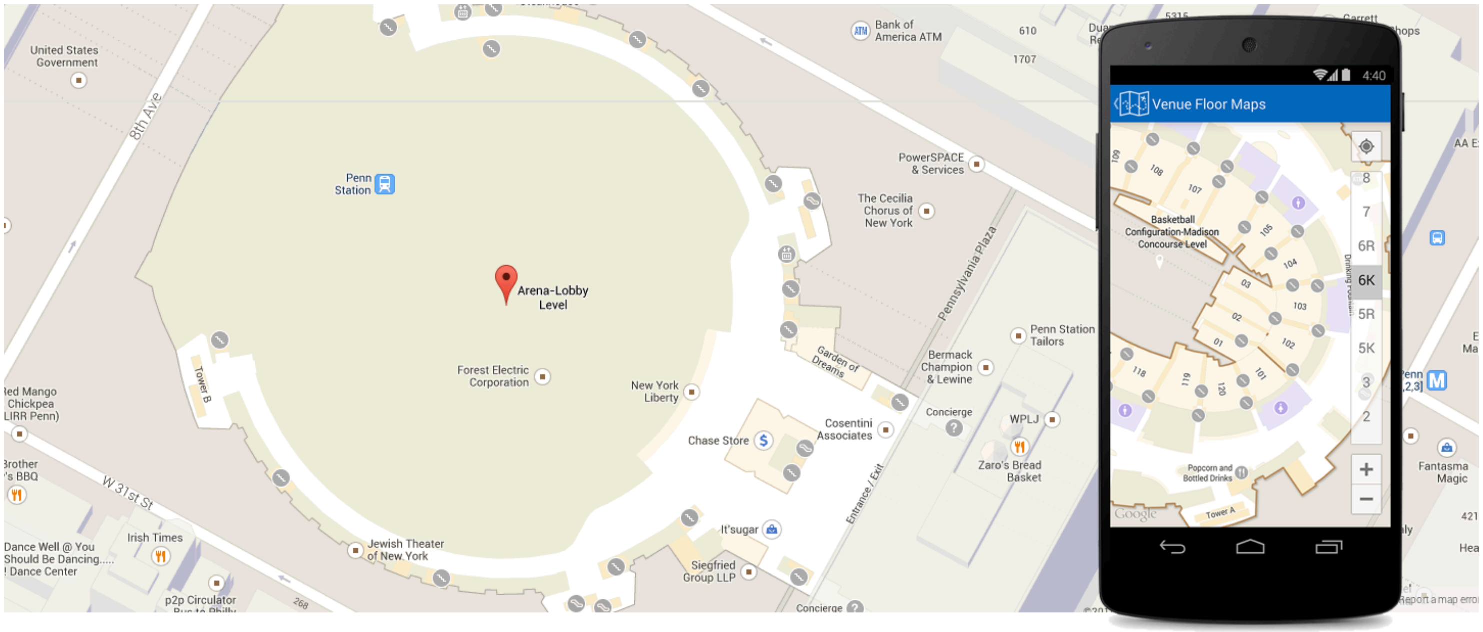
But I hate training!

Imagine training a building with 100 floors and 10K offices

Solution

GET A MAP!

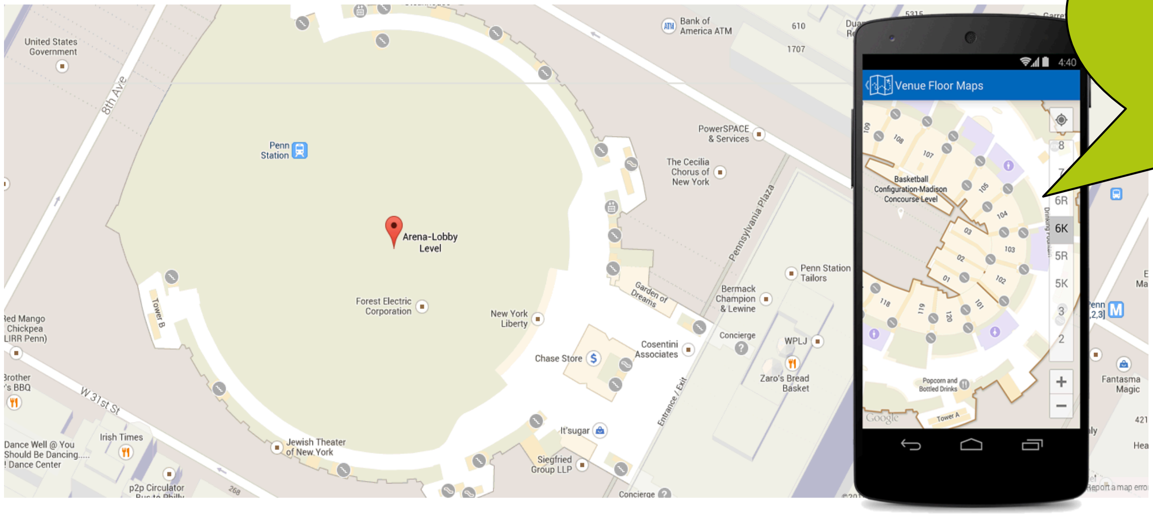
Indoor maps (google)



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.

