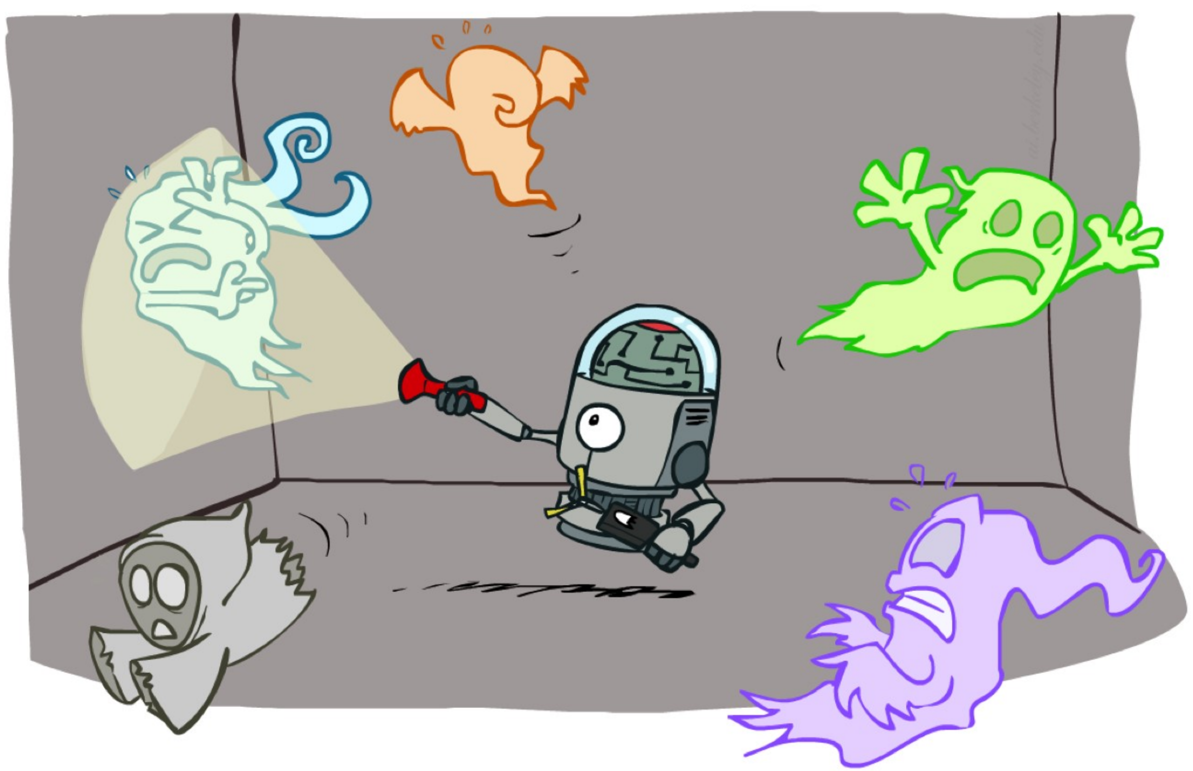
AI: Representation and Problem Solving

Particle Filtering



Instructors: Tuomas Sandholm and Vincent Conitzer

Slide credits: CMU AI and http://ai.berkeley.edu

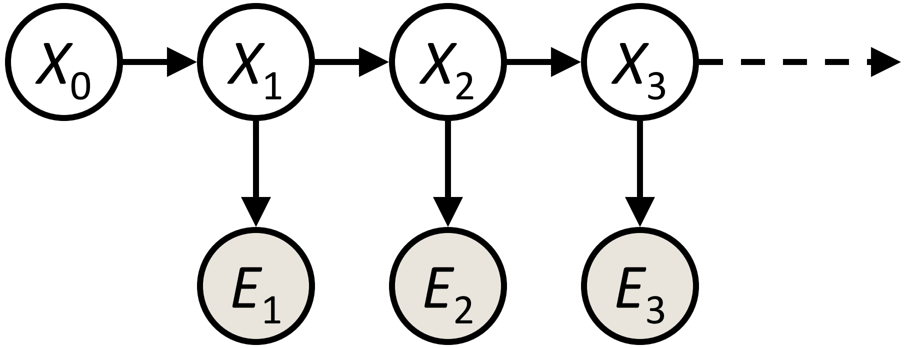
Logistics

- HW10 (written, online) due Thursday April 17
- P5 due Thursday April 24
- HW11 (online, not yet released) due Thursday April 24
- TA interview scheduling coming soon for those who applied

Hidden Markov Models

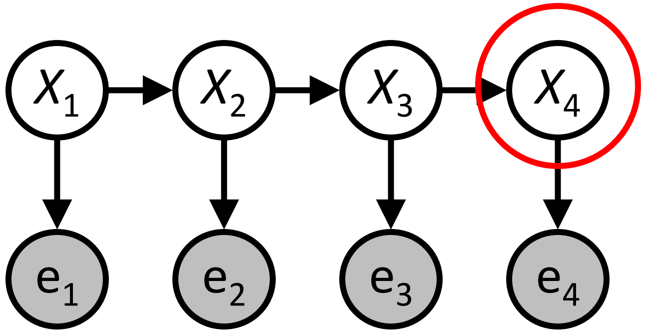
- Usually the true state is not observed directly

- Hidden Markov models (HMMs)
  - Underlying Markov chain over states X
  - You observe evidence E at each time step
  - X_t is a single discrete variable; E_t may be continuous and may consist of several variables

