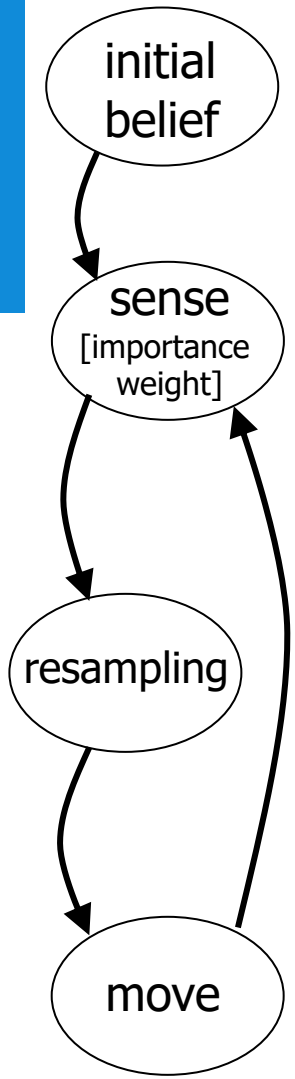
Lecture 06

SmartPhone Sensing

Back to the math, we need to add one more step: resampling



If you have no idea where you are, throw particles everywhere

---

current pdf (**posterior**) = perception model (sense) × pdf from last time step (prior) / normalization

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

---

take N new particles (with replacement) from new posterior

$$p(X_k \mid Z_{1:k})$$

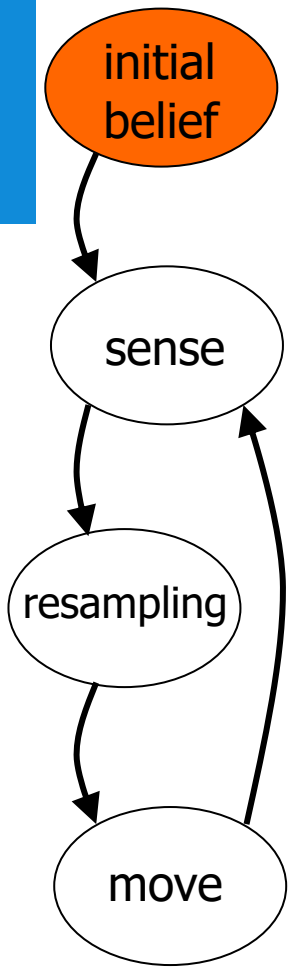
---

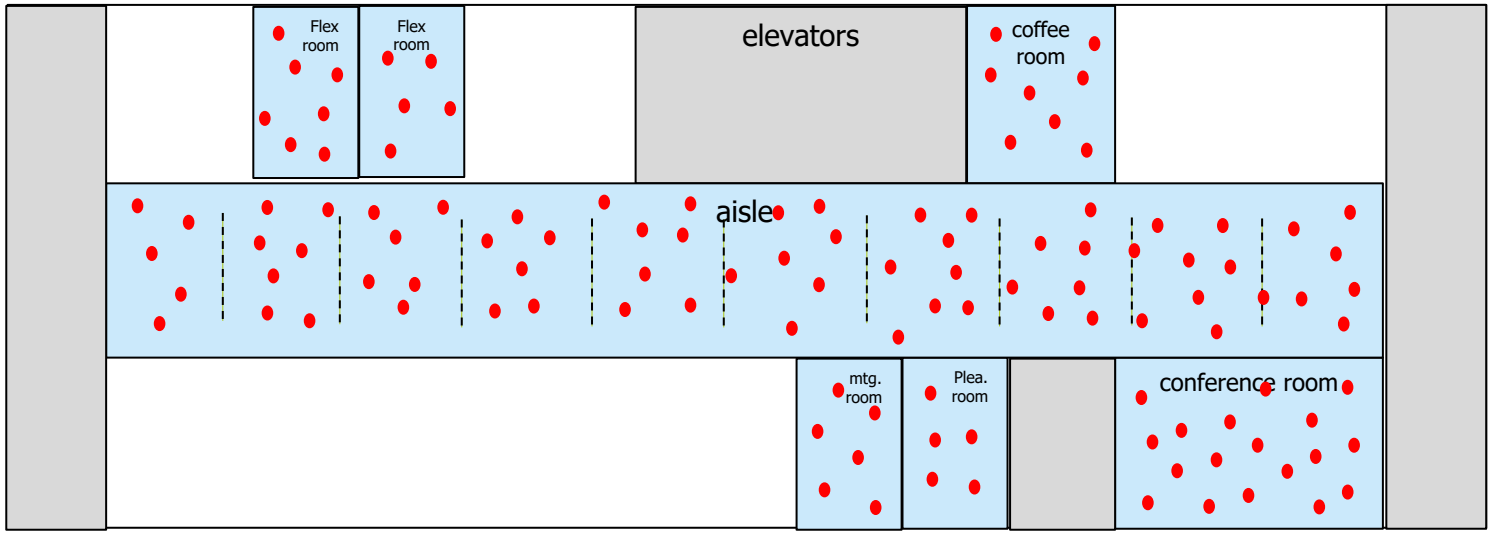
current pdf (**posterior**) = motion model (move) × pdf from last time step (prior)

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

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

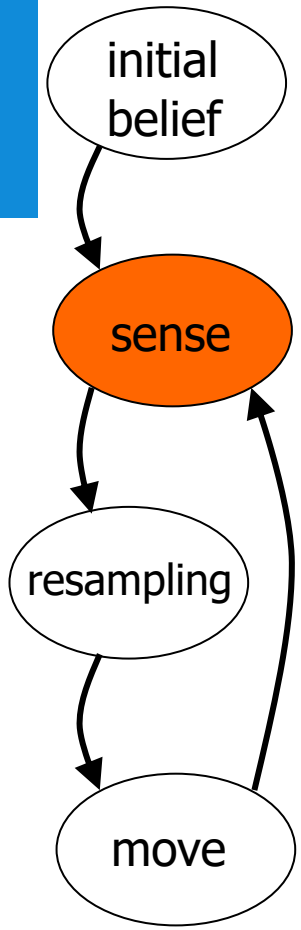
A toy example



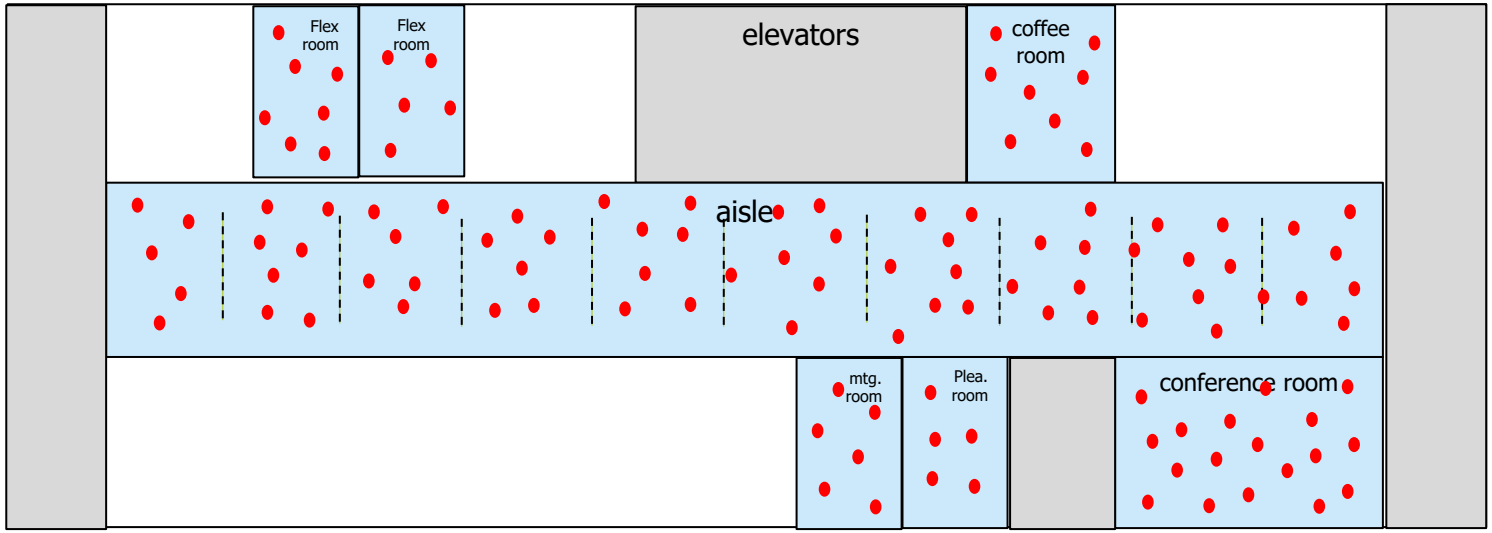


In your phone, you should have a table with (x,y) information for each particle. Put thousands of particles: 5k to10k.

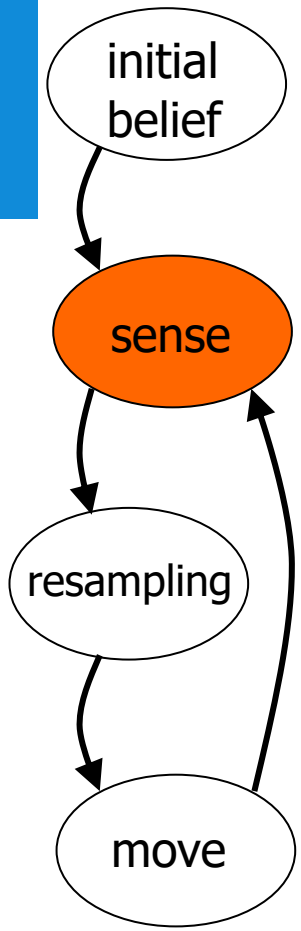
Sense



- We need to get the importance weight.
- What do we sense?
- How do we update the weight?



Sense



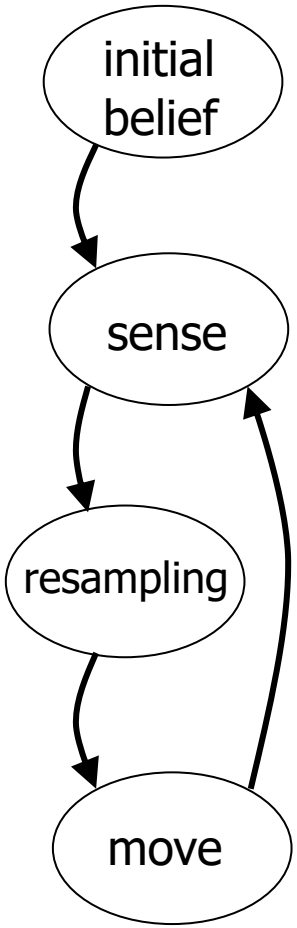
- We need to get the importance weight.
- What do we sense?
- How do we update the weight?

But hold on, we can't update much.
We don't know where we are, we have no training data, no model, nothing.

We can't calculate weights or do resampling.