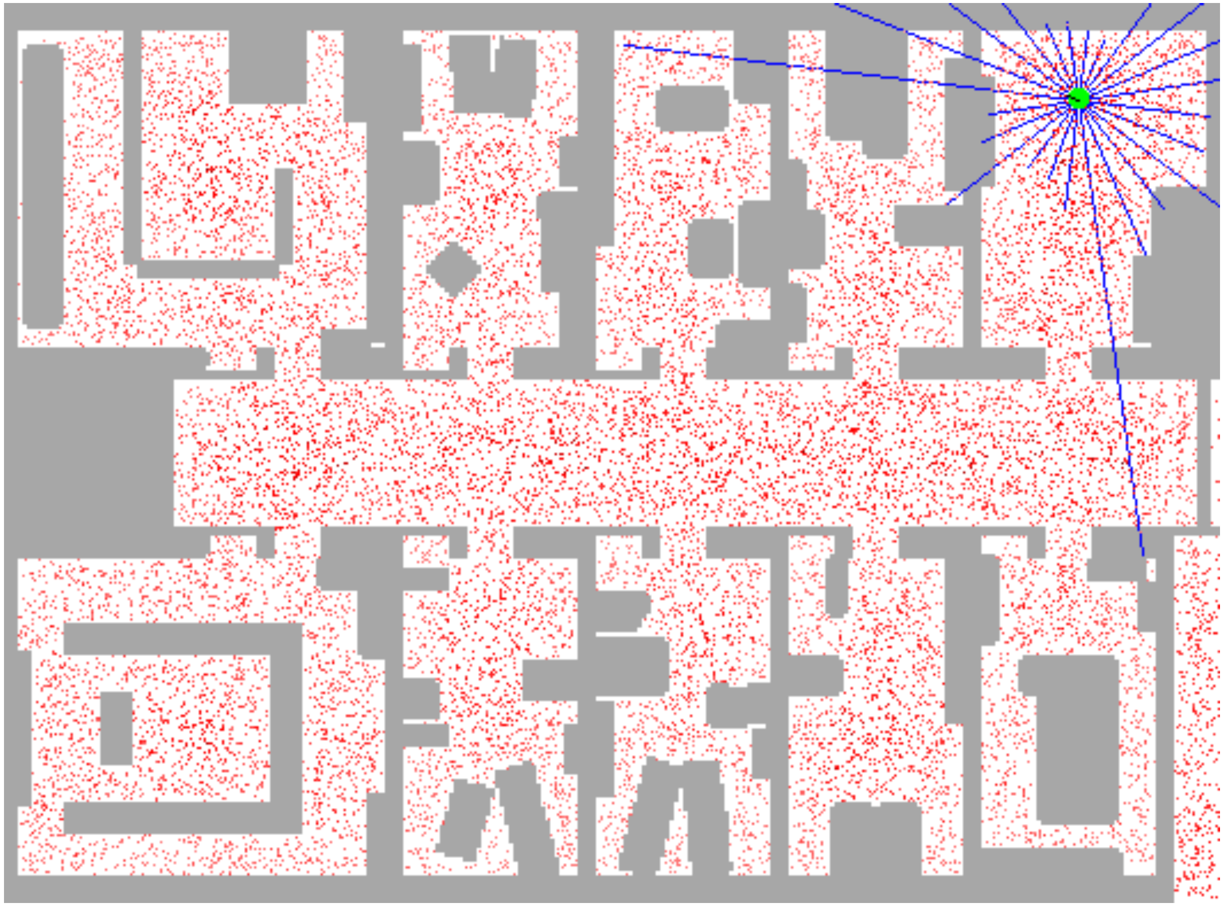
This Lecture has 3 parts

1) Particle Filters

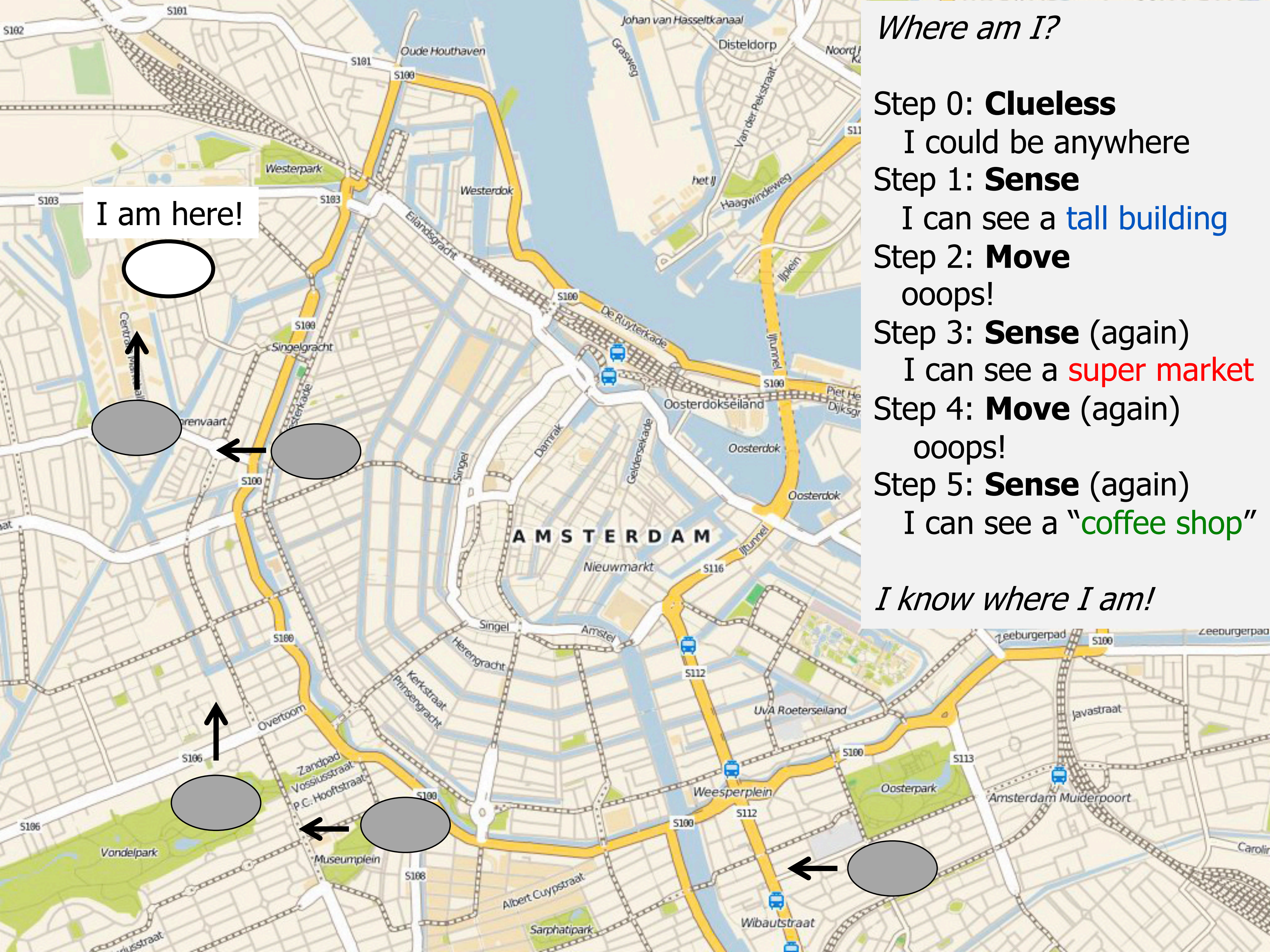
2) Motion model: distance and direction

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?

Step 0: **Clueless**

I could be anywhere

Step 1: **Sense**

I can see a tall building

Step 2: **Move**

ooops!

Step 3: **Sense** (again)

I can see a super market

Step 4: **Move** (again)

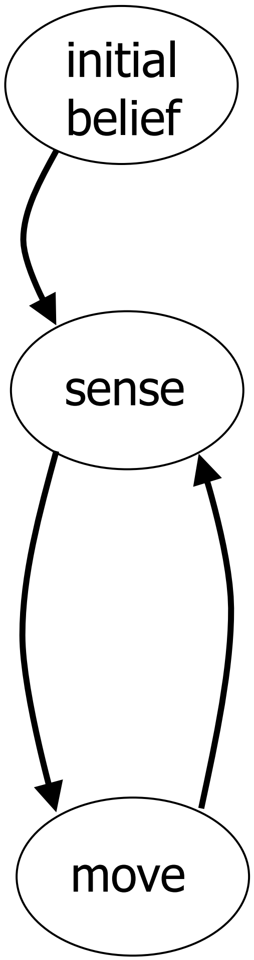
ooops!

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, X represents location and Z measurements



current pdf (**posterior**) — perception model (sense) — pdf from last time step (prior)

$$p(X_k \mid Z_{1:k}) = \frac{p(Z_k \mid X_k)\quad p(X_k \mid Z_{1:k-1})}{p(Z_k \mid Z_{1:k-1})}$$