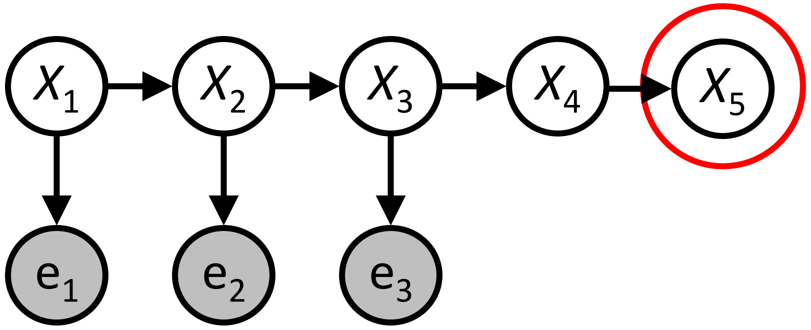


Recall: HMM Queries

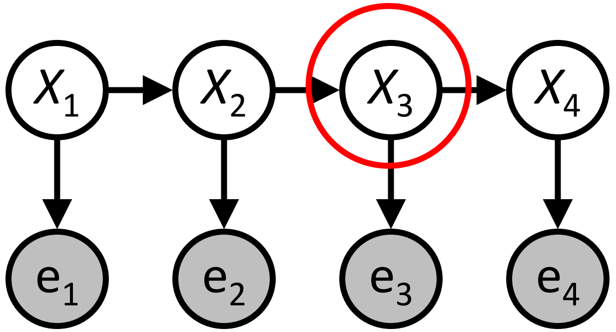
Filtering: $P(X_t | e_{1:t})$



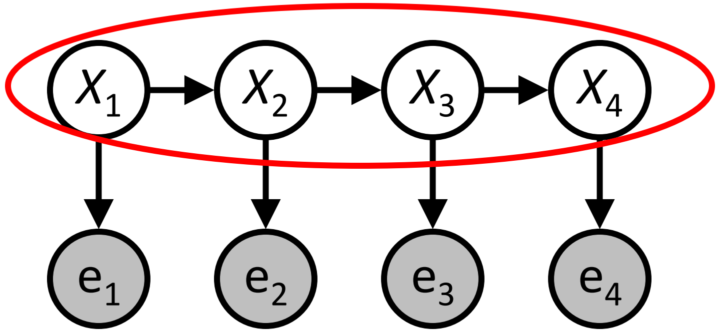
Prediction: $P(X_{t+k} | e_{1:t})$



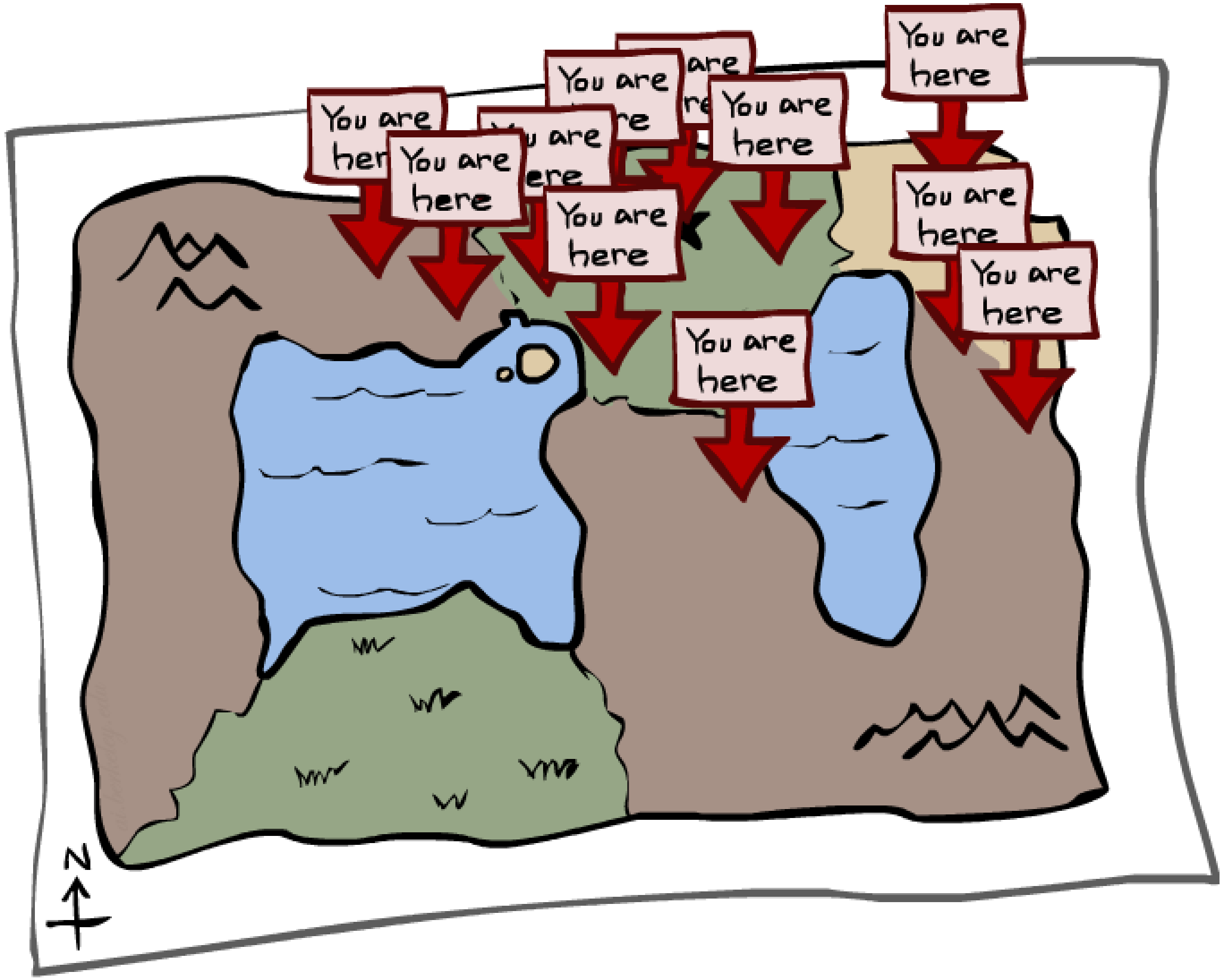
Smoothing: $P(X_k | e_{1:t})$, $k<t$



Explanation: $P(X_{1:t} | e_{1:t})$



Particle Filtering



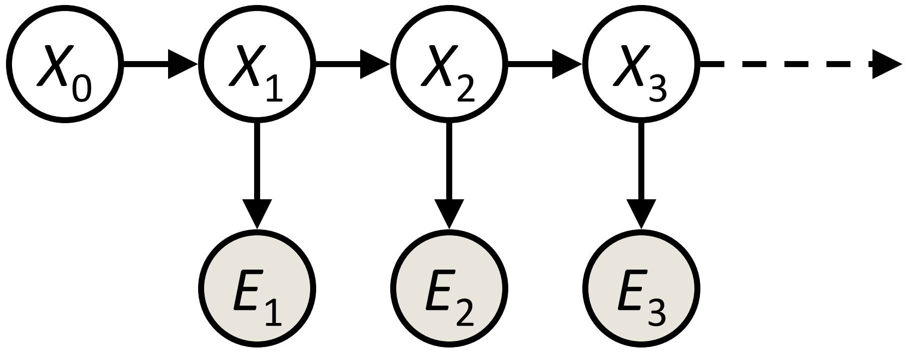
Belief States

When predicting the actual location we're in at each time step, X_k …

… really, what we're doing is maintaining a **probability distribution** over all possible states

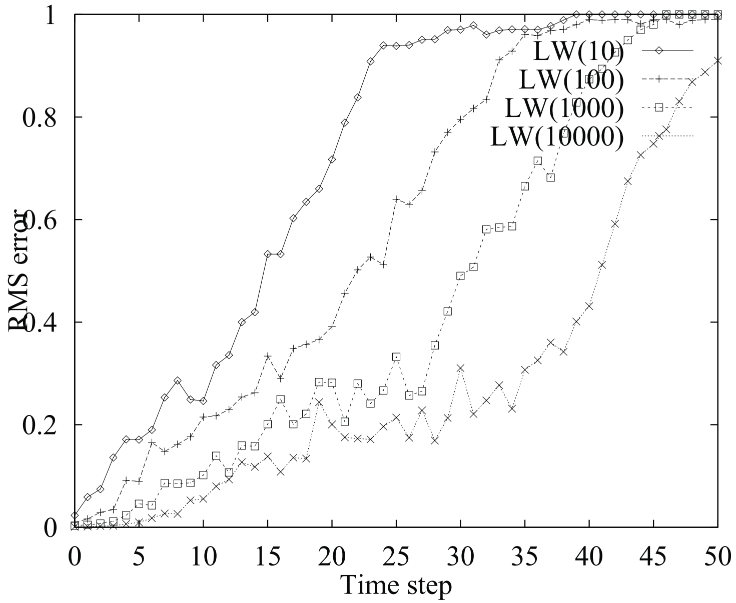
This distribution is called a **belief state**, it represents the belief of where we are

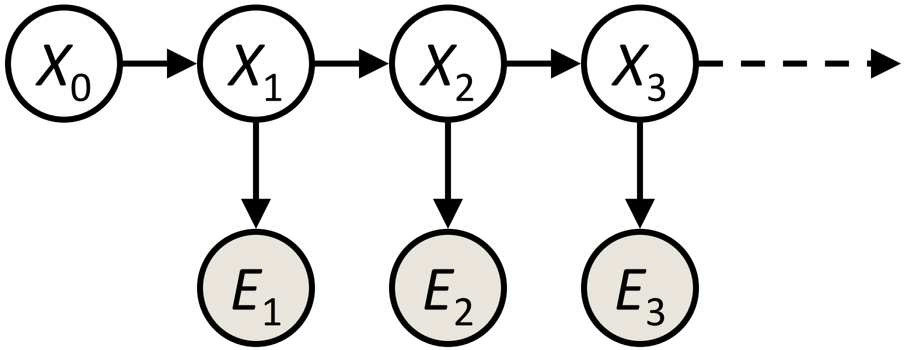
We denote the belief state for X at time 3 by $\mathbf{b(X_3) = P(X_3 \mid e_1, e_2, e_3)}$



We need a new algorithm!

- When $|X|$ is more than 10^6 or so (e.g., 3 ghosts in a 10x20 world), exact inference to compute the belief state becomes infeasible
- We could try to sample our Bayes net to compute b(X)
- Likelihood weighting fails completely – number of samples needed grows ***exponentially*** with T

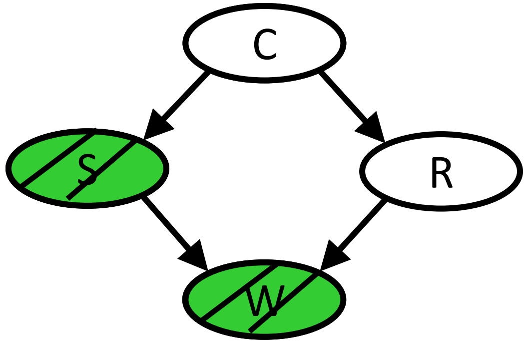




Recall: Likelihood Weighting

- Sampling distribution if z sampled and e fixed evidence

$$S_{WS}(\mathbf{z}, \mathbf{e}) = \prod_{i=1}^{l} P(z_i | \text{Parents}(Z_i))$$