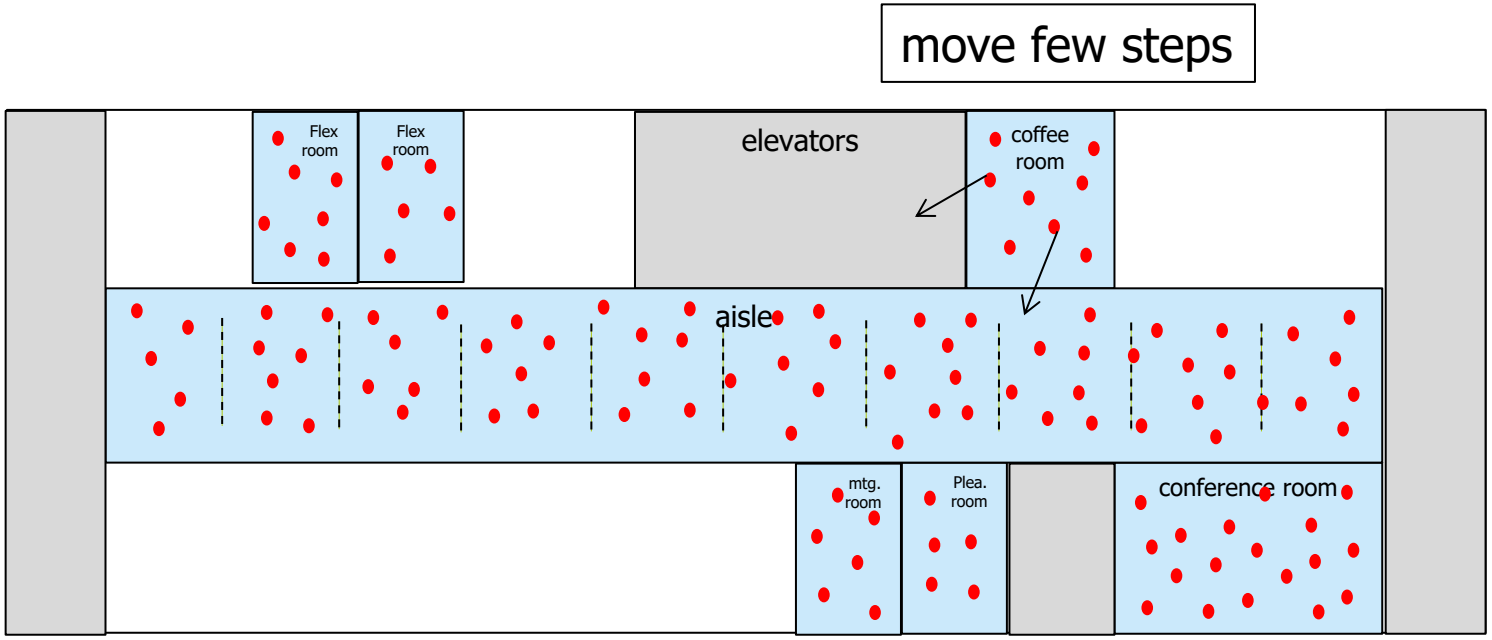
What do we do now? How do we update our prior?

Move



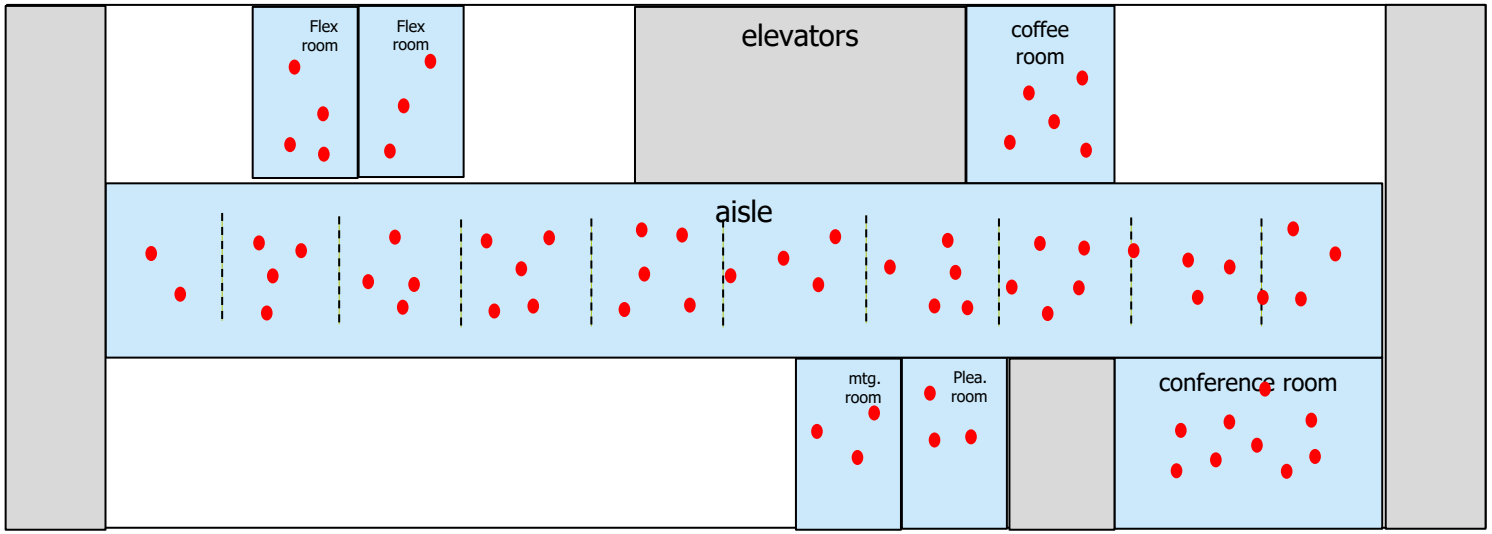
- Let's skip `sense' and `resampling' states … and `move'
- Assume you can count your steps
  - STEP_COUNTER in Android
- Initially with random direction
  - ROTATION_VECTOR in Android (to get direction)
  - Zee's contributions are in the motion model

Move & sense



Now we can **sense** physical constraints.
If a path intersects a wall, the particle is eliminated.

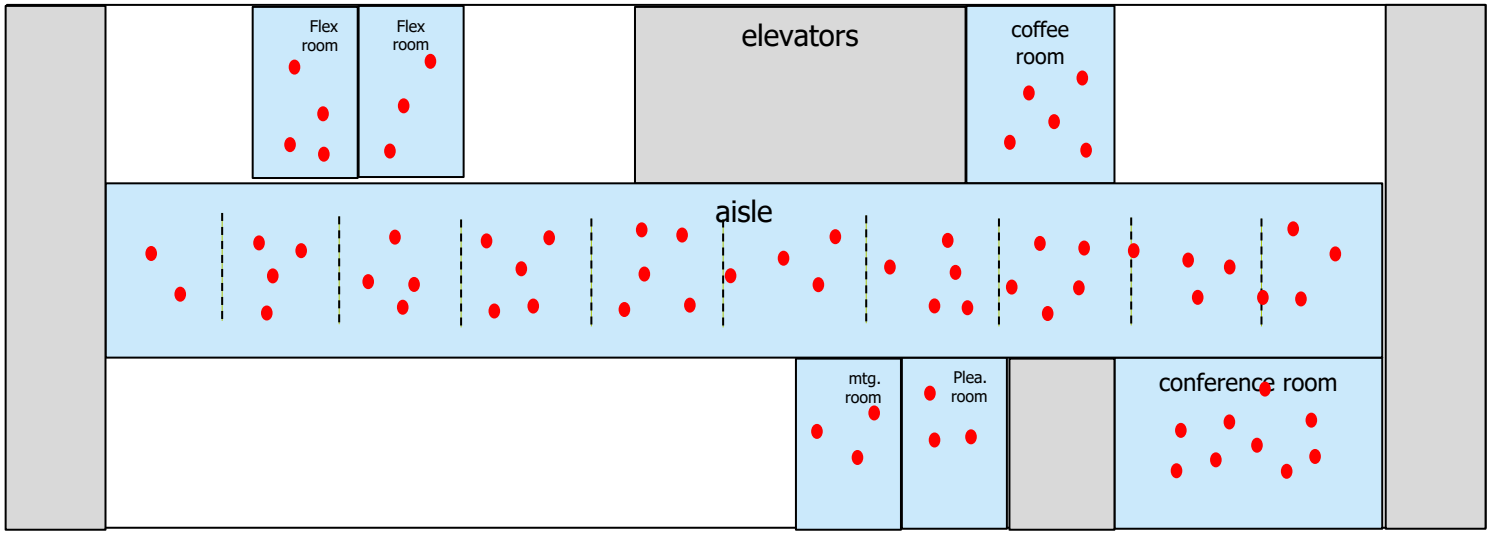
Resample



Particles close to walls should start disappearing.
To replace a particle, choose randomly among the set in the previous step and update.

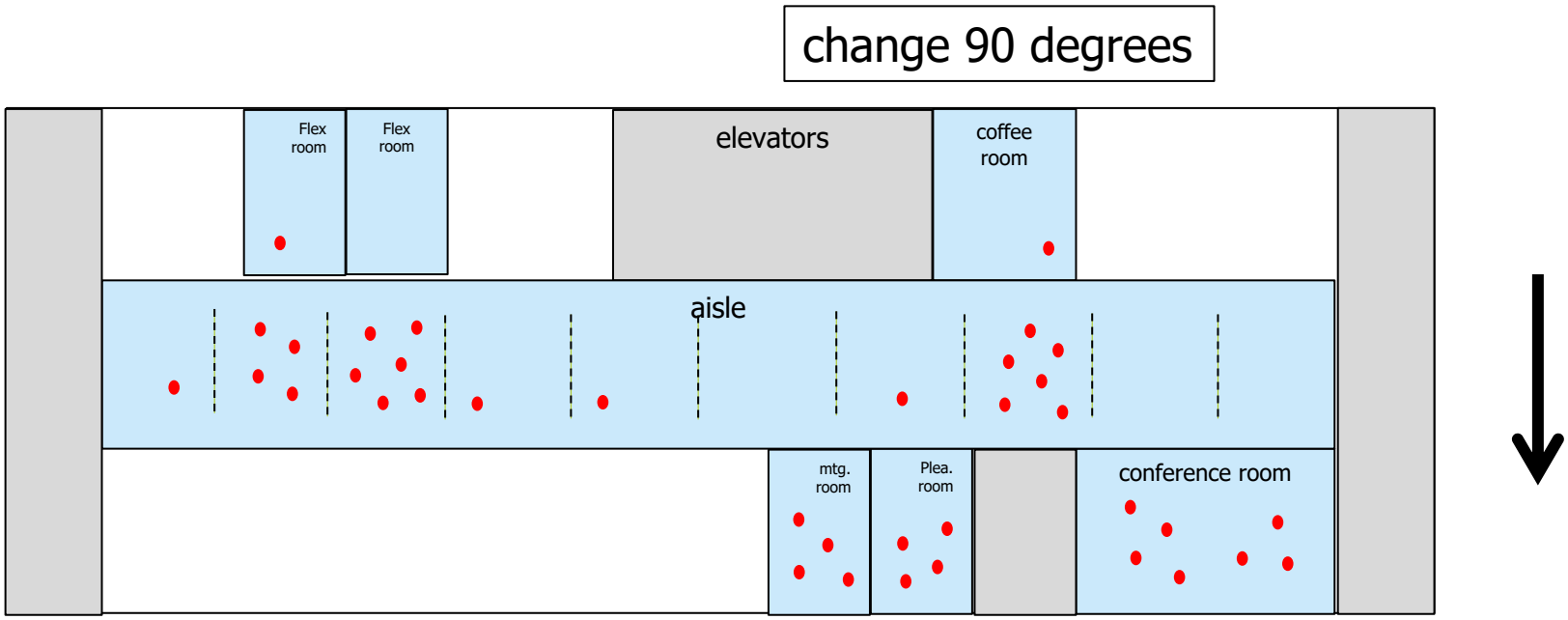
Importance of capturing motion accurately (1)

change 90 degrees



What cells would end up with more particles (concentration)?