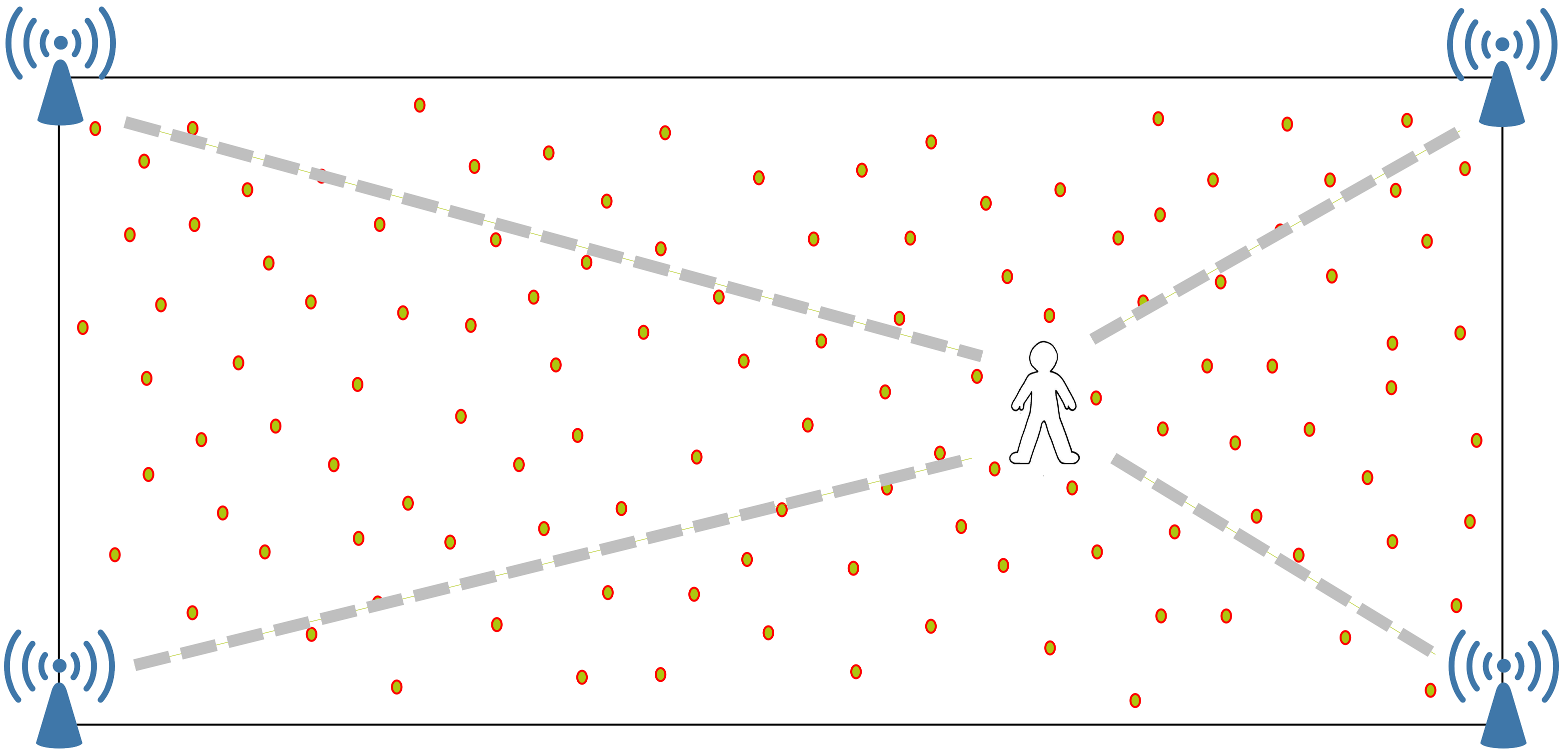
normalization

current pdf (**posterior**) — motion model (move) — pdf from last time step (prior)

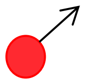
$$p(X_k \mid Z_{1:k-1}) = \int p(X_k \mid X_{k-1})\; p(X_{k-1} \mid Z_{1:k-1})\, dX_{k-1}$$