- Now, samples have weights

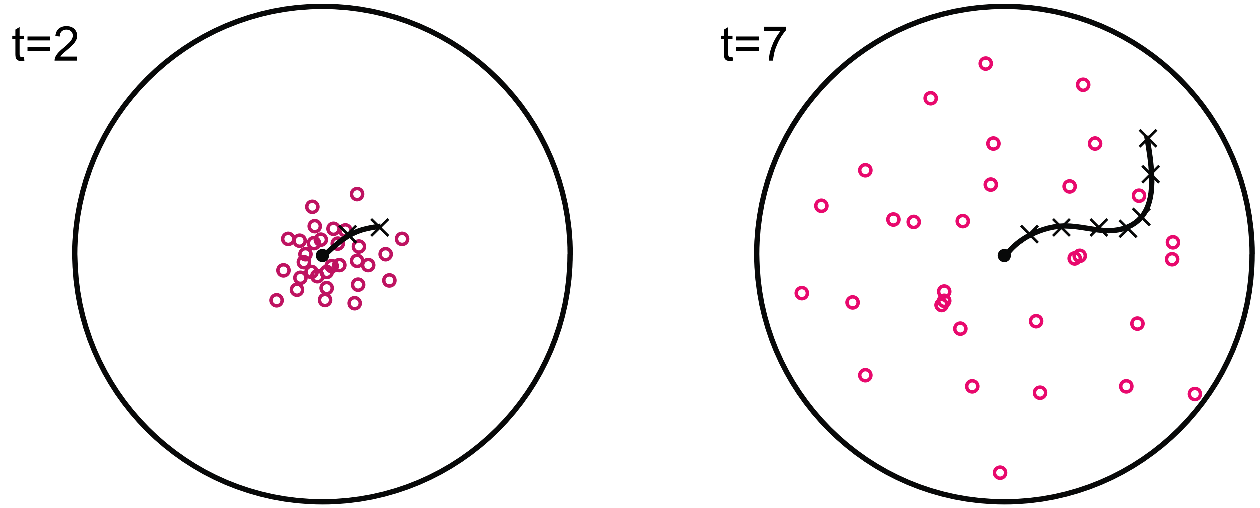
$$w(\mathbf{z}, \mathbf{e}) = \prod_{i=1}^{m} P(e_i | \text{Parents}(E_i))$$

- Together, weighted sampling distribution is consistent

$$S_{\text{WS}}(z, e) \cdot w(z, e) = \prod_{i=1}^{l} P(z_i | \text{Parents}(z_i)) \prod_{i=1}^{m} P(e_i | \text{Parents}(e_i))$$

$$= P(\mathbf{z}, \mathbf{e})$$

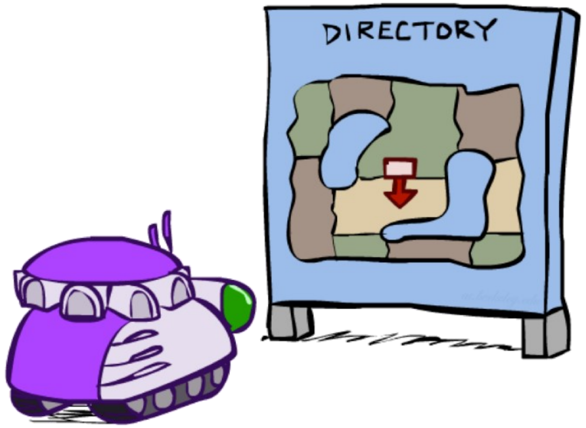
We need a new idea!

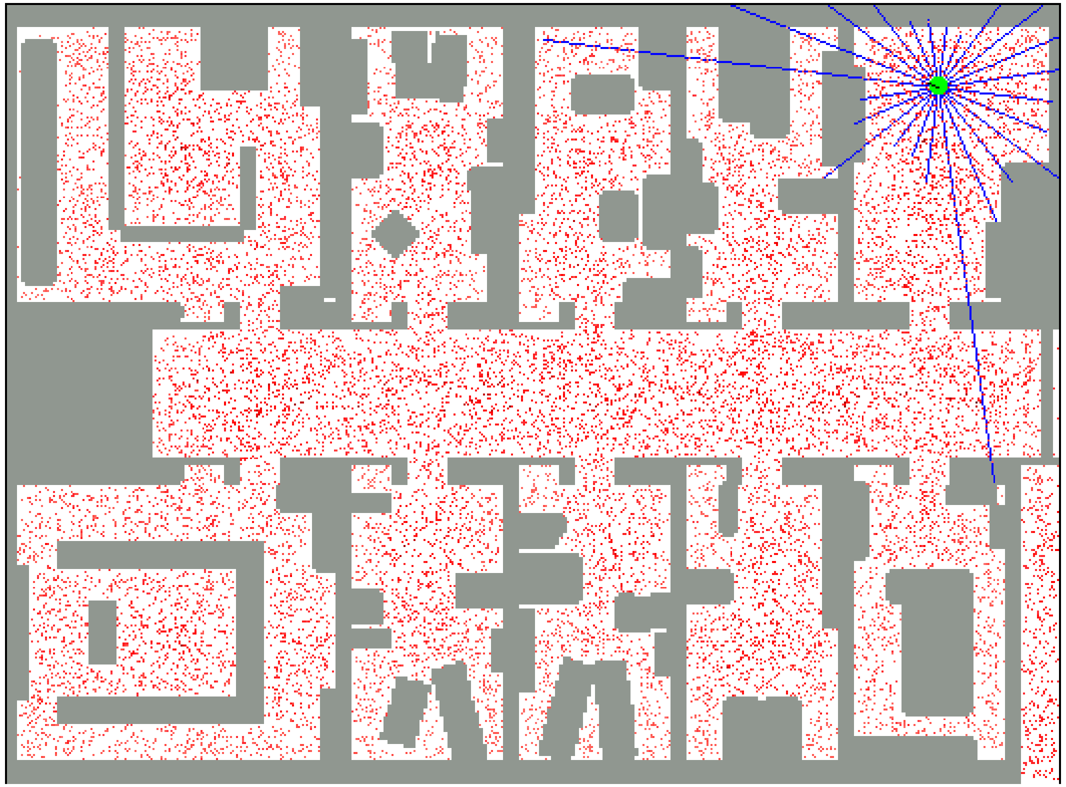


- Idea: Sample in the first state, and then move those samples by sampling the transition function
- The problem: sample state trajectories go off into low-probability regions, ignoring the evidence; should reweight, but anyway too few "reasonable" samples
- **Solution: get rid of the bad ones, make more of the good ones.** This way the population of samples stays in the high-probability region.
- This is called resampling or survival of the fittest

Robot Localization

- In robot localization:
  - We know the map, but not the robot's position
  - Observations may be vectors of range finder readings
  - State space and readings are typically continuous (works basically like a very fine grid) and so we cannot store B(X)
  - Particle filtering is a main technique





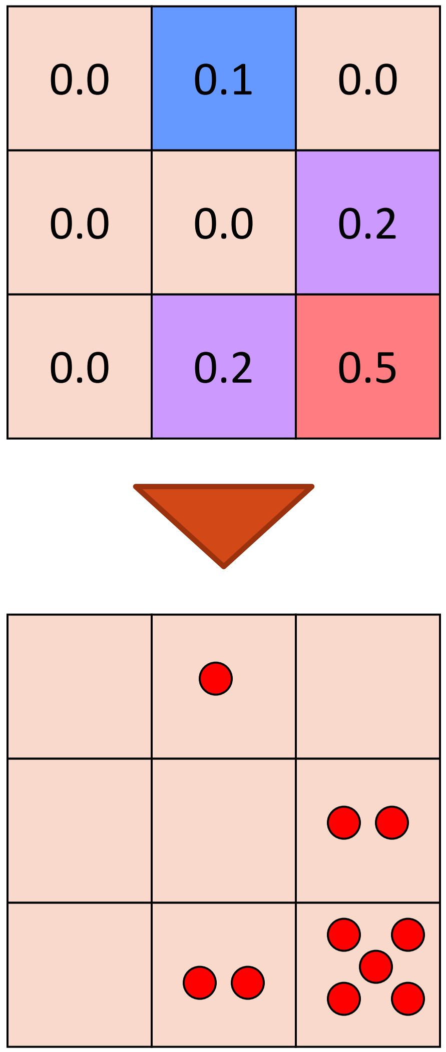
Particle Filter Localization (Sonar)

[Dieter Fox, et al.]