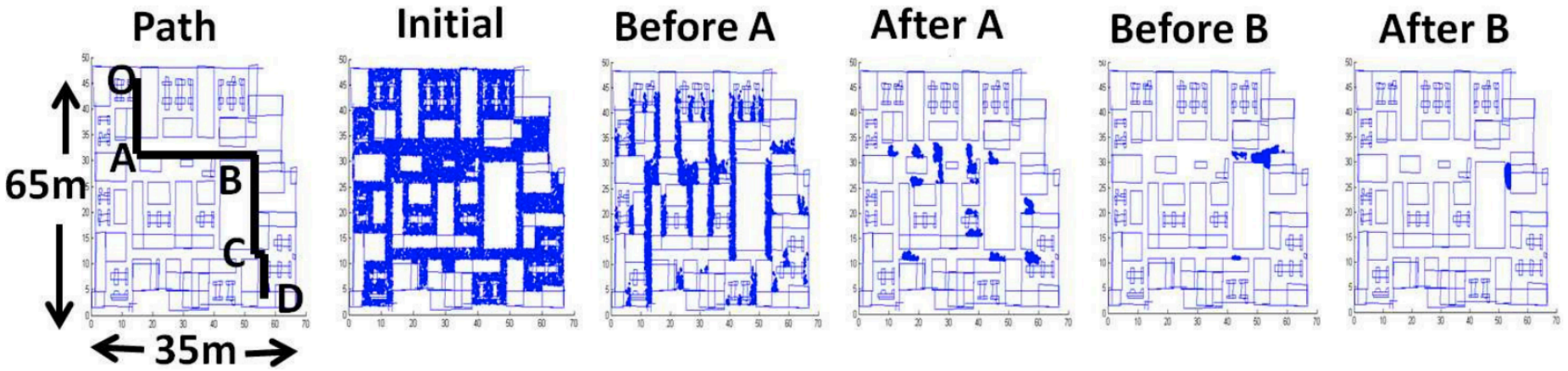
Importance of capturing motion accurately (2)



We are left with a dense (particle) areas!

A good model for distance and direction would accelerate 'convergence'. We don't want random walks.

Particle update in real scenario



Turns accelerate the convergence process significantly

IMPORTANT:

Only use these methods if you CANNOT use STEP_COUNTER and ROTATION_VECTOR.

If you have to develop the motion model on your own, you must notify me, to adjust your evaluation accordingly

MOTION MODEL

Capturing people's motion

- Each particle has (x, y, distance, direction)

- Given the importance of capturing motion accurately, the paper focuses on:

1) Counting steps (distance)
   - Standard deviation
   - Autocorrelation

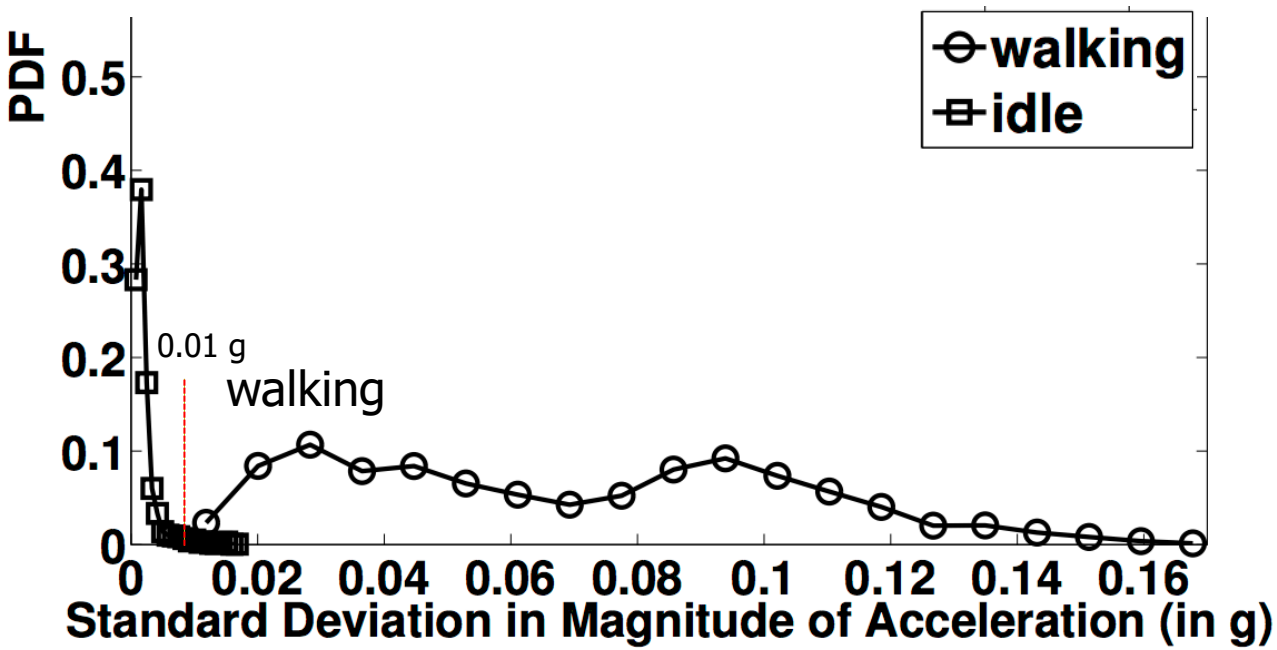
2) Heading Offset (direction)
   - Fourier transforms
   - Geometry

Counting steps

- Method works irrespective of device placement.
  - Tested in pockets, bags, belt, hands.

- Method relies on
  - Standard deviation of acceleration ☺
  - Autocorrelation

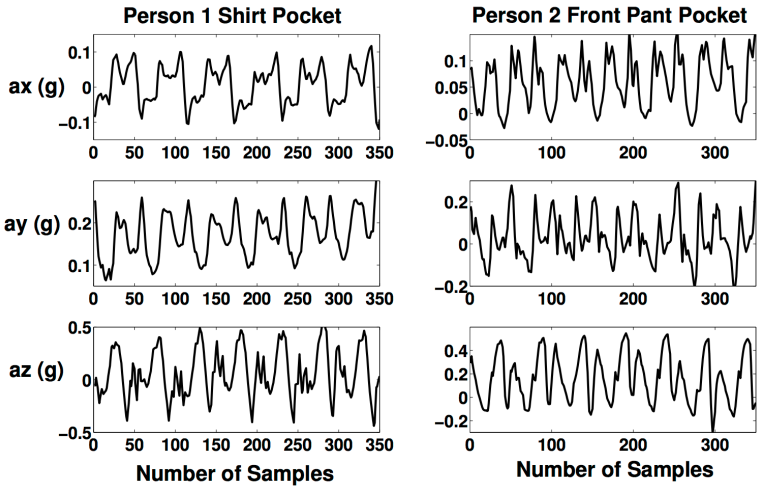
Standard deviation



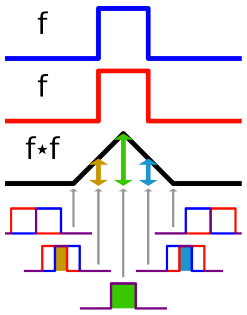
you know this already!

- 6 people (man/women) with phone in different positions.
- Feature: magnitude of acceleration. Window: 1 sec
- But acceleration is not sufficient, sudden movements such as hand waiving, chair rotation, standing up, also cause acceleration

Autocorrelation

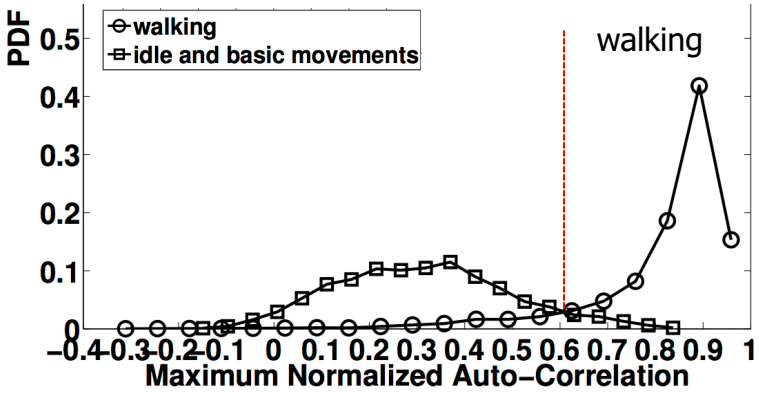


$$R(\tau) = \frac{\mathrm{E}[(X_t - \mu)(X_{t+\tau} - \mu)]}{\sigma^2},$$



We need to take advantage of repetitive nature of walk

The period also provides the time taken per step (τ/2)



Final algorithms and results

Algorithm

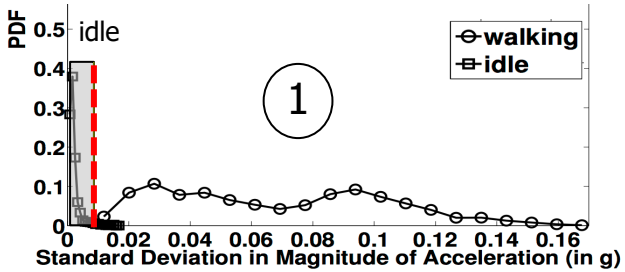
If σ|all| < 0.01 then *state* = IDLE.

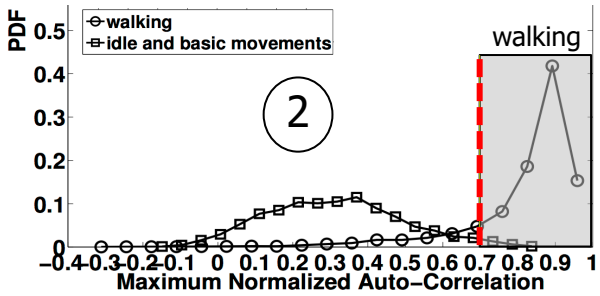
Else If ψ > 0.7 then *state* = WALKING.

Else no change in current value of *state*.

	Hand While Using	Pant Front Pocket	Pant Back Pocket	Hand Not Using	Shirt Pocket	Hand bag	Over (all)
False +ive	0%	0%	0%	0%	0%	0%	0%
False -ive	2%	0%	0%	0%	0%	0%	0.6%
True +ive	100%	100%	100%	100%	100%	100%	100%
True -ive	98%	100%	100%	100%	100%	100%	99.4%

Great results for various placements!
The method is a combination of what (some of) you guys are doing!





3

keep previous state

Recall that each particle has four parameters (x, y, distance, direction)

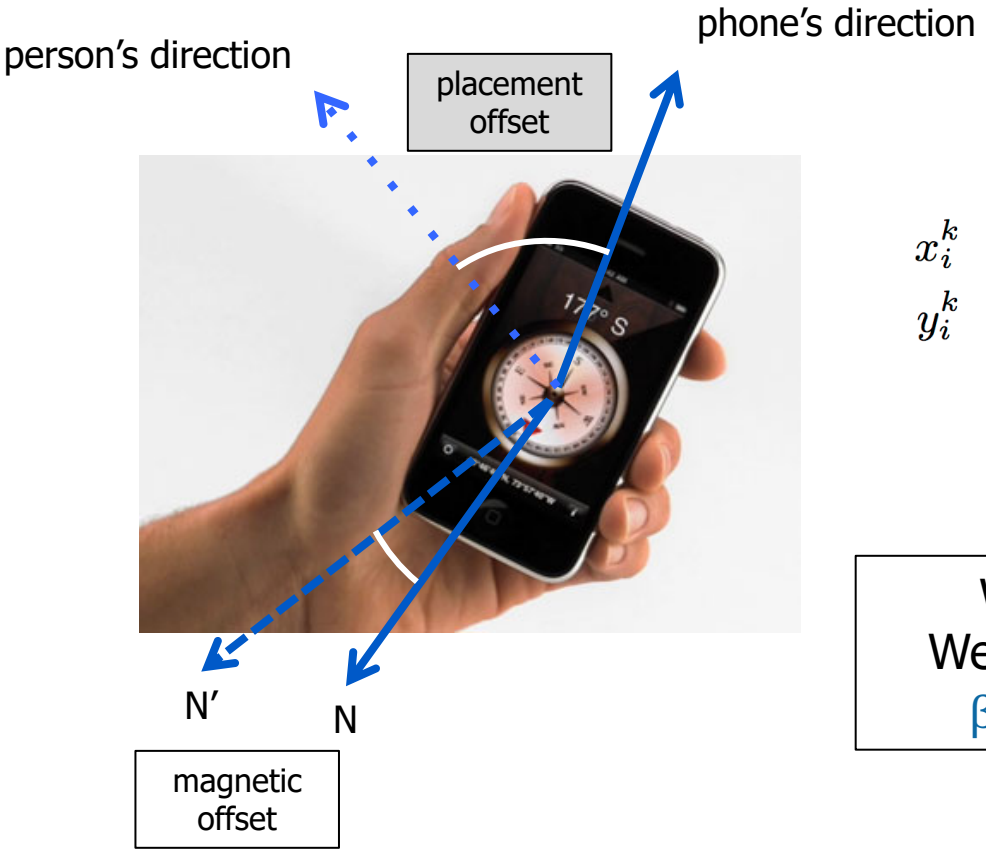
We now have distance

But we still need direction

Heading offset

The phone gives you a relative direction with respect to the cardinal North (like any compass would do)