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

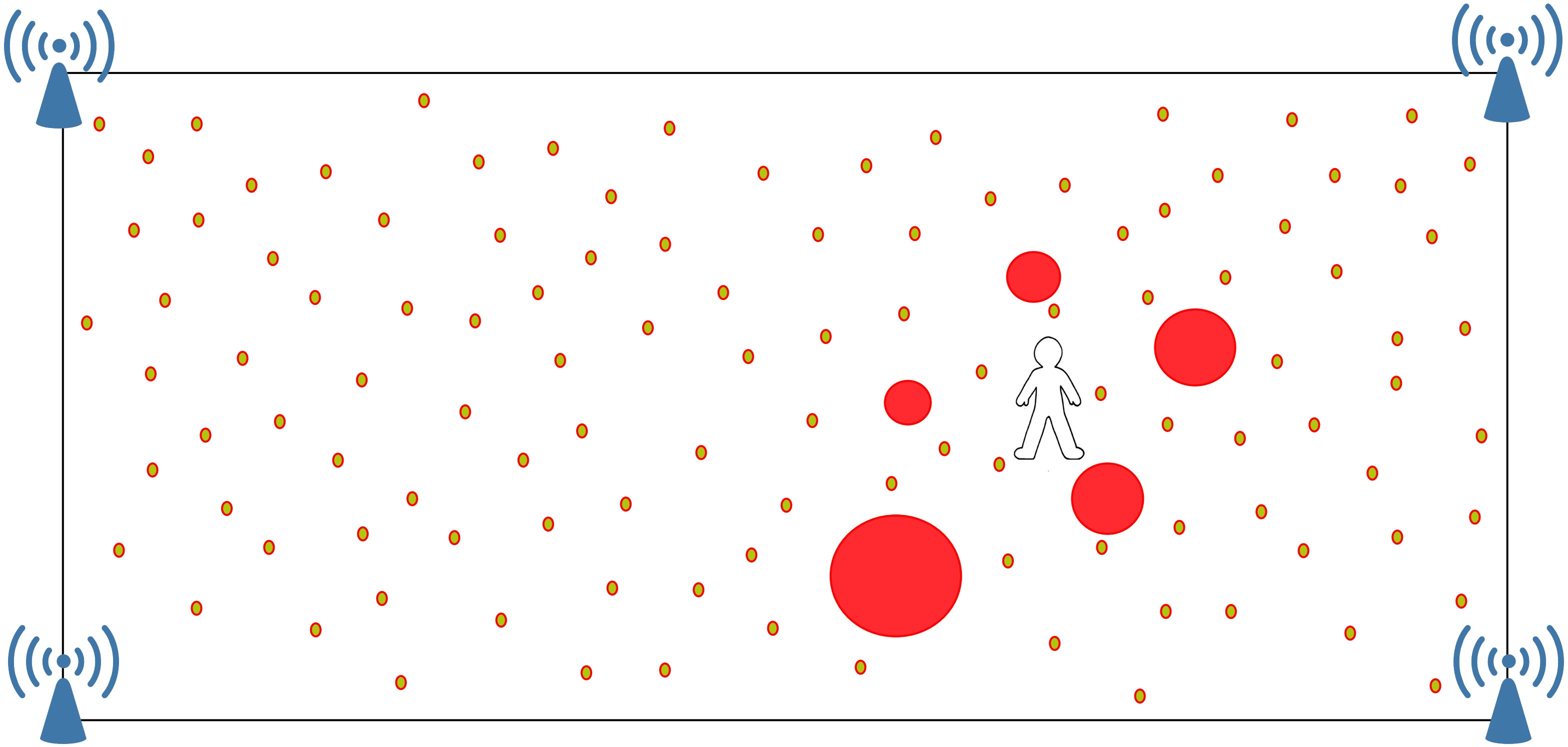
Initial distribution of particles



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



Importance weight

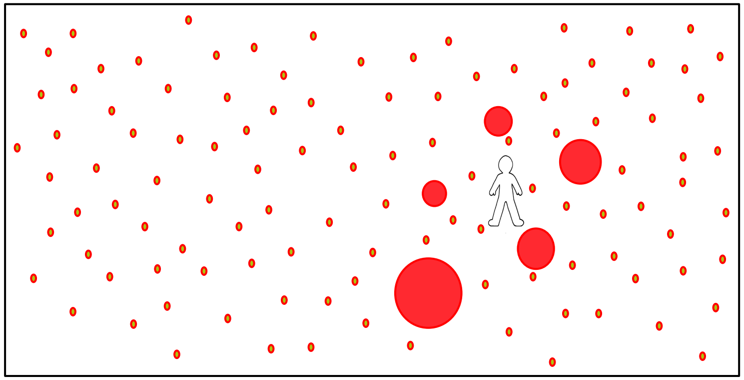


particles will have different weights depending on their likelihood of being the `right guess'