[Video: global-sonar-uw-annotated.avi]

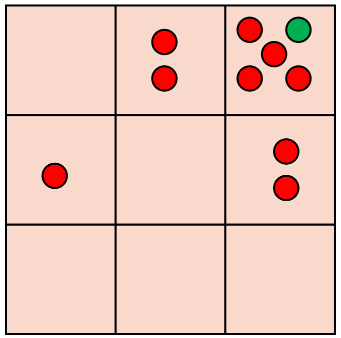
Particle Filtering

- Represent belief state by a set of samples
  - Samples are called ***particles***
  - Time per step is linear in the number of samples
  - But: number needed may be large
- This is how robot localization works in practice



Representation: Particles

- Our representation of P(X) is now a list of N particles (samples)
  - Generally, N << |X|
  - Storing dictionary mapping from X to counts would defeat the point
- P(x) approximated by number of particles with value x
  - So, many x may have P(x) = 0!
  - More particles, more accuracy
  - Usually we want a low-dimensional marginal
    - E.g., "Where is ghost 1?" rather than "Are ghosts 1,2,3 in {2,6], [5,6], and [8,11]?"
- For now, all particles have a weight of 1

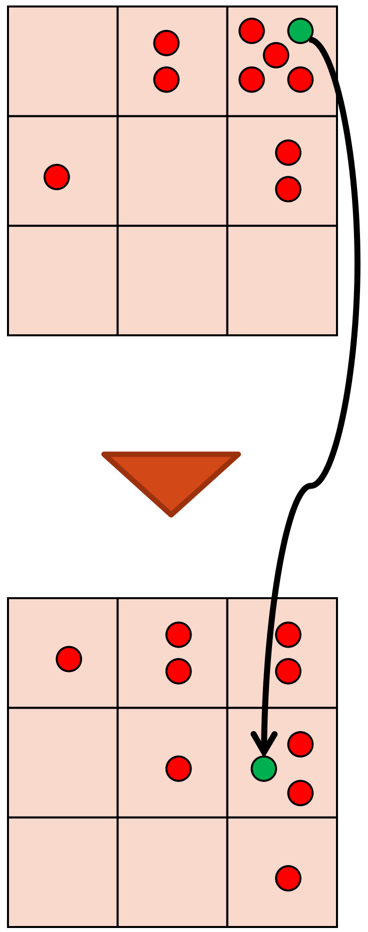


Particles:
(3,3)
(2,3)
(3,3)
(3,2)
(3,3)
(3,2)
(1,2)
(3,3)
(3,3)
(2,3)

Particle Filtering: Propagate forward ("Predict")

- A particle in state x_t is moved by sampling its next position directly from the transition model:
  - $x_{t+1} \sim P(X_{t+1} \mid x_t)$
  - In this example, most samples move clockwise, but some move in another direction or stay in place
- This captures the passage of time
  - With enough samples, close to exact values before and after (consistent)

Particles:
(3,3)
(2,3)
(3,3)
(3,2)
(3,3)
(3,2)
(1,2)
(3,3)
(3,3)
(2,3)

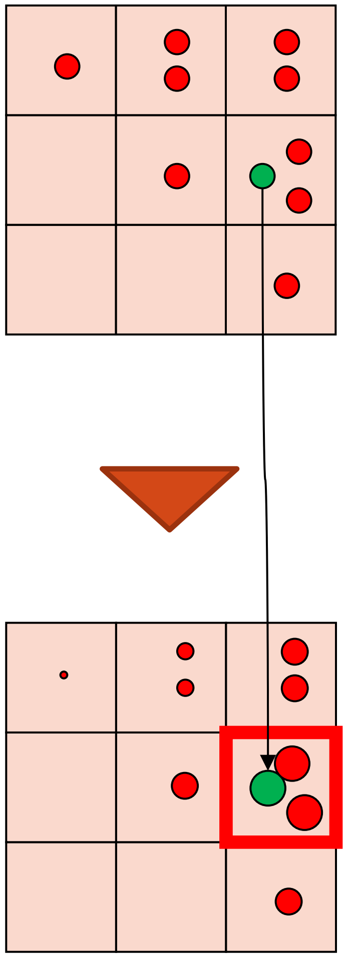


Particles:
(3,2)
(2,3)
(3,2)
(3,1)
(3,3)
(3,2)
(1,3)
(2,3)
(3,3)
(2,2)

Particle Filtering: Observe/Weight ("Update" part 1)

- Slightly trickier:
  - Don't sample observation, fix it
  - Similar to likelihood weighting, weight samples based on the evidence
    - $W = P(e_t \mid x_t)$
  - Normalize the weights: particles that fit the data better get higher weights, others get lower weights

Particles:
(3,2)
(2,3)
(3,2)
(3,1)
(3,3)
(3,2)
(1,3)
(2,3)
(3,2)
(2,2)



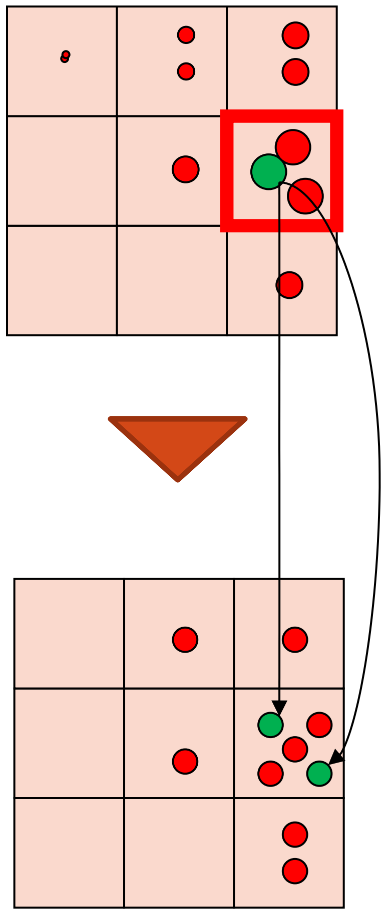
Particles:
(3,2) w=.9
(2,3) w=.2
(3,2) w=.9
(3,1) w=.4
(3,3) w=.4
(3,2) w=.9
(1,3) w=.1
(2,3) w=.2
(3,3) w=.4
(2,2) w=.4

Particle Filtering: Resample ("Update" part 2)

- Rather than tracking weighted samples, we ***resample***
- We have an updated belief distribution based on the weighted particles
- We sample N new particles from the weighted belief distributions
- Now the update is complete for this time step; continue with the next one

Particles:
(3,2) w=.9
(2,3) w=.2
(3,2) w=.9
(3,1) w=.4
(3,3) w=.4
(3,2) w=.9
(1,3) w=.1
(2,3) w=.2
(3,3) w=.4
(2,2) w=.4

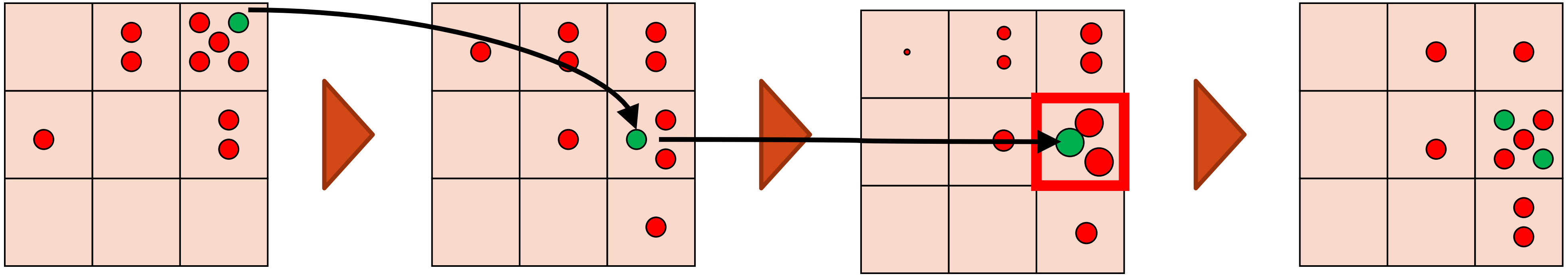
(New) Particles:
(3,2)
(2,2)
(3,2)
(2,3)
(3,3)
(3,2)
(1,3)
(2,3)
(3,2)
(3,2)



Summary: Particle Filtering

- Particles: track samples of states rather than an explicit distribution

Propagate forward based on transition function — Weight based on observation function — Resample using weighted particles



Particles:	Particles:	Particles:	(New) Particles:
(3,3)	(3,2)	(3,2) w=.9	(3,2)
(2,3)	(2,3)	(2,3) w=.2	(2,2)
(3,3)	(3,2)	(3,2) w=.9	(3,2)
(3,2)	(3,1)	(3,1) w=.4	(2,3)
(3,3)	(3,3)	(3,3) w=.4	(3,3)
(3,2)	(3,2)	(3,2) w=.9	(3,2)
(1,2)	(1,3)	(1,3) w=.1	(1,3)
(3,3)	(2,3)	(2,3) w=.2	(2,3)
(3,3)	(3,2)	(3,3) w=.4	(3,2)
(2,3)	(2,2)	(2,2) w=.4	(3,2)