Placement & magnetic offsets



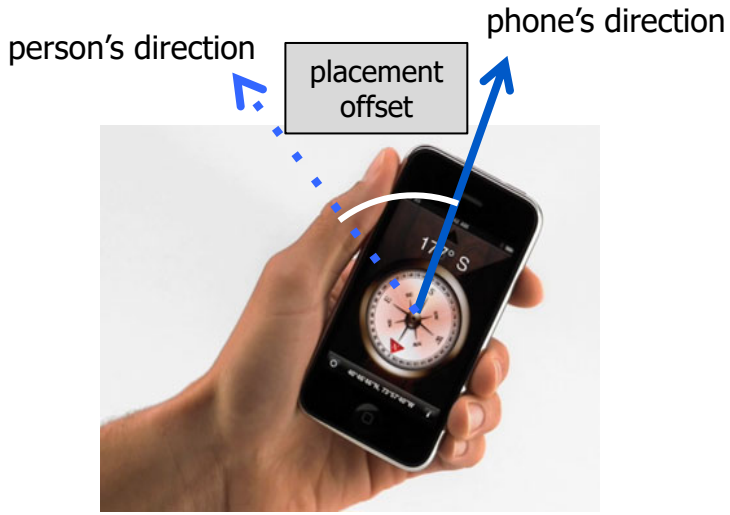
$$x_i^k = x_i^{k-1} + (s_i + \delta_i)\cos(\alpha_i + \theta + \beta_i)$$
$$y_i^k = y_i^{k-1} + (s_i + \delta_i)\sin(\alpha_i + \theta + \beta_i)$$

distance direction

We have Θ (phone direction).
We need α (placement offset) and β(magnetic offset plus errors).

Placement offset

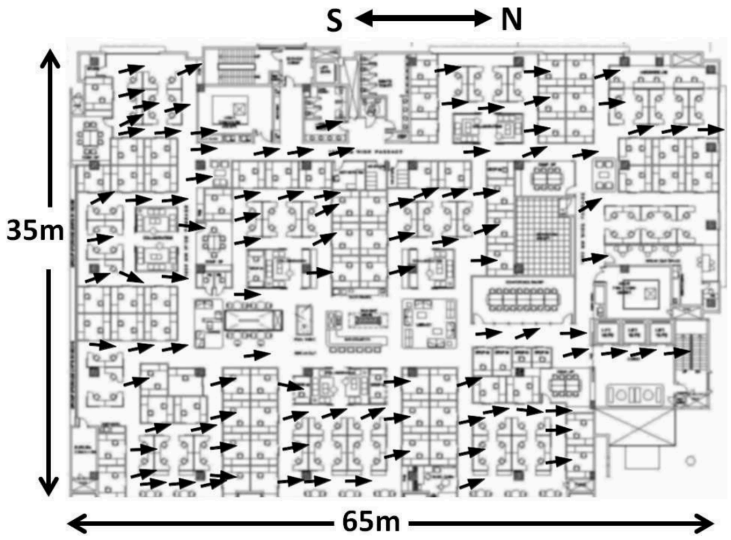
- The phone very likely points to a direction different from our moving direction.



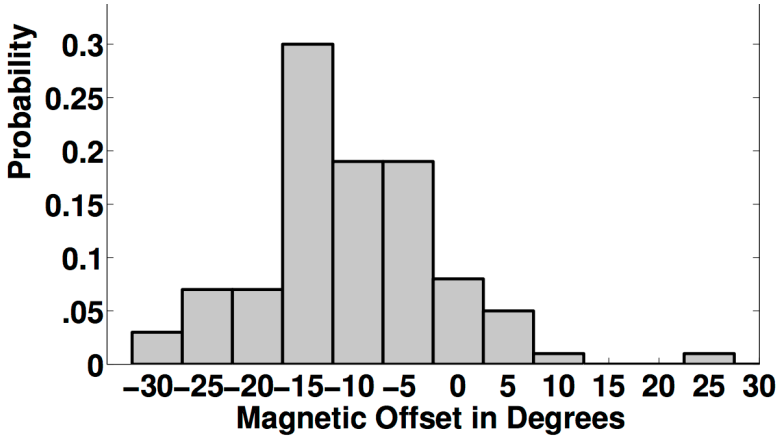
The placement offset (α) is an important factor, but it is not mandatory to deal with it in this course.

- Typical offsets
  - watching a movie with phone held laterally: 90
  - phone in shirt/pants pockets: +/- 45
  - bags: anywhere

Magnetic offset



$$x_i^k = x_i^{k-1} + (s_i + \delta_i)\cos(\alpha_i + \theta + \beta_i)$$
$$y_i^k = y_i^{k-1} + (s_i + \delta_i)\sin(\alpha_i + \theta + \beta_i)$$

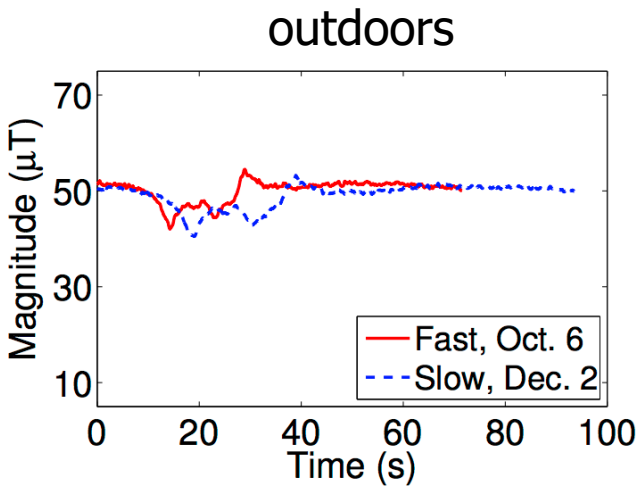


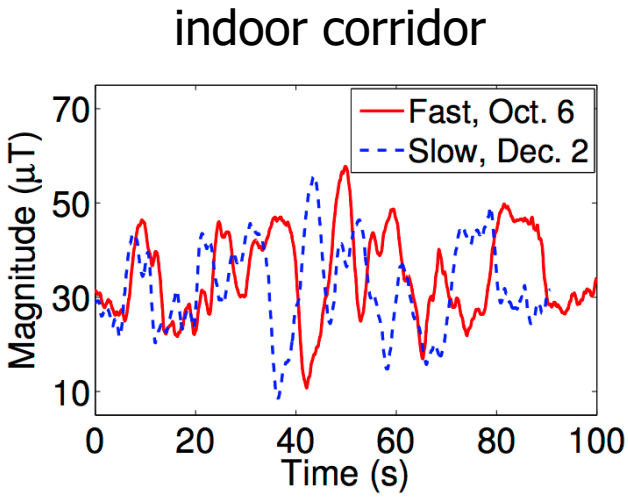
The magnetic offset depends on the building materials and surrounding metallic elements.

This may not be the most important factor, but we will only test this factor in your app.

The problem with compass (1)

- Compass is very sensitive in indoor environments

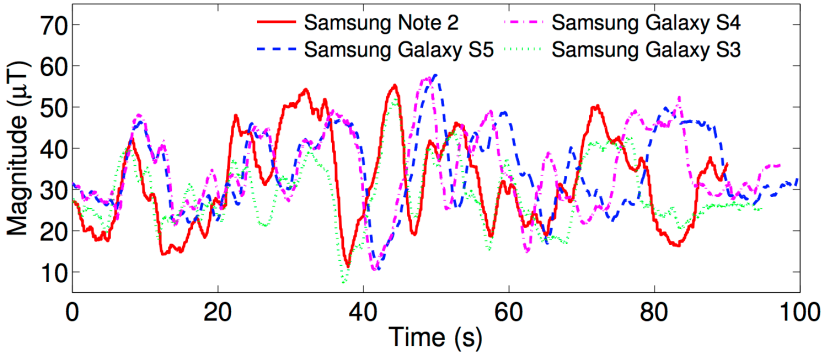




Images taken from: "Last-Mile Navigation Using Smartphones", ACM Mobicom 2015

The problem with compass (2)

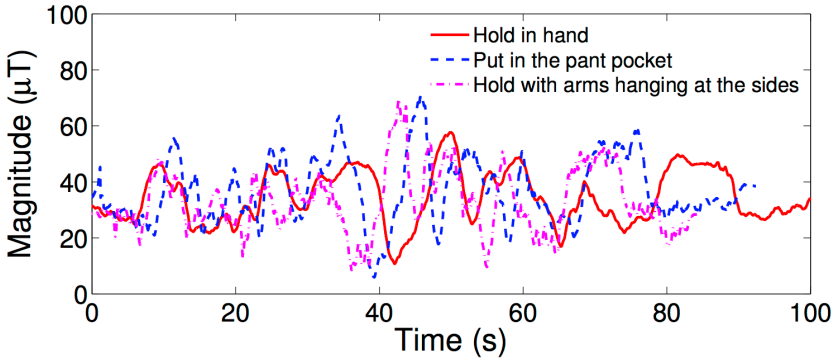
- The noise is phone-dependent and location-dependent.



(a) Device diversity

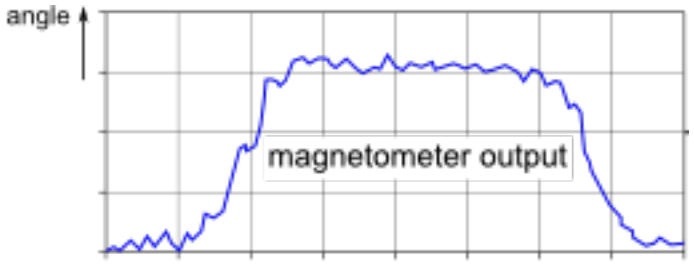
different phones will have different values (sometimes it gets weird)

different body locations will have different values

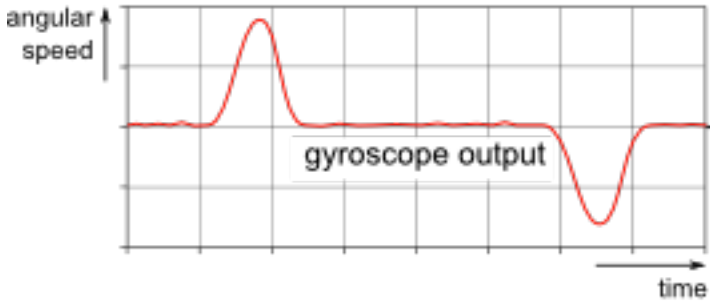


(b) Usage diversity

Combine Compass with Gyroscope



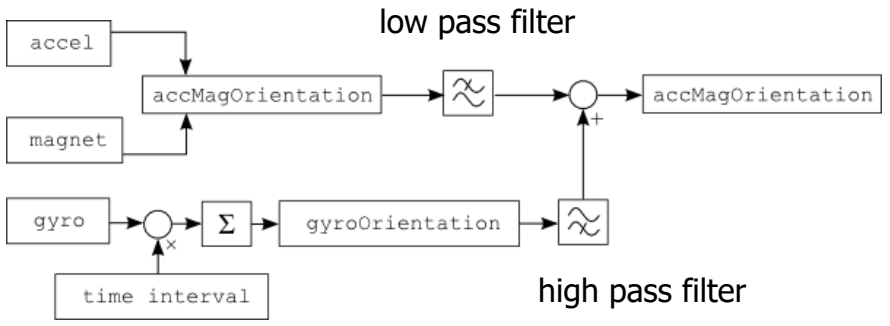
Pro: good for macro direction
Con: bad for micro direction
- magnetic field is easily affected in modern buildings