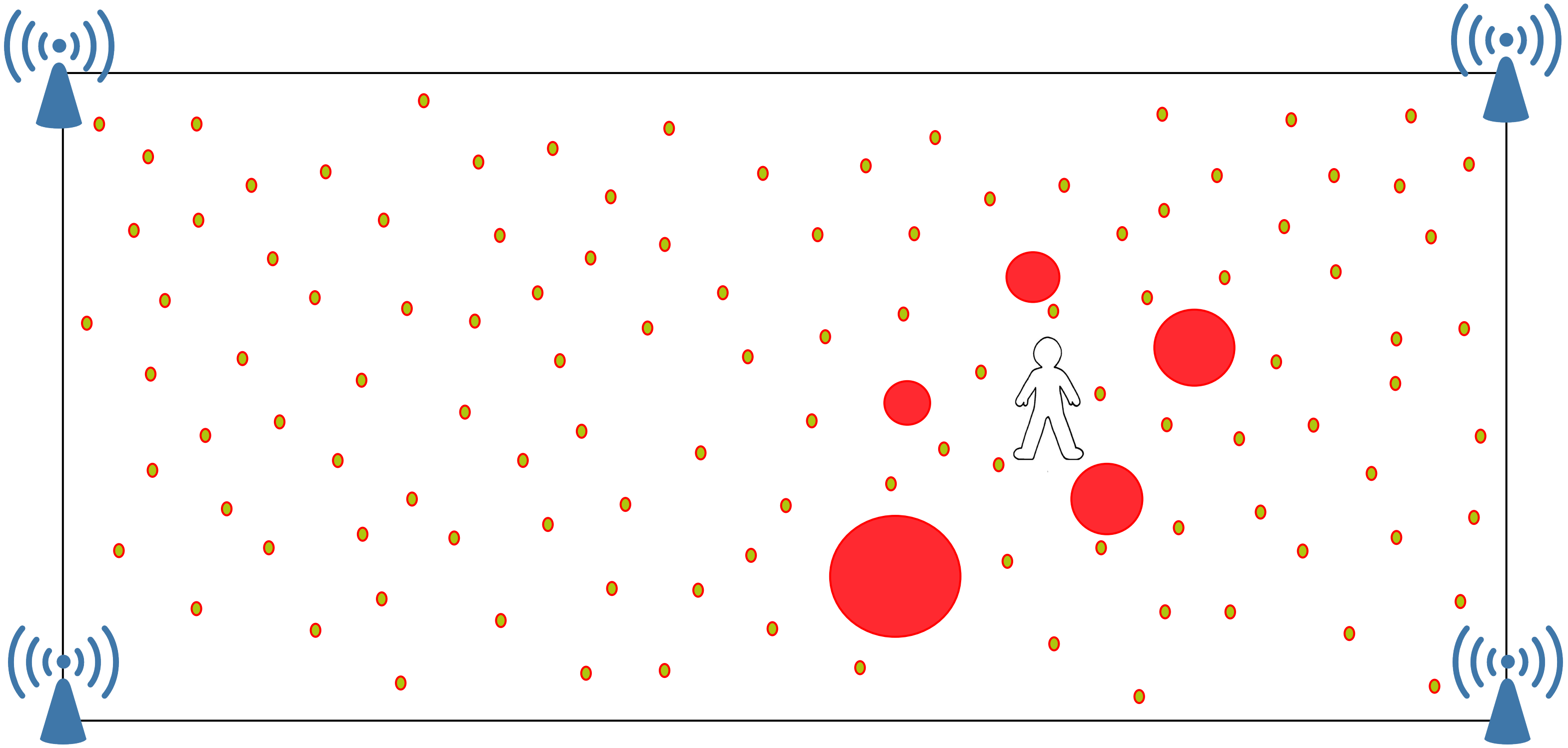
Resampling

- 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

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

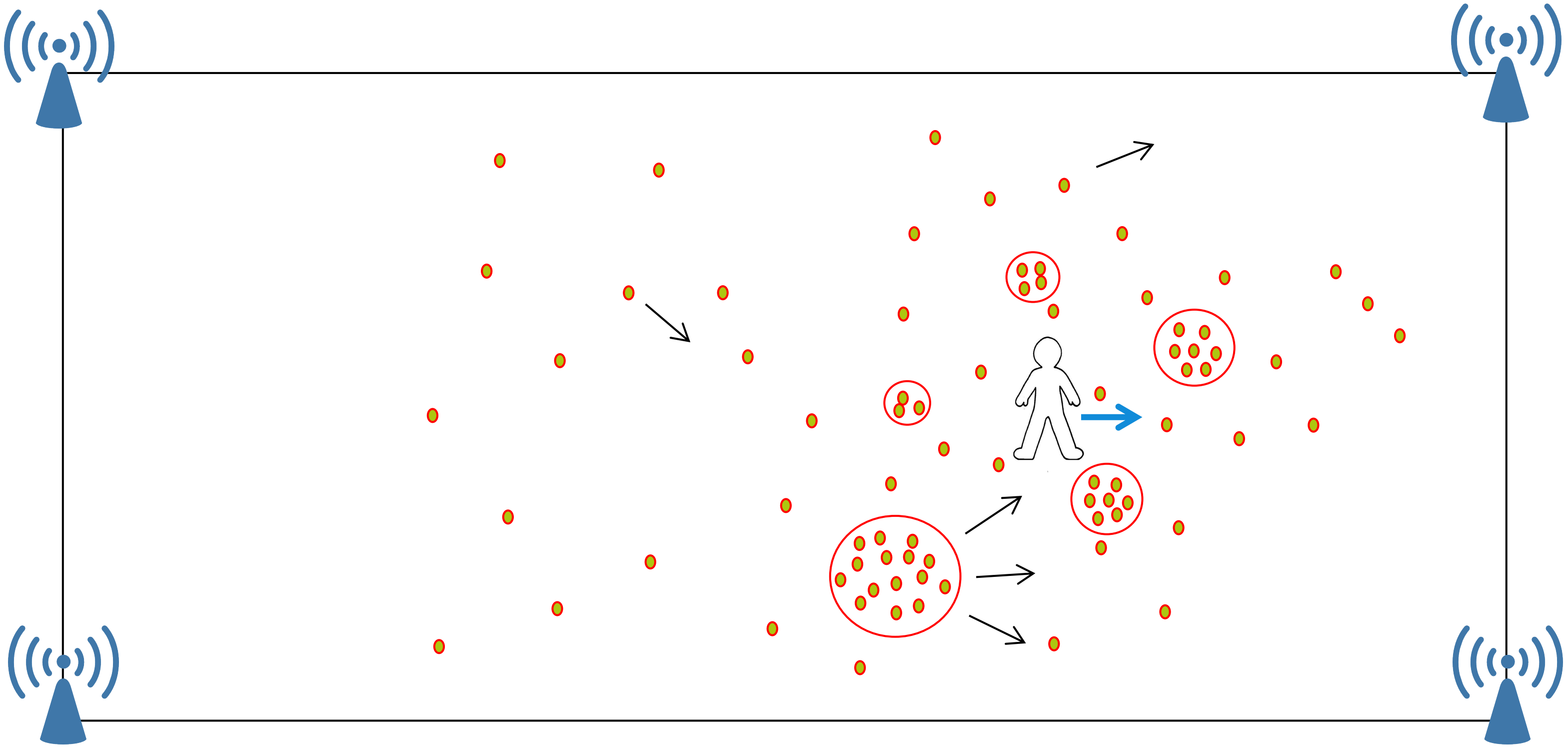


Resampling (1)