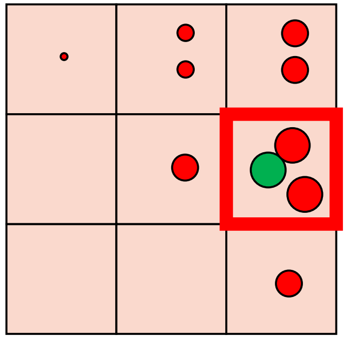
Consistency: see proof in AIMA Ch. 14

[Demos: ghostbusters particle filtering (L15D3,4,5)]

Weighting and Resampling

- How to compute a belief distribution given weighted particles

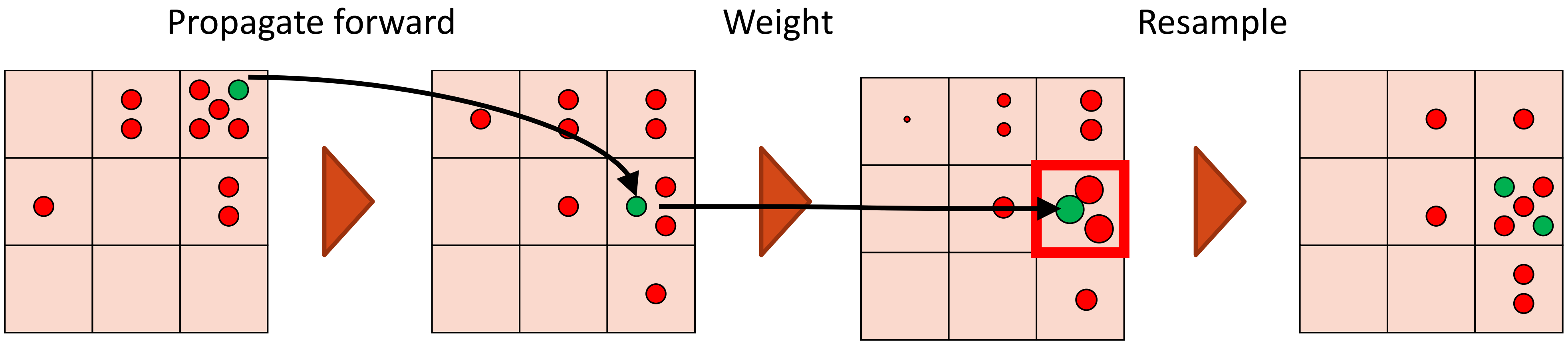
Weight



Particles:
(3,2) w=.9
(2,3) w=.2
(3,2) w=.9
(3,1) w=.4
(3,3) w=.4
(3,2) w=.9
(1,3) w=.1
(2,3) w=.2
(3,3) w=.4
(2,2) w=.4

Poll 1

- If we only have one particle which of these steps are unnecessary?

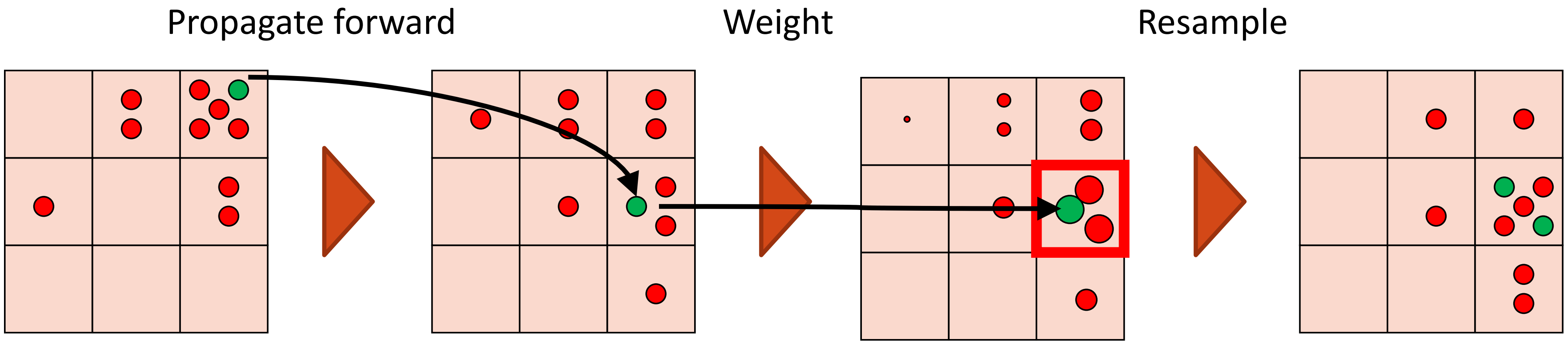


Select all that are unnecessary.

A. Propagate forward
B. Weight
C. Resample
D. None of the above

Poll 1

- If we only have one particle which of these steps are unnecessary?

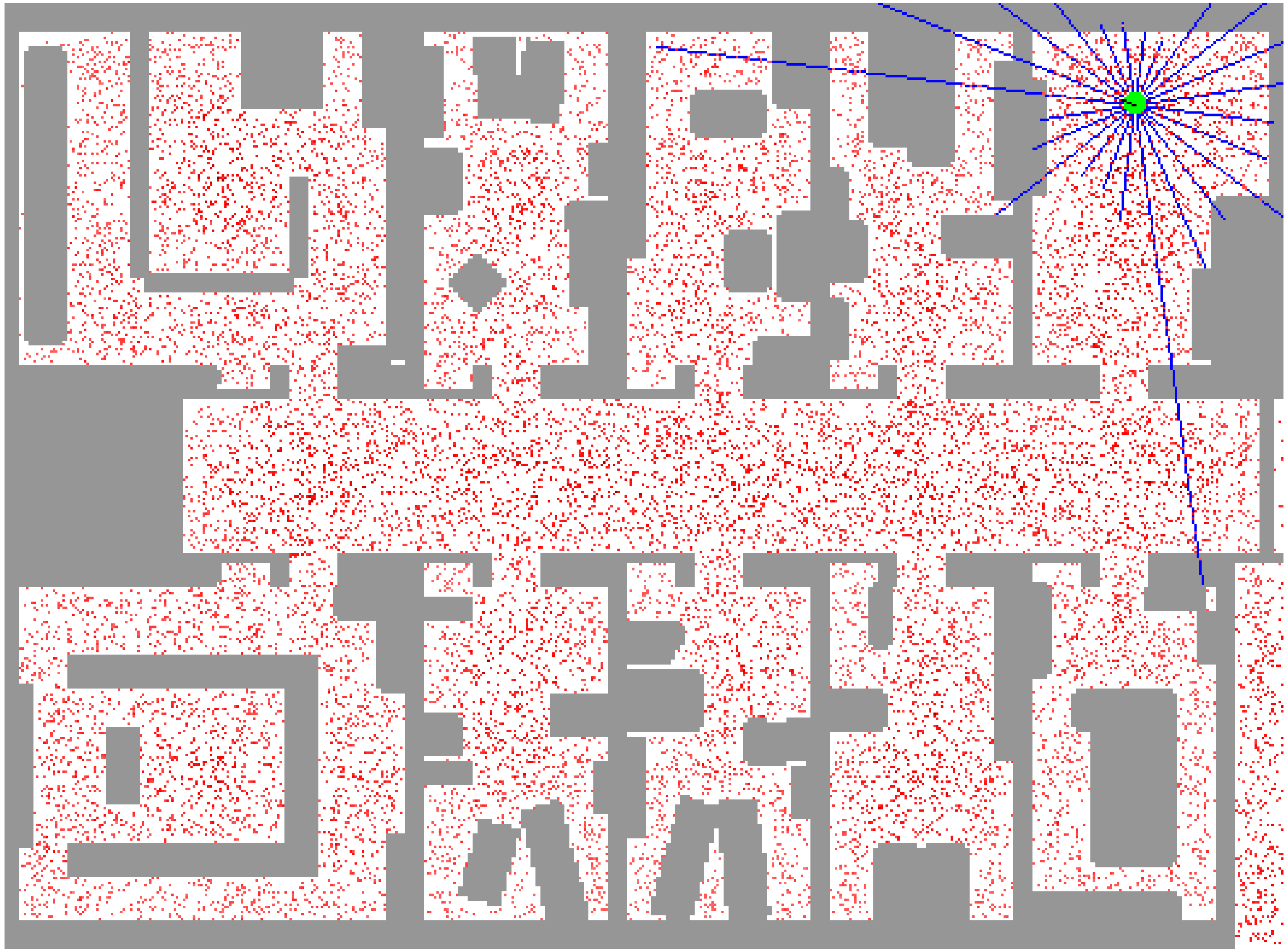


Select all that are unnecessary.

