Particle Filtering

AI+X
INSTITUTE FOR ARTIFICIAL INTELLIGENCE

Particle Filtering

- Sometimes **|X|** (space of coordinates) is too big to use exact inference
  - E.g. **X** is continuous
- Solution: approximate inference
  - Track samples of **X**, not all values
  - Samples are called particles
  - Computational cost per step is linear in the number of samples
    - Number of samples needed may be large
  - In memory: list of particles, not states
- Particle is just a new name for sample

Particles

- Our representation of **P(X)** is now a list of **N** particles (samples)
  - Generally, **N << |X|**
  - Storing map 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
- For now, all particles have a weight of 1

Elapse Time

- Each particle is moved by sampling its next position from the transition model
  - **x’ = sample(P(X’|x))**
  - This is like prior sampling - samples’ frequencies reflect the transition probabilities
- This captures the passage of time
  - If enough samples, close to exact values before and after (consistent)

Observe

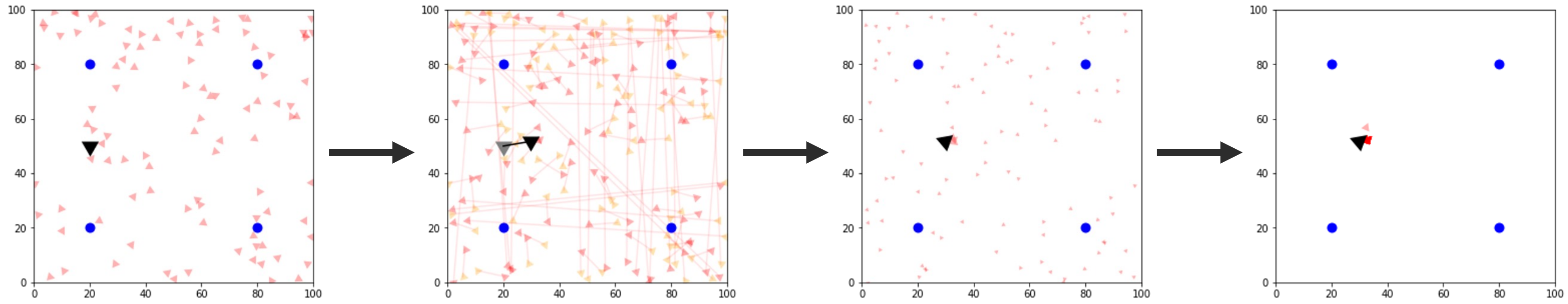
- Don’t sample observation, fix it
  - **$w(x) = P(e|x)$**
  - **$B(X) \propto P(e|X)B'(X)$**
- Similar to likelihood weighting, downweight samples based on the evidence
- As before, the probabilities don’t sum to one, since all have been downweighted (in fact they now sum to **N** times an approximation of **P(e)**)

Resample

- Rather than tracking weighted samples, we resample **N** times
    - Choose from our weighted sample distribution (i.e. draw with replacement)
- This is equivalent to renormalizing the distribution
- Now the update is complete for this time step, continue with the next one