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

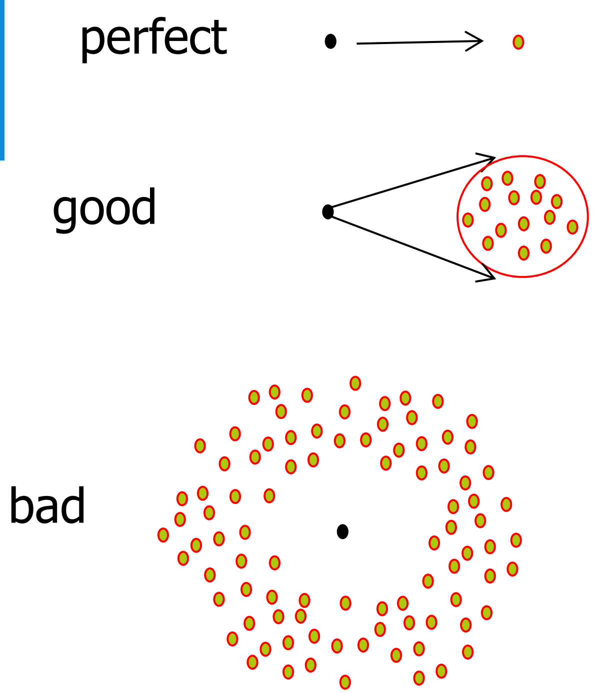
- Each particle i will have a likelihood p_i
- The weight of each particle will be