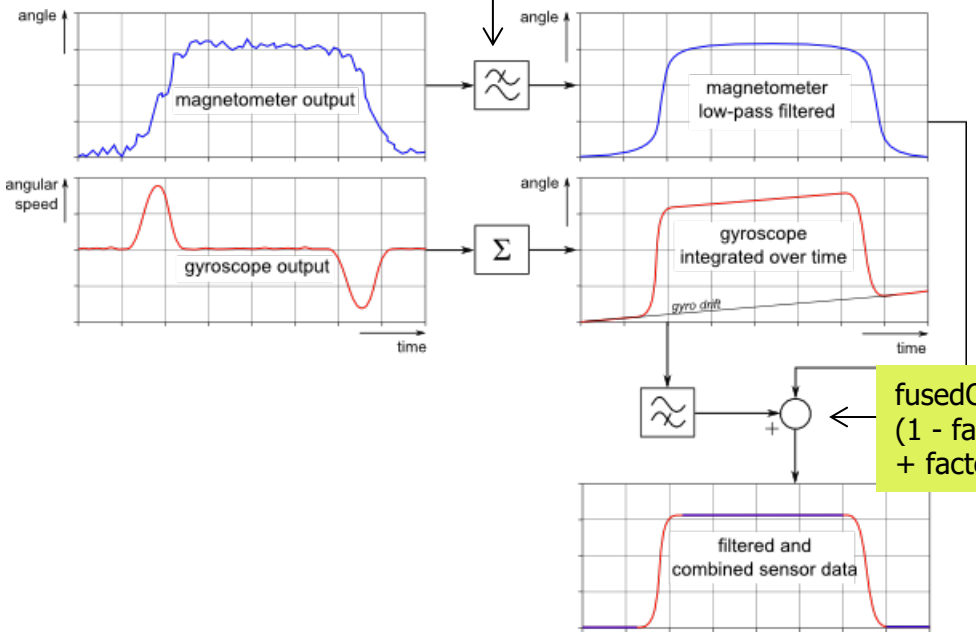
Pro: good for micro direction
Con: bad for macro direction
- accumulated error grows in time

http://www.codeproject.com/Articles/729759/Android-Sensor-Fusion-Tutorial

Sensor Fusion: combine acc, gyro and magnetometer



accMagOrientation =
(1 - factor) * accMagOrientation +
factor * newAccMagValue;



Sensor fusion is necessary for games. For your app the compass low-pass filter may be all you need. You will only move on four cardinal directions.

fusedOrientation =
(1 - factor) * newGyroValue // high-frequency component
+ factor * accMagOrientation; // low-frequency component

Directionality: not an easy problem in general

- Do it incrementally
  - Hold phone in hand in same direction of walk
    - distance = step count + noise
    - direction = phone direction + magnetic offset + noise
- Related paper
  - "I am a Smartphone and I can Tell my User's Walking direction", ACM Mobisys 2014
    - http://synrg.csl.illinois.edu/papers/walkcompass.pdf

Particle Filters (Continuous):

at the beginning a blanket represents the pdf, then prior and posteriors lead to peaks and valleys until we have a single peak (hopefully)

Bayesian Filters (Discrete):

similar to particles but with "building heights"

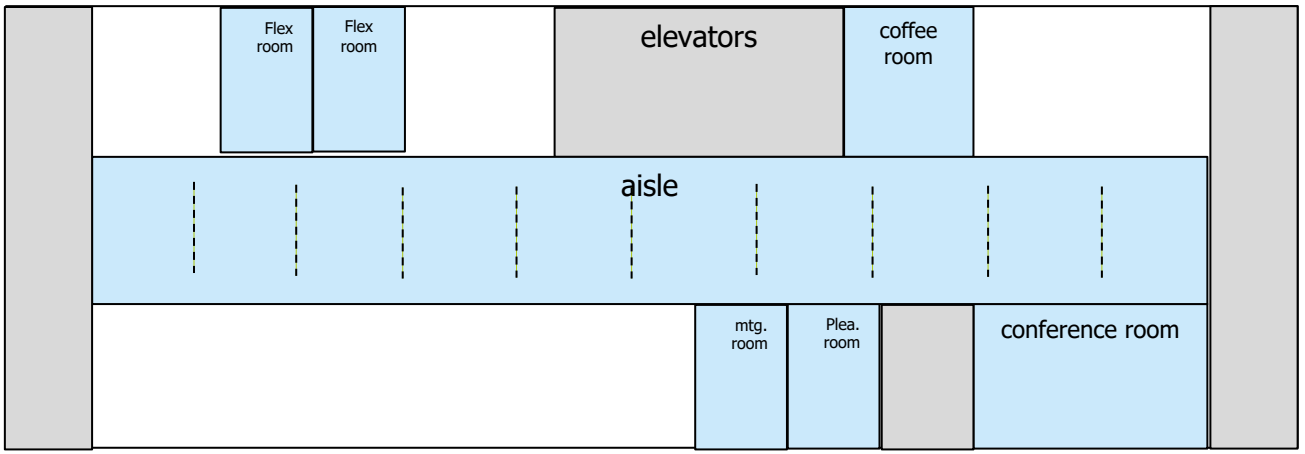
GRANDPA(MA)'S EXPLANATION

A cookbook for Particle Filters

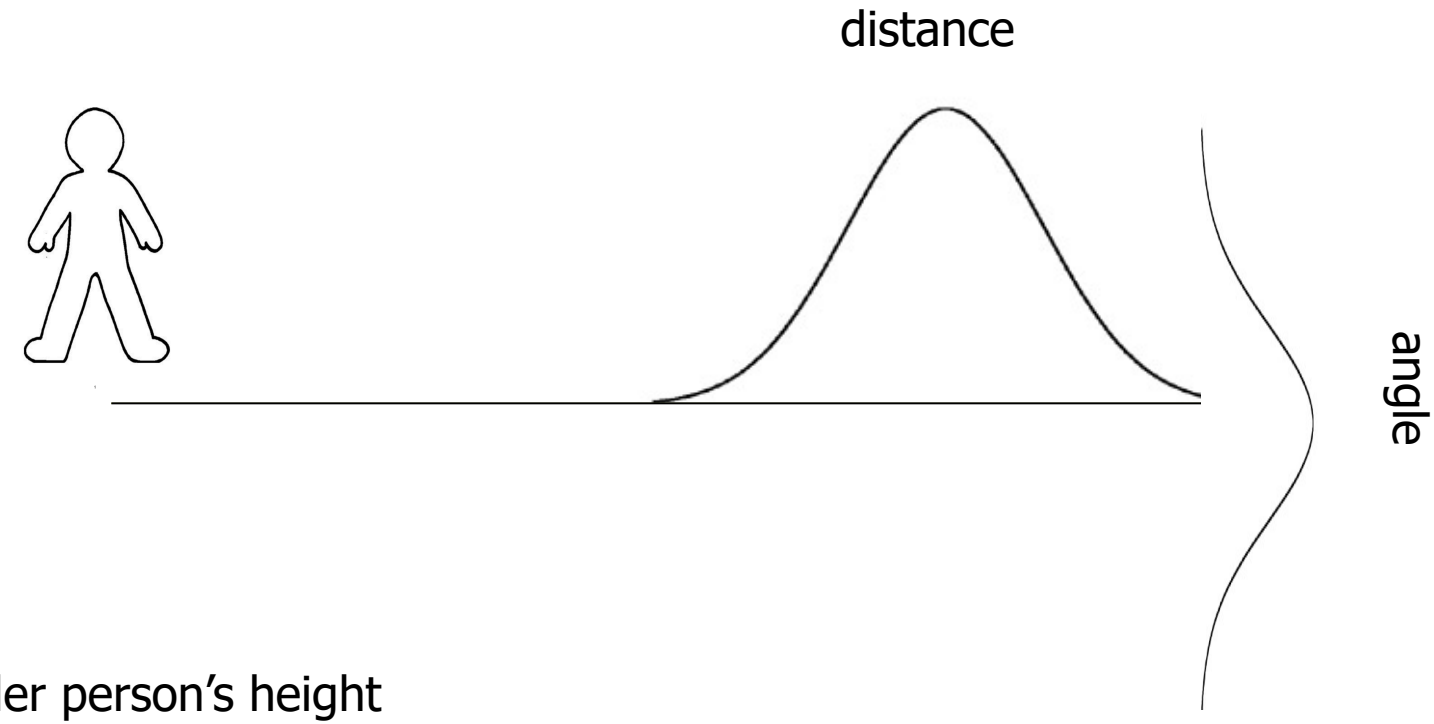
1) Create map with boundaries in your phone (check example)
2) Define motion model: distance & direction (consider person's height)
3) Deploy N particles. Big N is good (thousands), but consider phone capabilities.
4) Move particles, it can be done in three main ways:
   - Preferred: TYPE_ROTATION_VECTOR, TYPE_STEP_COUNTER, TYPE_STEP_DETECTOR (API 19)
   - Simple but inaccurate. Distance: moving/idle. Direction: Quadrant.
   - Accurate but challenging. Develop your own STEP_COUNTER and ROTATION_VECTOR
5) Identify particles that violate constraints (dead particles).
6) Resample: place dead particles on top of surviving ones.
7) Check for convergence. Go back to step 5
8) Test it online in our floor!

Step 1) Create Map

- Different ways to do this in Android (Canvas)
- More elaborated than simple Bayesian
- You will need your own map.