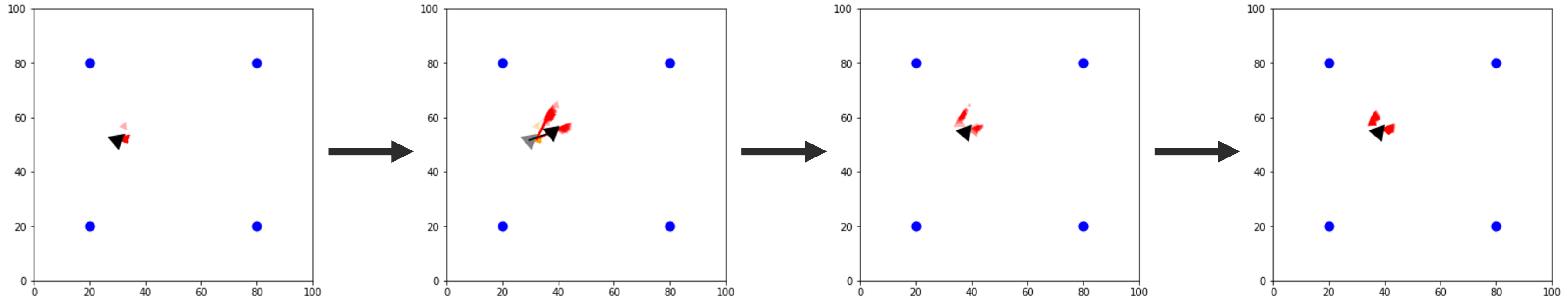
Particle Filtering

Elapse **Observe** **Resample**

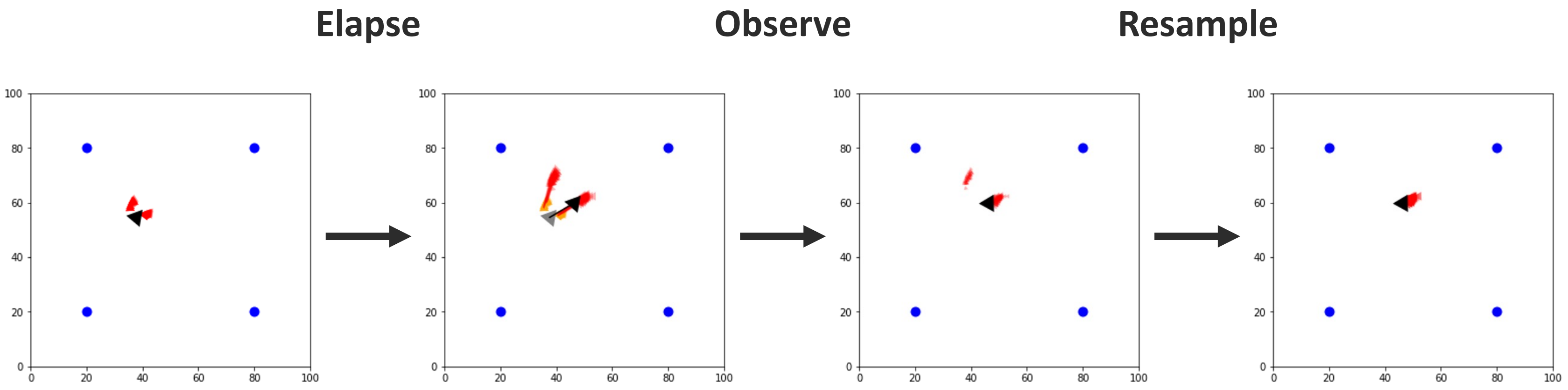


Particle Filtering

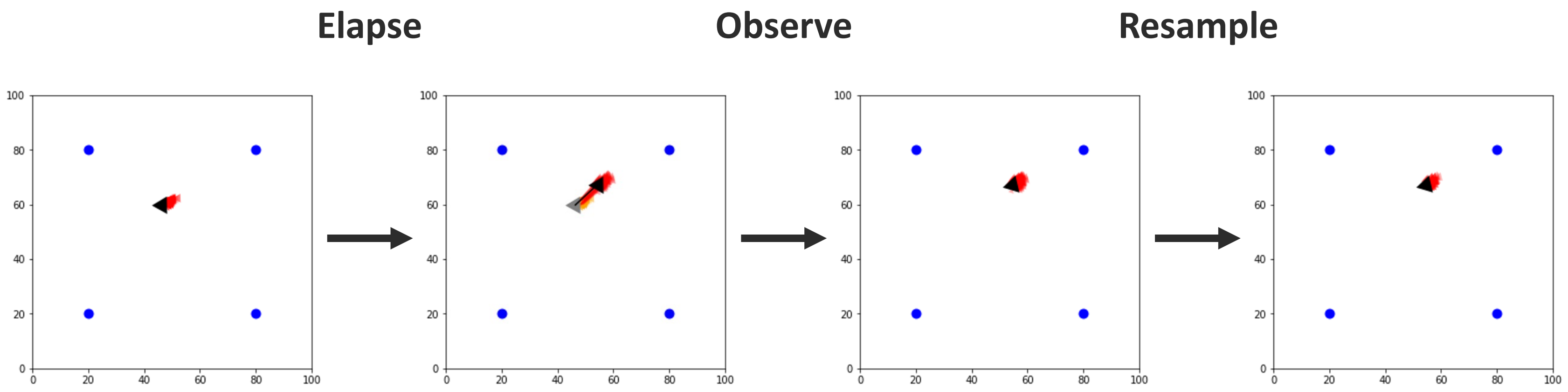
Elapse **Observe** **Resample**



Particle Filtering



Particle Filtering



Knowledge Check 1

When programming your own self-driving car, which of the methods below would be more adequate to estimate the location of the car?

A There is no need for such thing, we can use GPS

B Naive Bayes Model

C Particle Filtering

You have reached the end of the lecture.