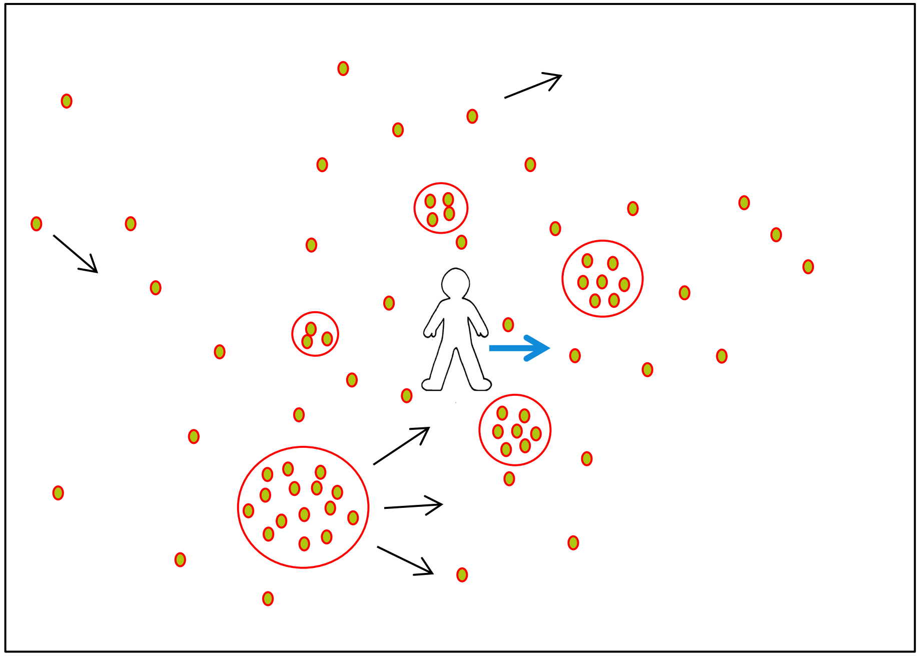
$$w_i = \frac{p_i}{\Sigma p_i}$$

- 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





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

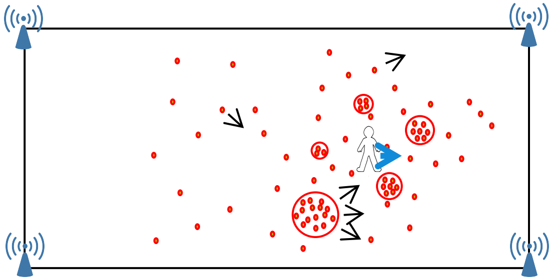
Resampling

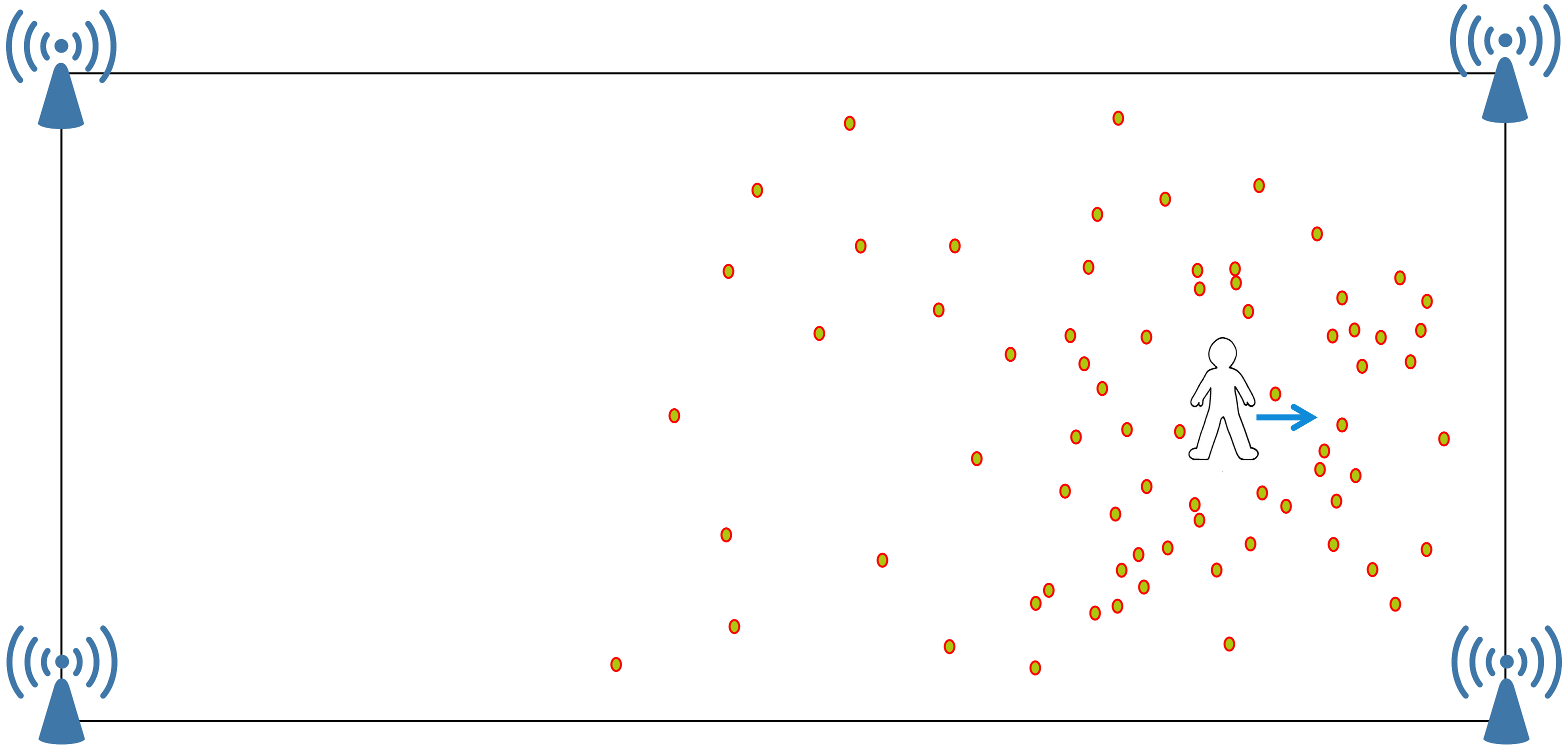
- Each particle i will have a likelihood p_i
- The weight of each particle will be

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

- 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.
- The new particles will have different destinations according to the mobility model

Motion model

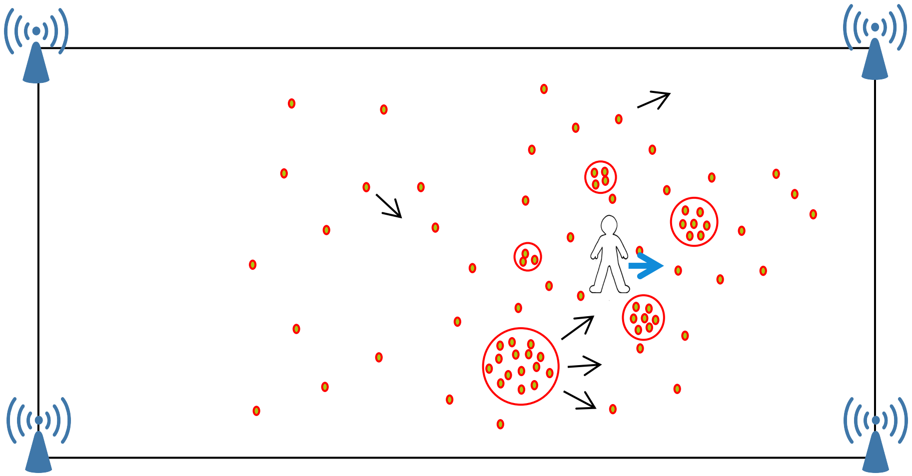




After moving each particle, repeat the *importance weight* and *resampling* steps.
In time only the most likelihood options will remain (survival of the fittest)

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