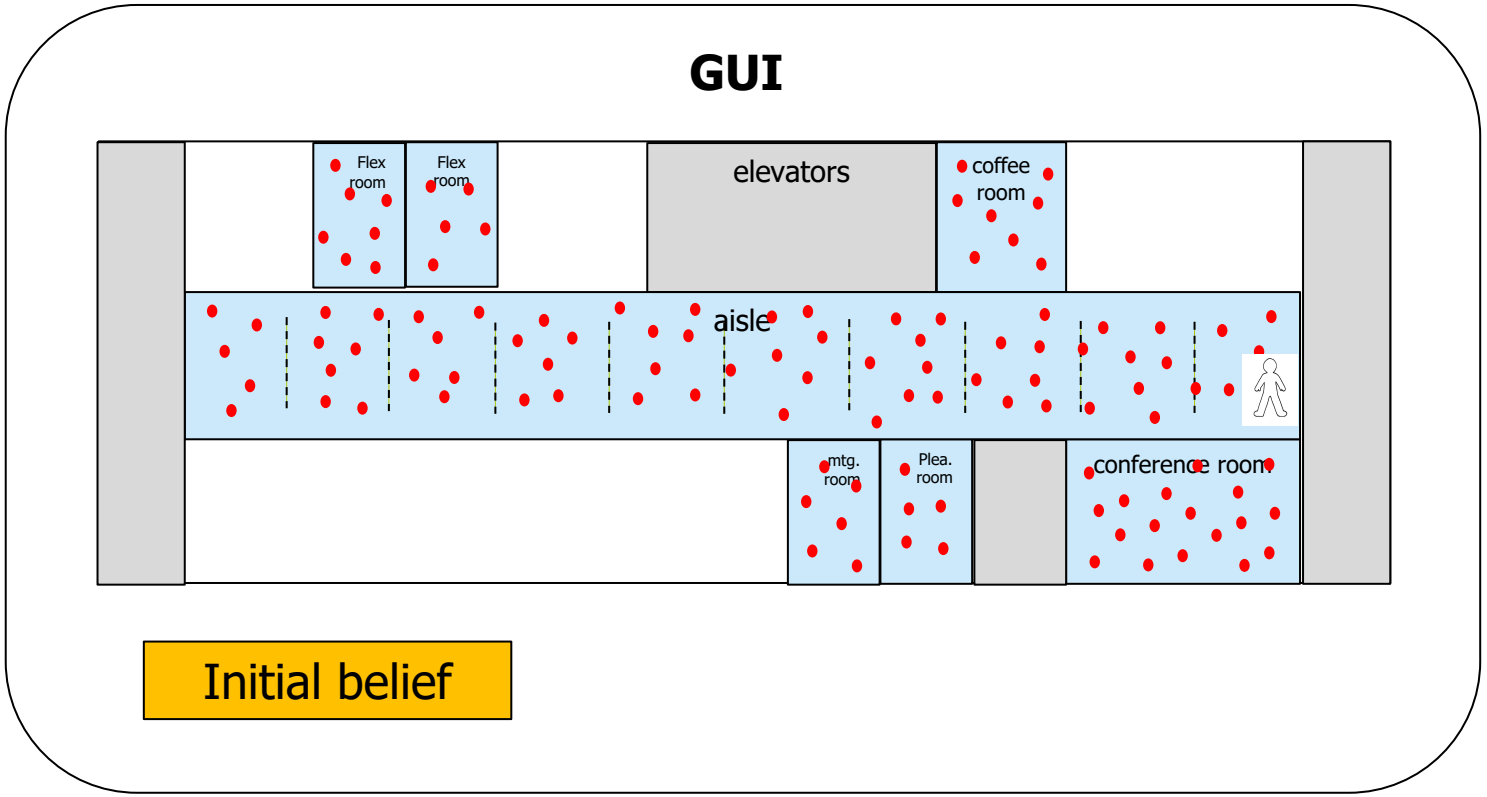
Step 2) Define motion model



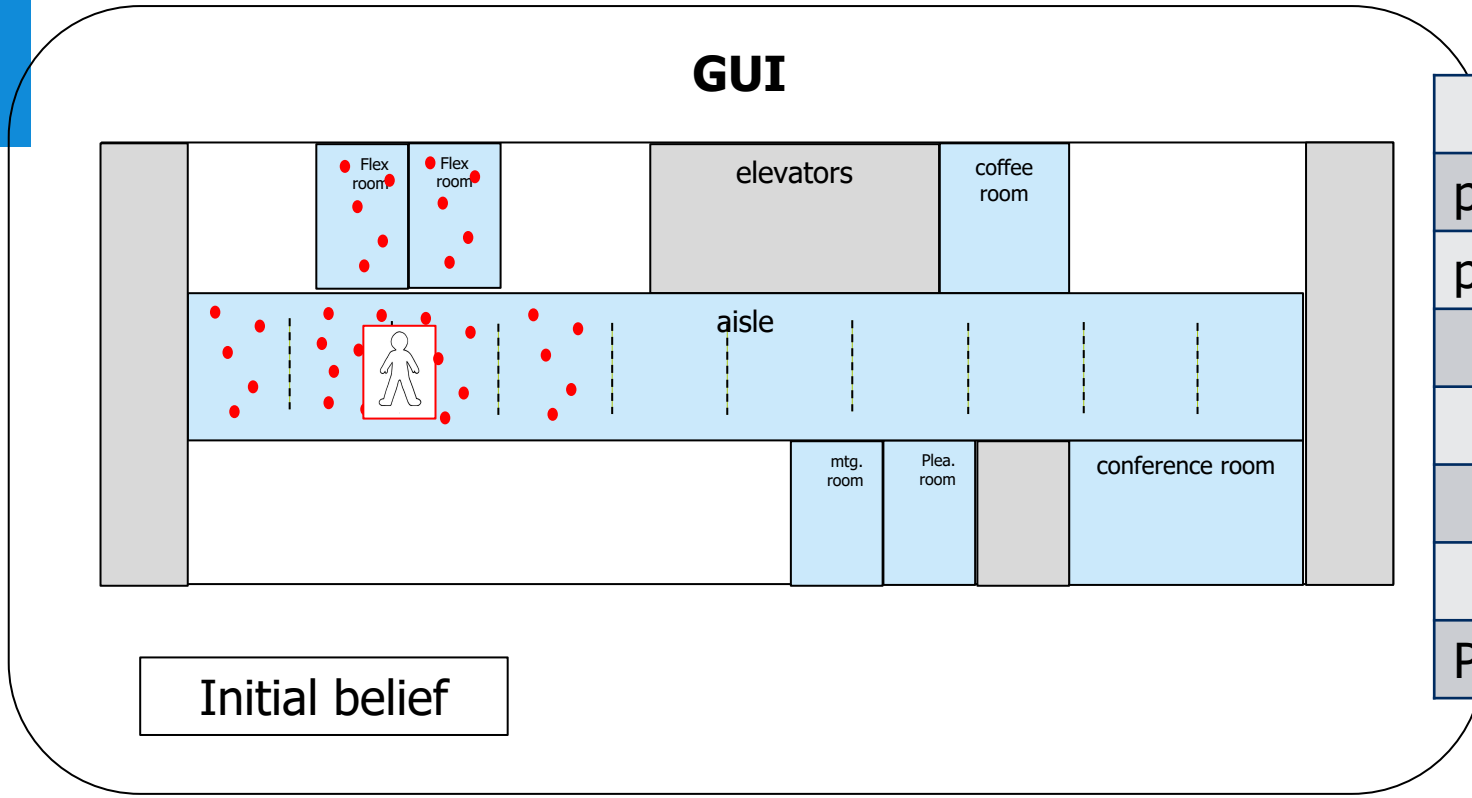
- Consider person's height
- Perform minor training (walk a known distance and count steps)
- This model depends fundamentally on how you implement particle motion (step 5)
- You could do this also in an automatic manner by exploiting maps.
- Tradeoff between accuracy and convergence

Step 3) Deploy N particles

Big N is good, but consider your phone's processing capabilities!