A. Propagate forward
B. Weight
C. Resample
D. None of the above

Unless the weight is zero, in which case, you'll want to resample from the beginning ☹

Particle Filter Localization (Laser)



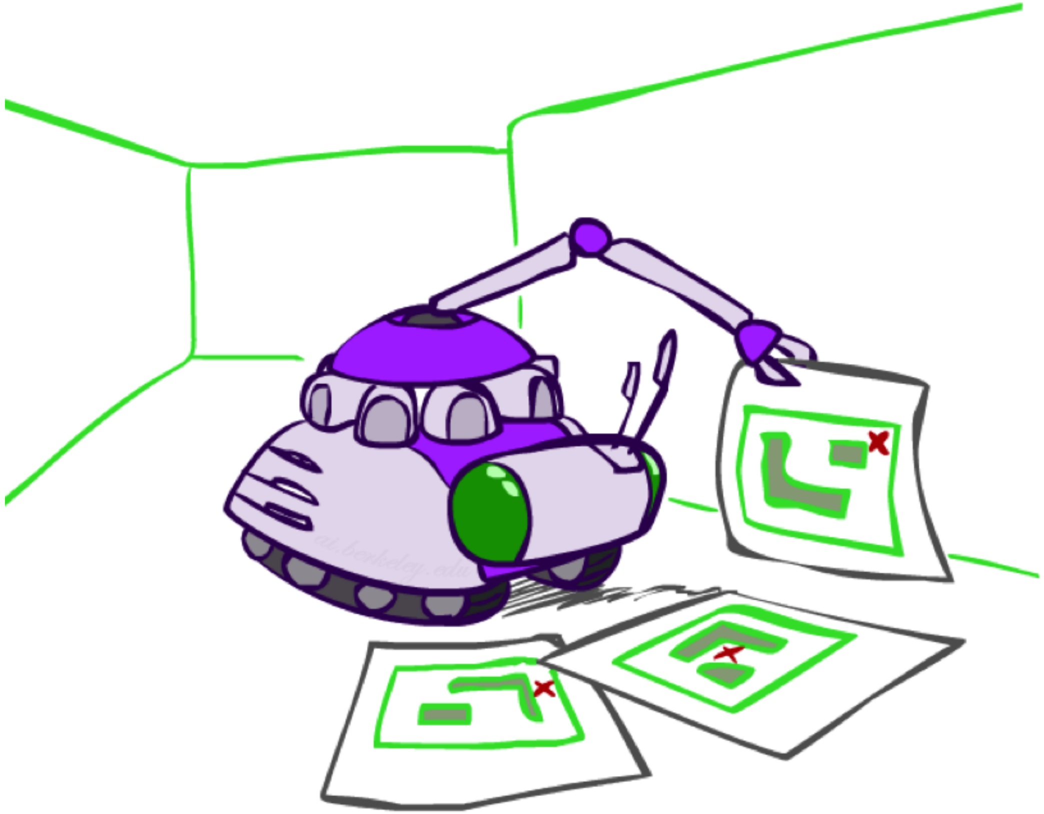
[Dieter Fox, et al.]

[Video: global-floor.gif]

Robot Mapping

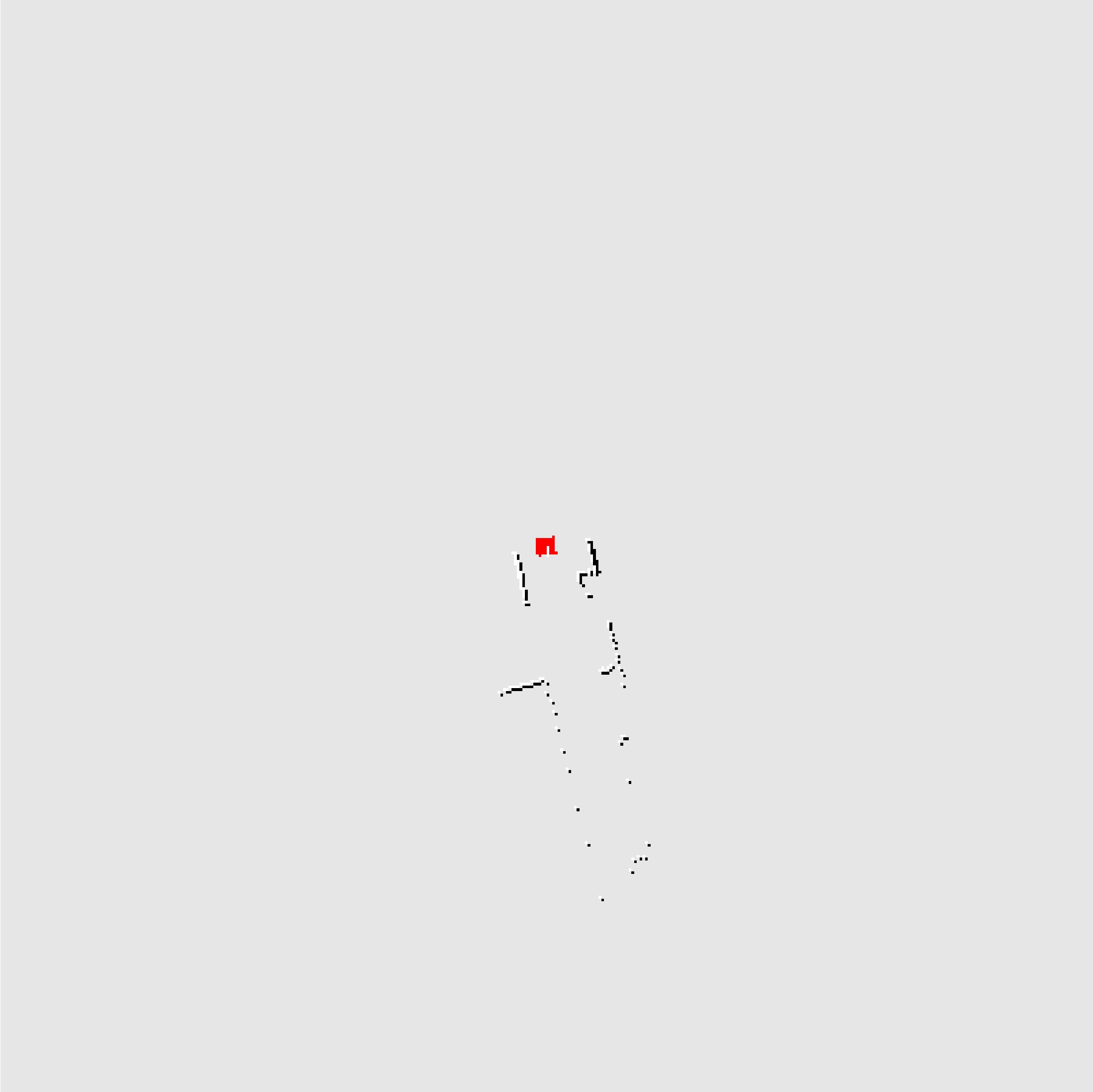
- SLAM: Simultaneous Localization And Mapping
  - We do not know the map or our location
  - State consists of position AND map!
  - Main techniques: Kalman filtering (Gaussian HMMs) and particle methods

DP-SLAM, Ron Parr



[Demo: PARTICLES-SLAM-mapping1-new.avi]