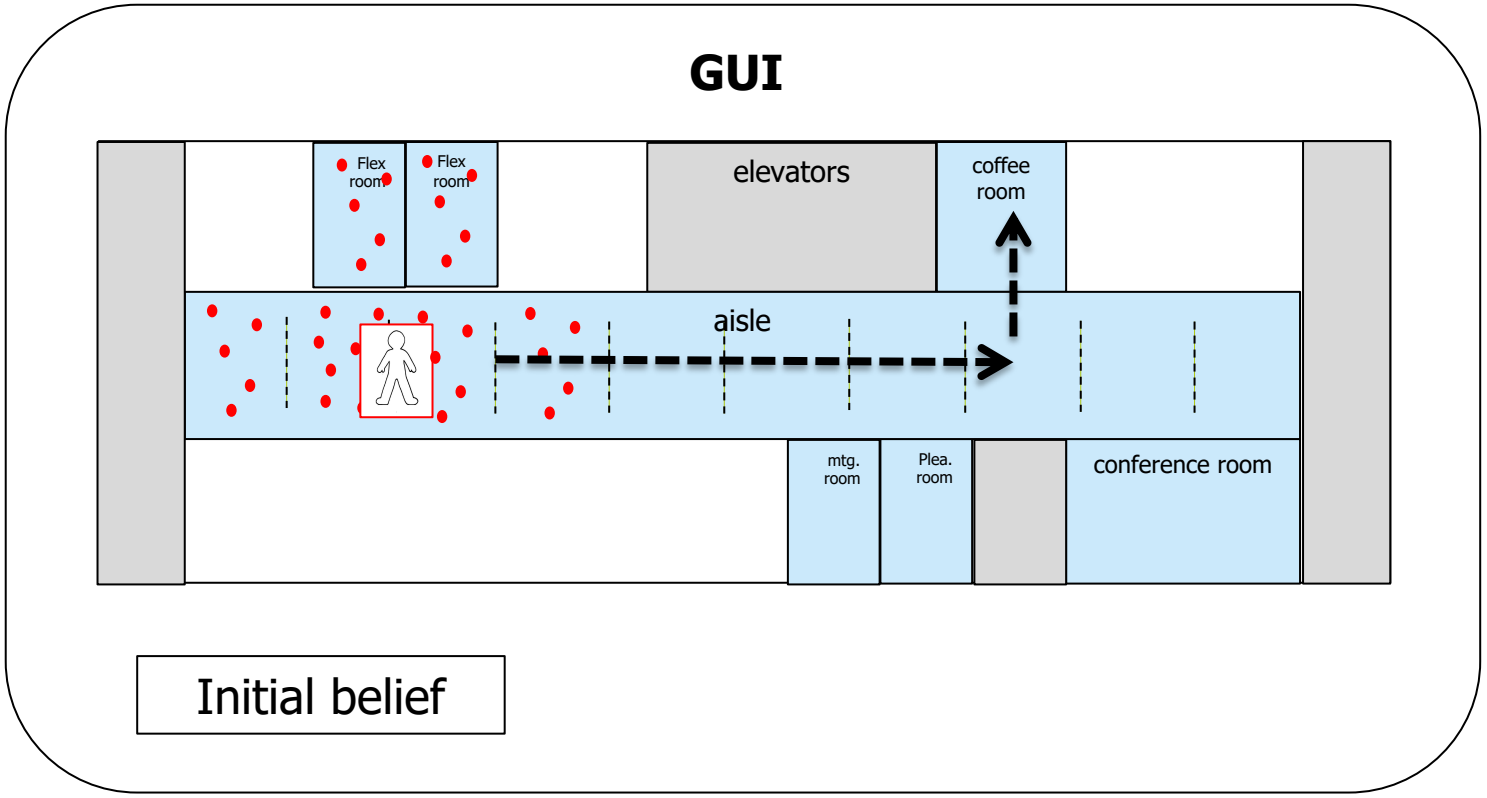


Remember: Keep track of particles in table



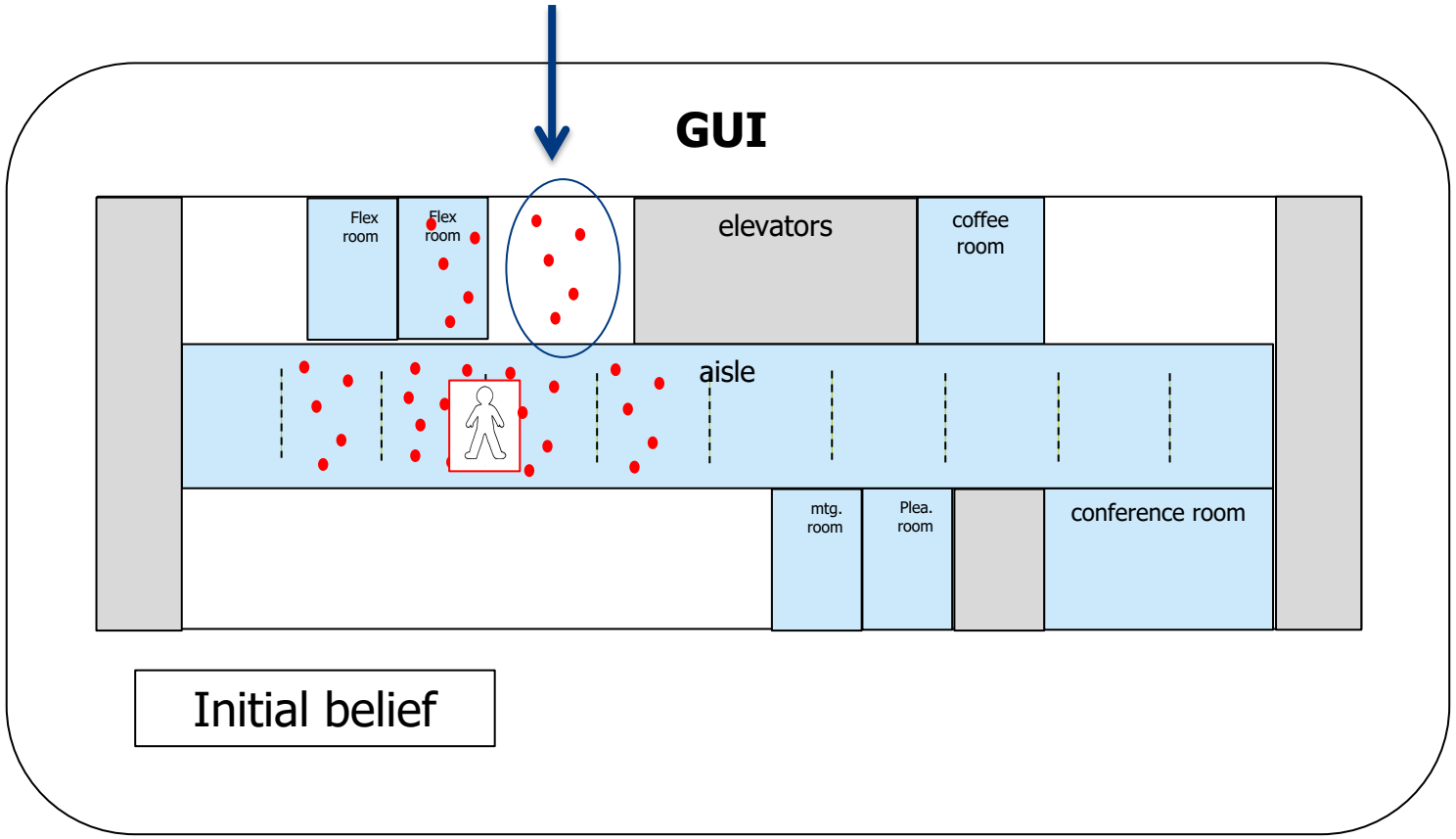
	x	y	d
p1	X1	Y1	D1
p2			
Pn	Xn	Yn	Dn

Step 4) Move particles

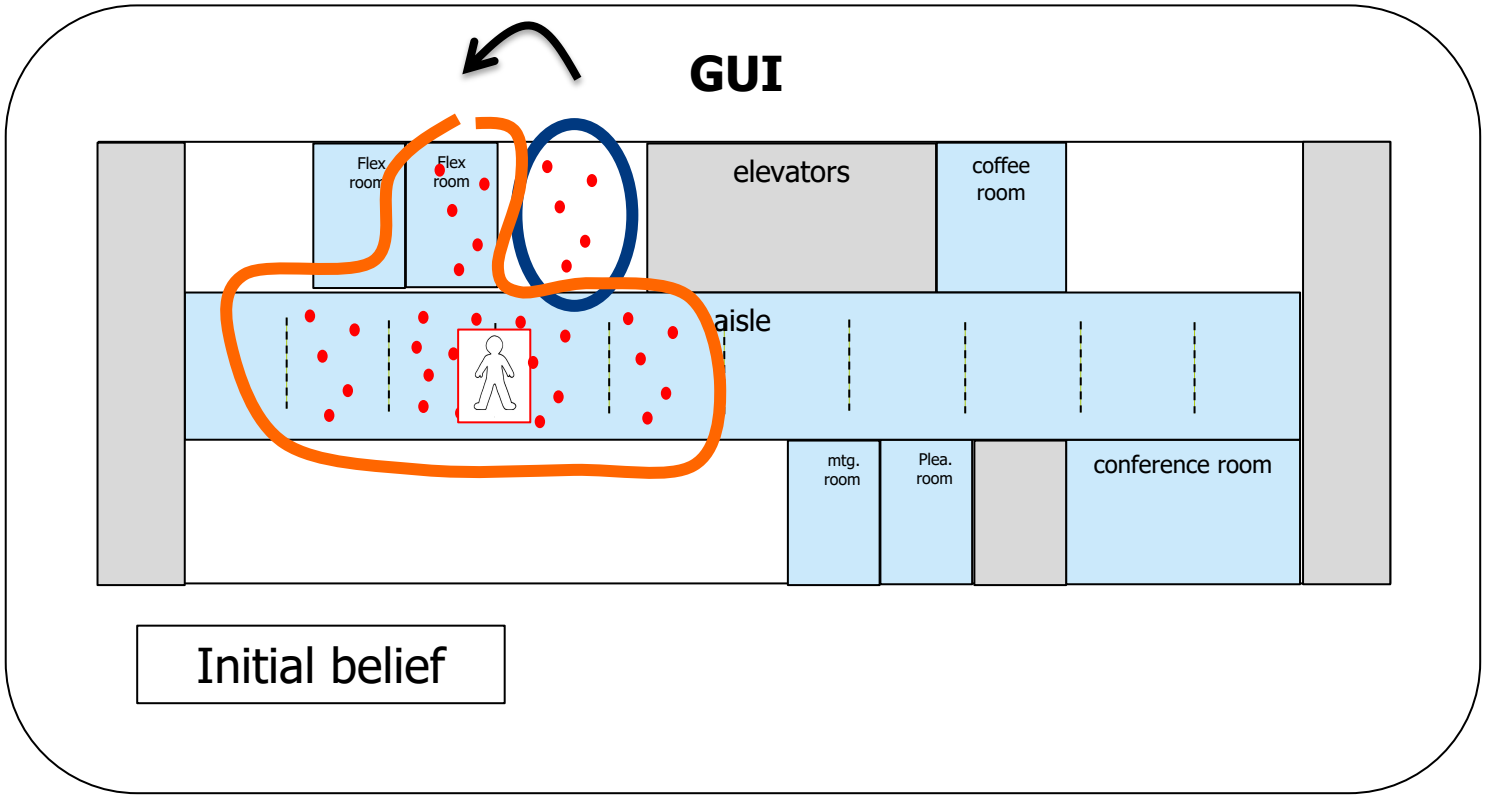


- **Preferred.** TYPE_ROTATION_VECTOR, TYPE_STEP_COUNTER,
- **Simple but inaccurate.** Distance: moving/idle. Direction: Quadrant.
- **Accurate but challenging**. Develop your own STEP_COUNTER and ROTATION_VECTOR

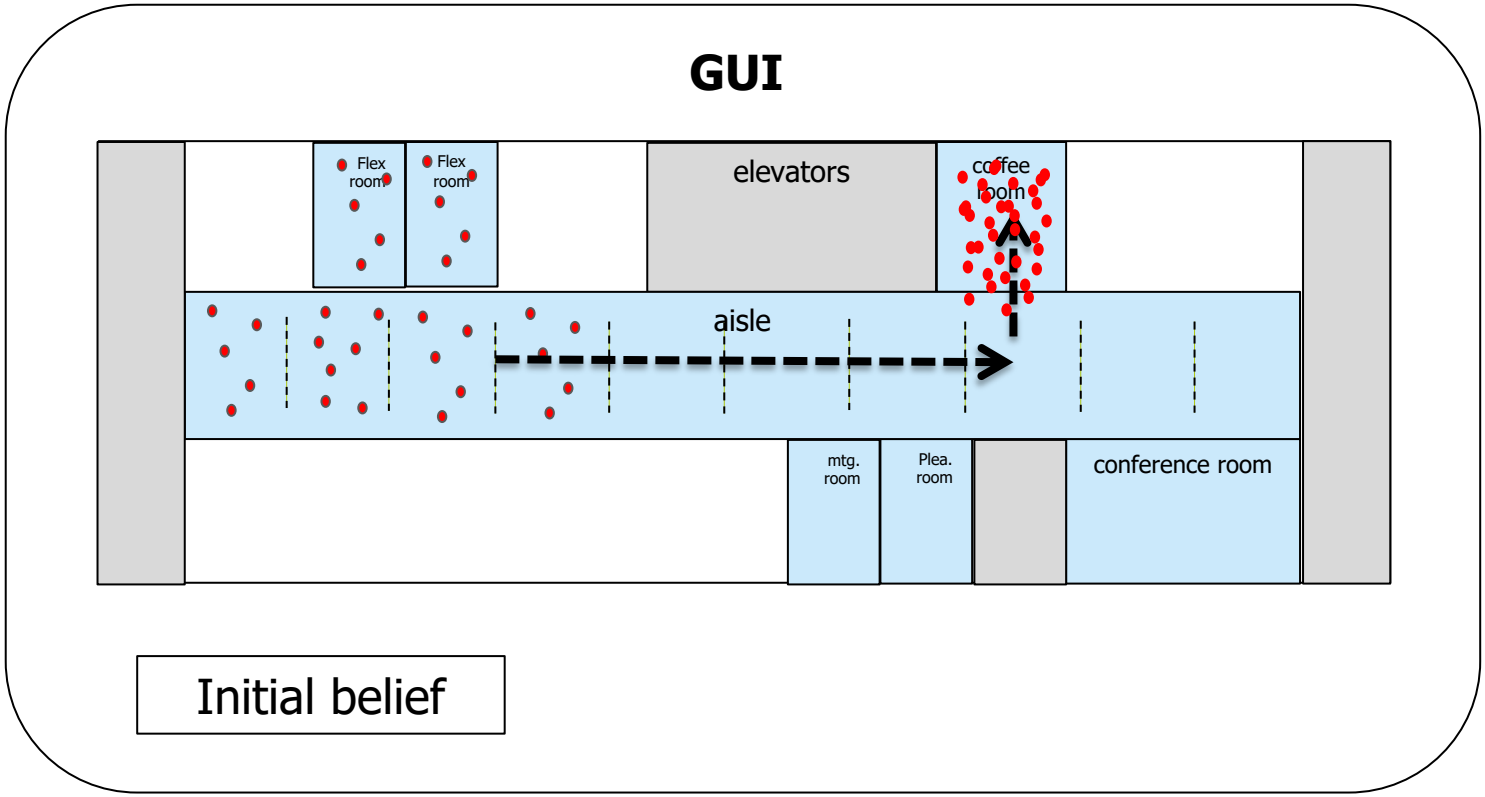
Step 5) Eliminate particles that violate constraints



Step 6) Resample



Step 7) Convergence



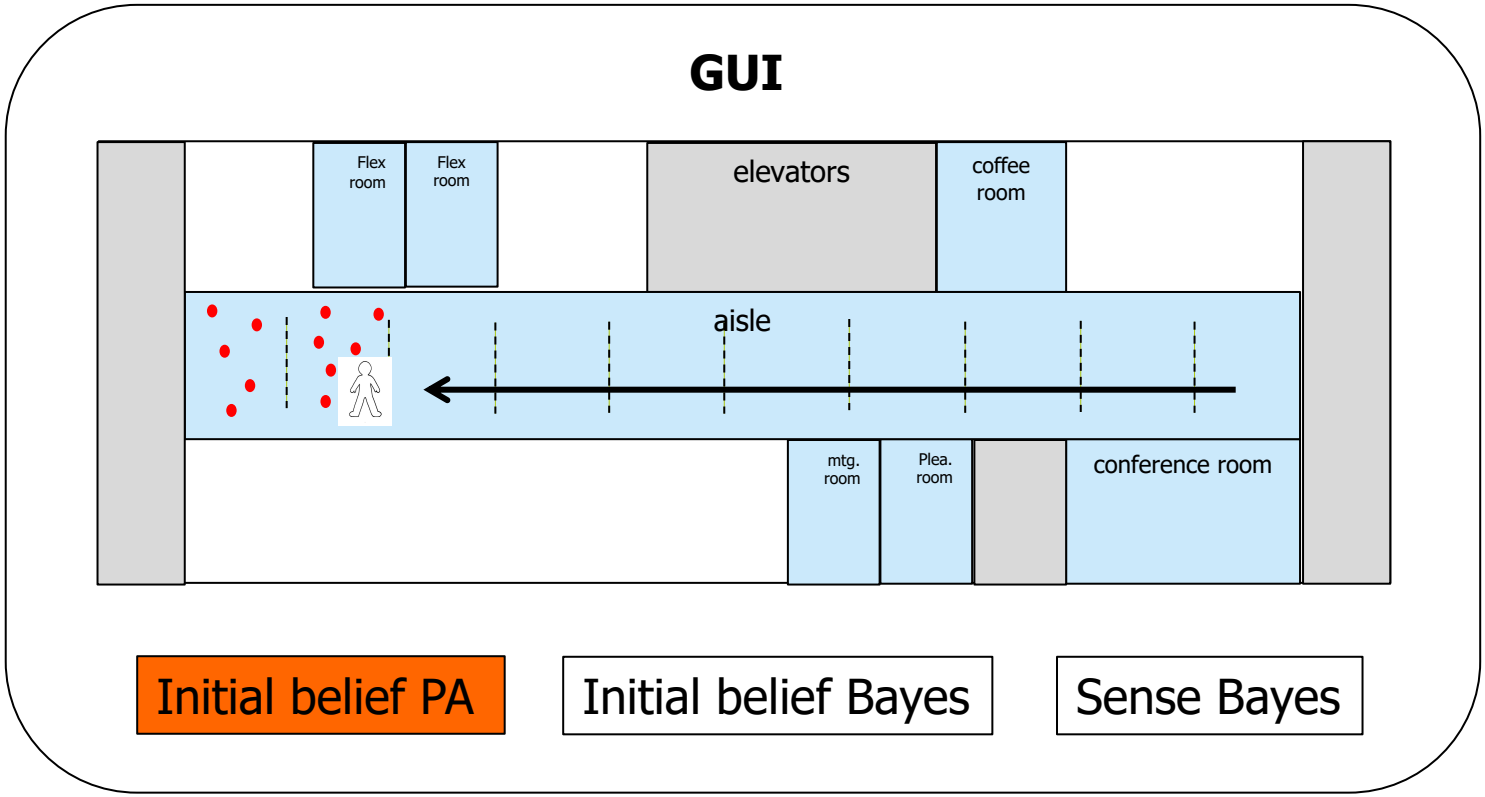
Be careful with particle traps

- If your motion model is NOT accurate. The particles may get stuck at a given point.