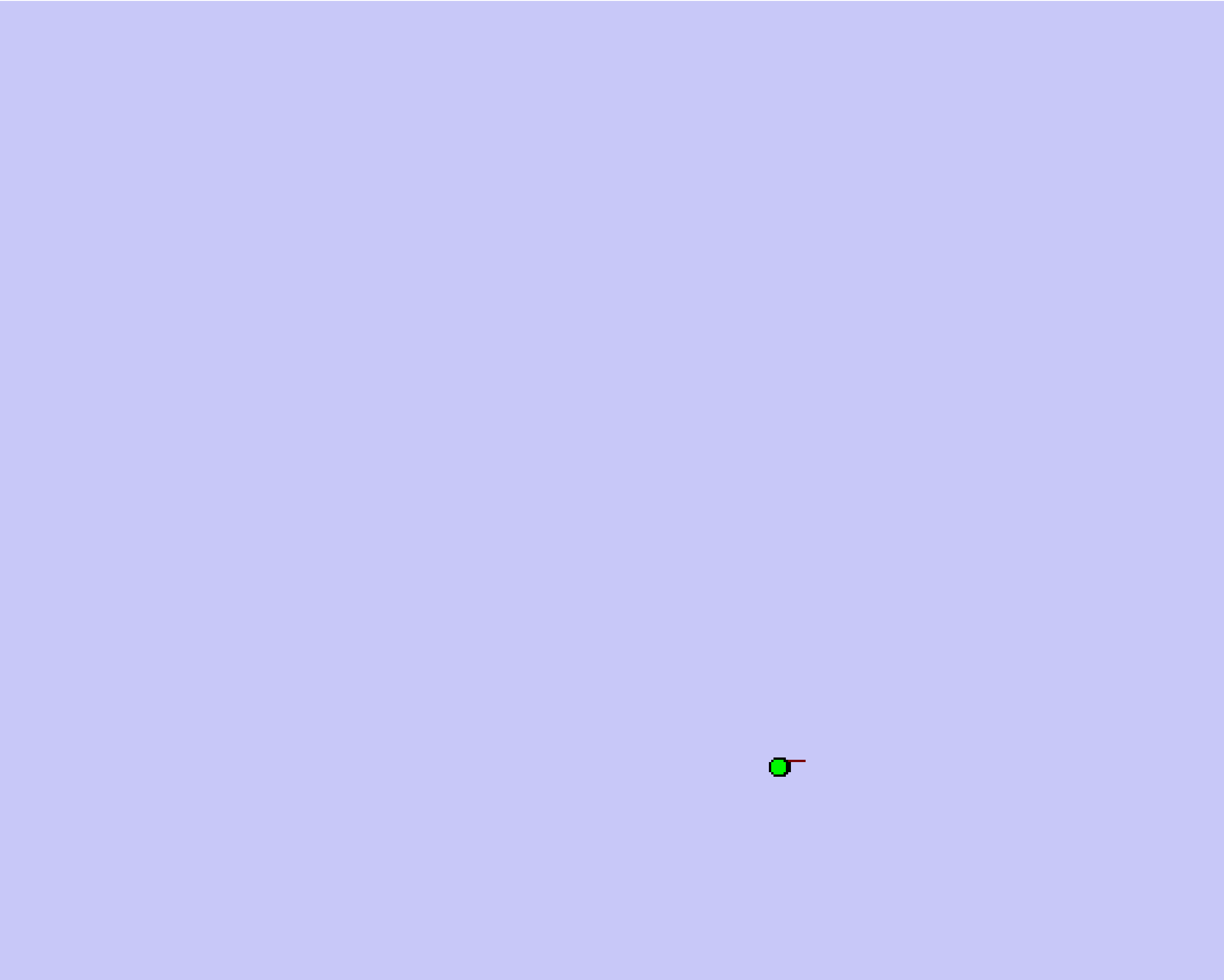
Particle Filter SLAM – Video 1



[Sebastian Thrun, et al.]

[Demo: PARTICLES-SLAM-mapping1-new.avi]

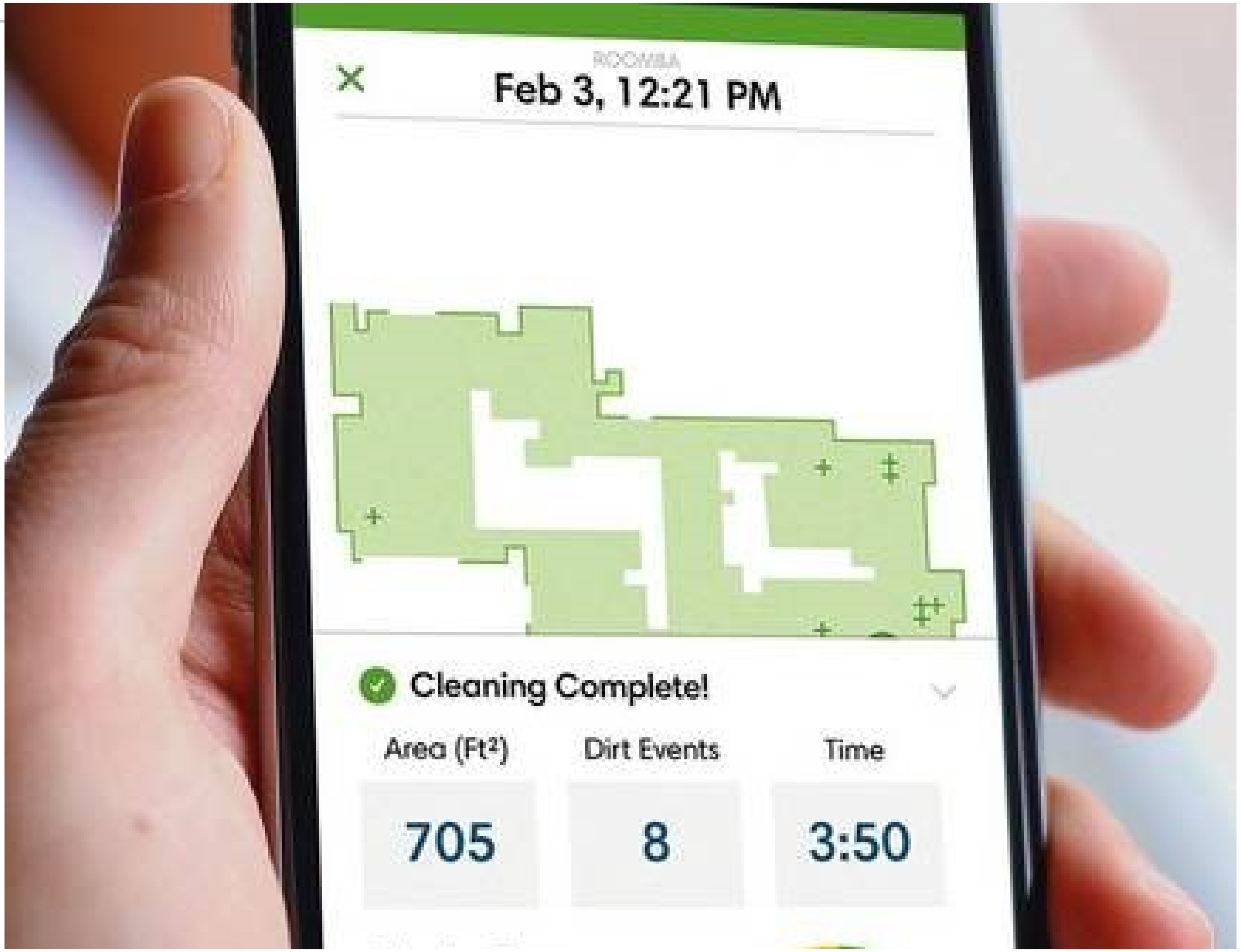
Particle Filter SLAM – Video 2



[Dirk Haehnel, et al.]

[Demo: PARTICLES-SLAM-fastslam.avi]

SLAM

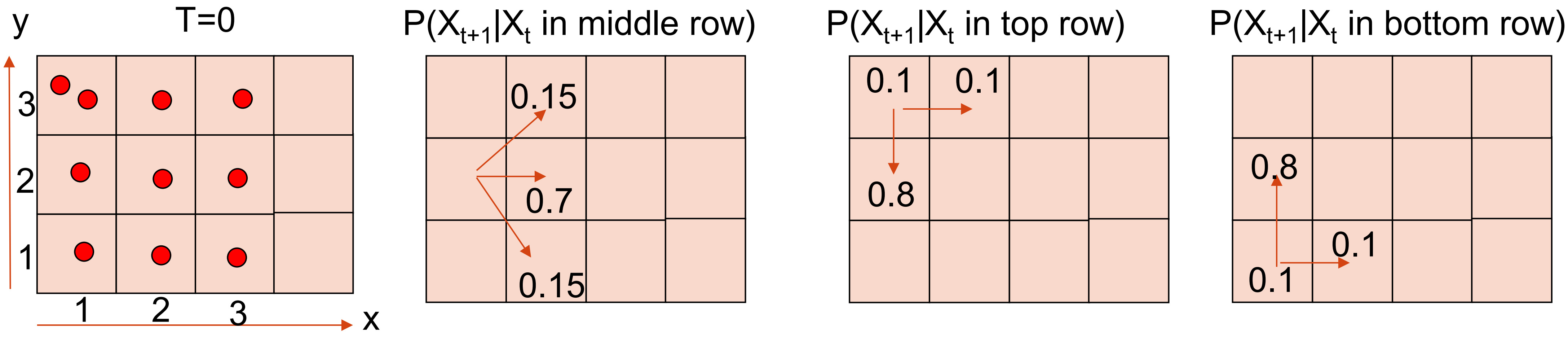


https://www.irobot.com/

Use Python random.random() or Google to sample

In Class Activity

- Given the following starting particles, transition model, and e_1 and e_2 observed at time 1 and time 2, what is the approximate belief state at time 2?