- You will have three chances during the evaluation to overcome this problem. After that we won't count any more points.

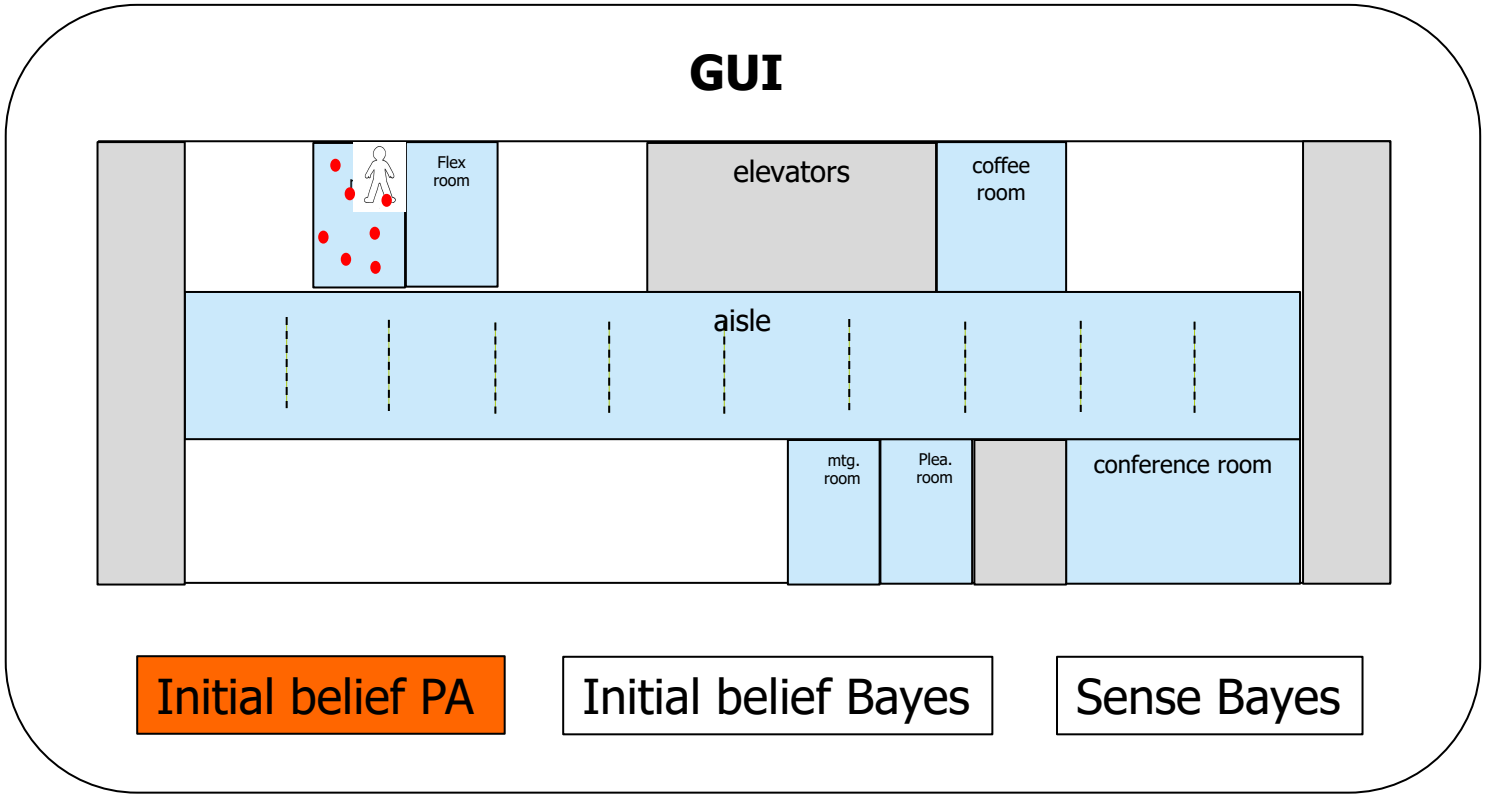
WHAT THE APP SHOULD DO

App: find convergence (1)



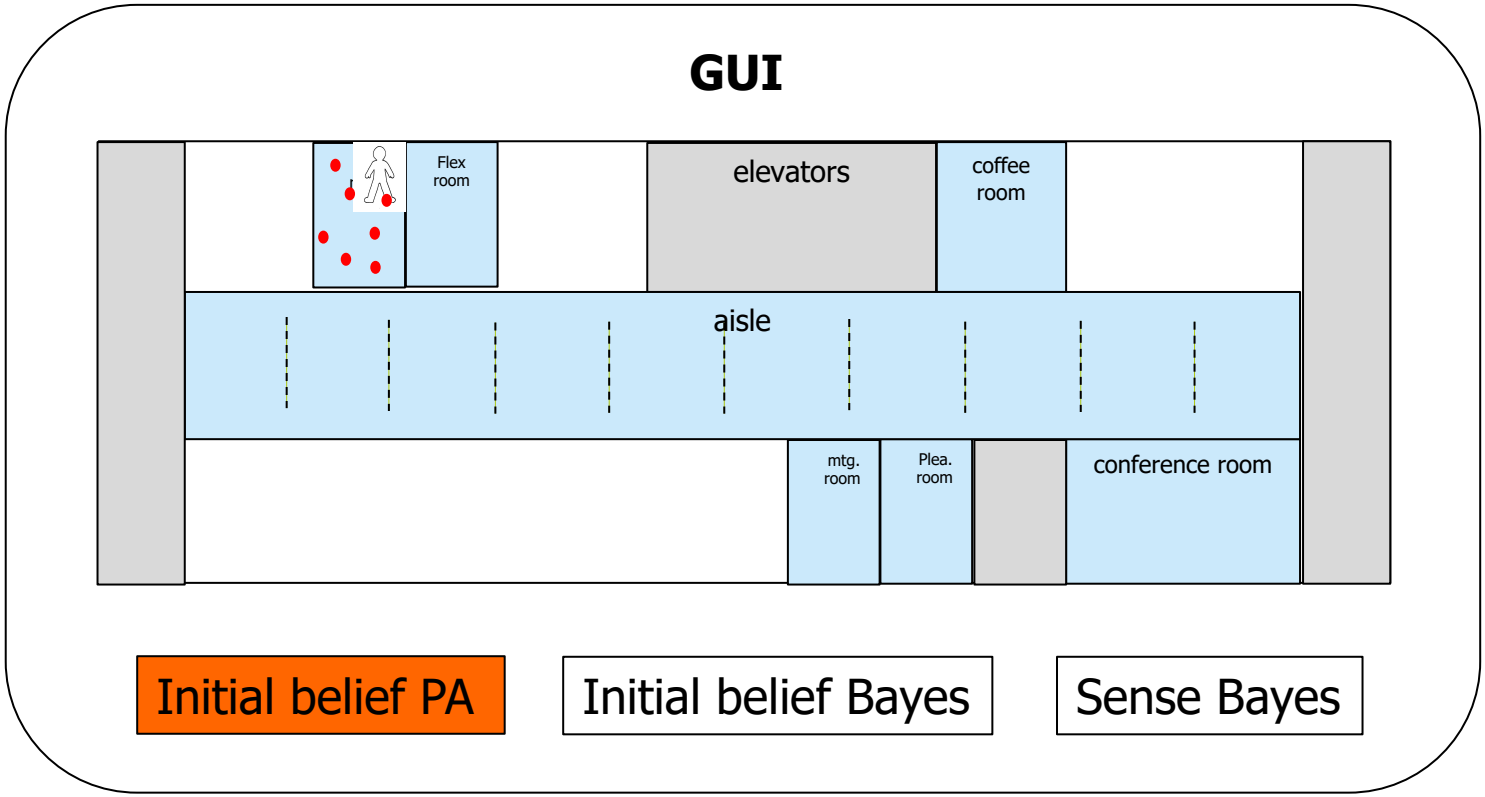
We will perform a `uniquely determined' walk to find convergence.
How you determine convergence is up to you.

App: find convergence (2)



Once you converge we start testing the accuracy of particle filters.

App: testing of cells



We will visit all cells.
Your App should state the cell where you are

Pros and Cons of Particle filters

- Bayesian Filters
  - discrete, multimodal, computationally expensive, easy to program.
- Kalman Filters
  - continuous, unimodal, computationally inexpensive but assumes linearity and Gaussian distributions
- Particle filters
  - continuous, multimodal, computationally expensive, easy to program.
- Notes:
  - discrete: good for room-level localization
  - unimodal: can be a limitation
  - computationally expensive: really? this is the 2010's!

Let's look at FF

WRITING GUIDELINES FOR SECOND REPORT

Assignment description

- You need to develop an App for indoor localization using RSS signals from WiFi using Bayes filters.
- NO motion sensors (IMU) need to be used for this assignment.
- You will need to gather training data from your own location according the layout you propose (and got approved). Then, you will need to evaluate the accuracy of your method online and provide a confusion matrix with accuracy results. By online, we mean that you must use your phone to run the code in real-time (as opposed to gathering the data with your phone, offloading it to a laptop and processing the data off-line)
- Maintain social distance guidelines.

- Submission: BrightSpace
- File name: sps<year>_<group_id>_report2_optionX.pdf
- Max 2 pages including figures, tables and references. Single or double column. We will NOT look at any information beyond 2-pages.
- Only one member of the group needs to submit the report.
- At the top of the report mention
  - your group id, names and student ids, phone used, and version of android
  - provide pointers for code you copied/modified.
  - describe who did what in a concise manner.

Guidelines for Report: Bayesian (max 2 pages)

- The first part of the report should include the names, ids, load distribution, etc. mentioned in the prior slide. Be concise.
- Data collection
  - Sampling rate, sampling time per cell, were all samples gathered handling the phone in the same direction?, number of APs observed etc.
  - Figure with your map layout.
- Data Processing
  - Filters used for APs and RSS (if any)
  - Do NOT explain Bayes. Only describe how you filter APs and RSS values (if you decide to to do that). If you do not filter them, state why.
- Sample Radio Maps
  - Figure 1: pmf of RSS for 2 cells where the distributions are similar (i.e. cells are hard to localize)
  - Figure 2: pmf of RSS for 2 cells where the distributions are different (i.e. cells are easy to localize).
  - Explain the figures and the reasons for the similarity & difference.
- Evaluation
  - Describe how you stop the iterative Bayes process (number of tries?, reaching steady state?).
  - Describe if you use a parallel or serial approach for the iterative Bayes process.
  - Snapshot of App
  - Confusion Matrix (at least 10 attempts per cell).
- Discussion (bulletpoints)
  - What is **hard**? What is **novel**? i.e. new methods that were not described in class.