$P(e_1|X_1)$

.3	.5		
.5	.5		
.2	.5		

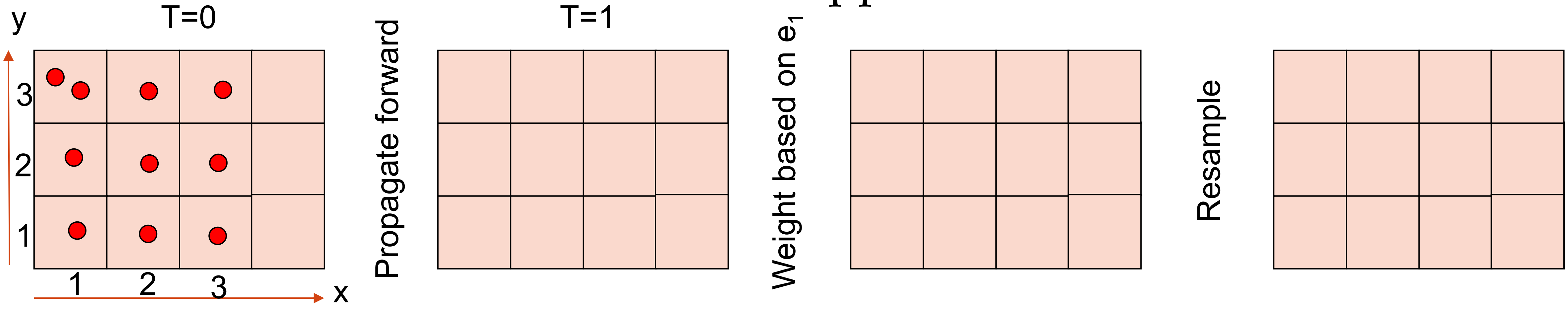
$P(e_2|X_2)$

	.05	.4	
	.3	.5	
	.05	.2	

In Class Activity

Use random.random() or Google to sample

- Given the following starting particles, transition model, and e_1 observed at time 1, what is the approximate belief state at time 1?



$P(e_1|X_1)$

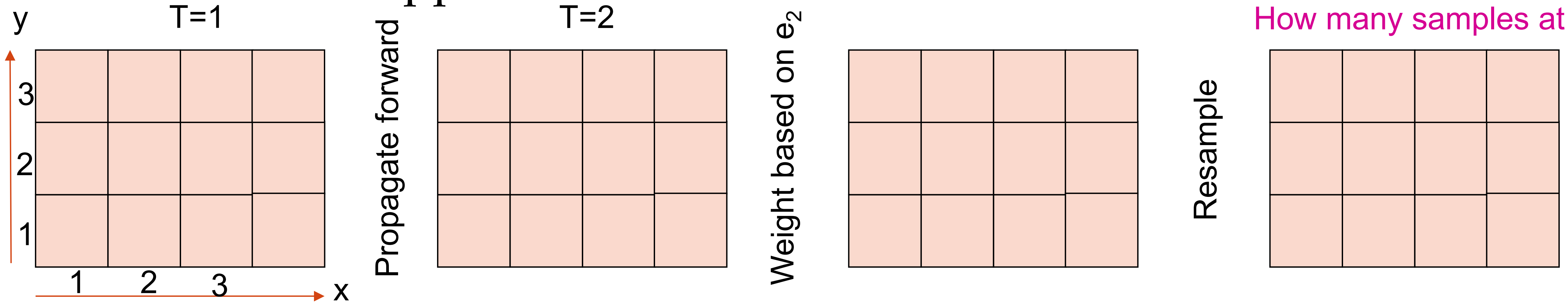
.3	.5		
.5	.5		
.2	.5		

Use random.random() or Google to sample

In Class Activity

- Given the particles at T=1, transition model, and e_2 observed at time 2, what is the approximate belief state at time 2?

How many samples at (3,2)?



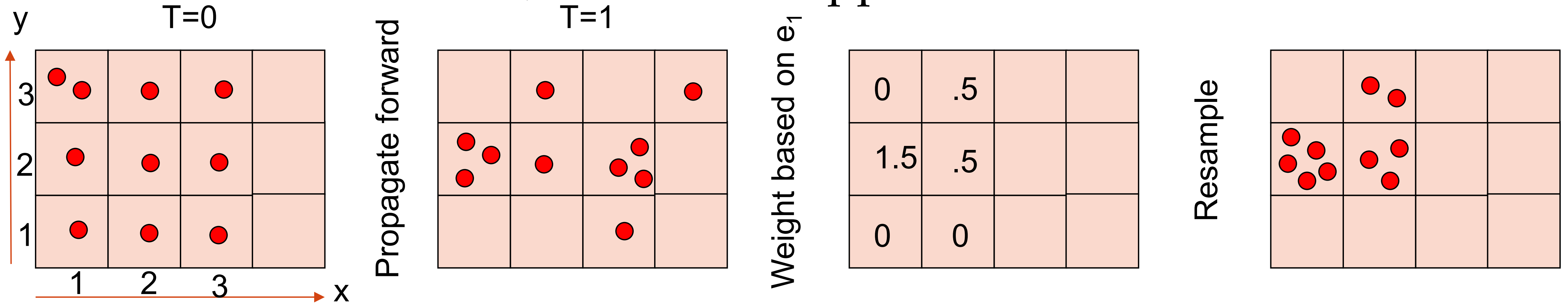
$P(e_2|X_2)$

	.05	.4	
	.3	.5	
	.05	.2	

Use random.random() to sample

In Class Activity – Example Solution

- Given the following starting particles, transition model, and e_1 observed at time 1, what is the approximate belief state at time 1?



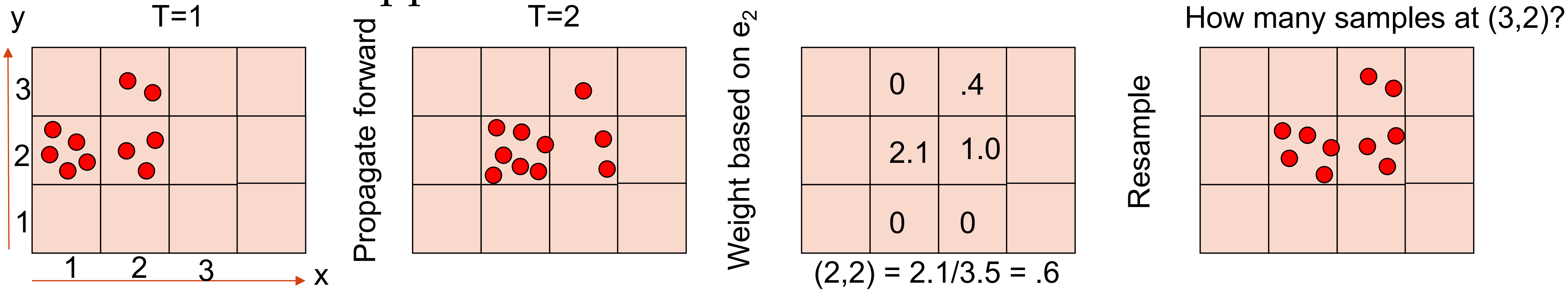
$P(e_1|X_1)$

.3	.5		
.5	.5		
.2	.5		

Use random.random() to sample

In Class Activity – Example Solution

- Given the T=1 particles, transition model, and e_2 observed at time 2, what is the approximate belief state at time 2?

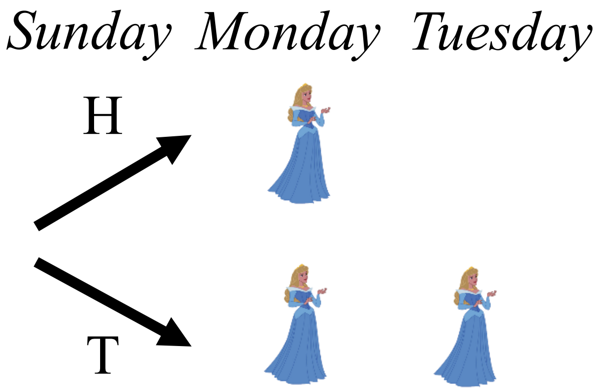


(2,2) = 2.1/3.5 = .6
(3,2) = 1.0/3.5 = .29
(3,3) = .4/3.5 = .11

$P(e_2|X_2)$

	.05	.4	
	.3	.5	
	.05	.2	

A different type of self-locating belief: Sleeping Beauty problem [Piccione and Rubinstein'97, Elga'00]



- There is a participant in a study (call her Sleeping Beauty)
- On Sunday, she is given drugs to fall asleep
- A coin is tossed (H or T)
- If H, she is awoken on Monday, then made to sleep again
- If T, she is awoken Monday, made to sleep again, then **again** awoken on Tuesday
- Due to drugs she **cannot remember what day it is or whether she has already been awoken once**, but she remembers all the rules
- Imagine **you** are SB and you've just been awoken. What is your (subjective) probability that the coin came up H?

don't do this at home / without IRB approval...