Sequential Monte Carlo: Particle Filter

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Importance sampling again

To approximate the integral, but $p(z)$ is hard to sample.

$$\begin{aligned} \mathrm{E}_{p(z)}[f(z)] &= \int f(z)p(z)dz \\ &= \int \underbrace{f(z)\frac{p(z)}{q(z)}}_{\text{new}\tilde{f}(z)} q(z)dz \\ &\approx \frac{1}{N}\sum_{n=1}^{N} f(z^i)\frac{p(z^i)}{q(z^i)} \end{aligned} \tag{1}$$

Revision on SMC

Take Importance Sampling to higher dimensions, the importance weights are:

$$w_n(x_{1:n}) = \frac{\gamma(x_{1:n})}{q_n(x_{1:n})} \tag{2}$$

Hard to choose $q(.)$ in high-dimension
Solution : rewrite equation (2) in the following:

$$w_n(x_{1:n}) = \frac{\gamma(x_{1:n})}{q_n(x_n|x_{1:n-1})q_{n-1}(x_{1:n-1})} \times \frac{\gamma(x_{1:n-1})}{\gamma(x_{1:n-1})}$$

re-arrange:

$$w_n(x_{1:n}) = \frac{\gamma(x_{1:n})}{q(x_{1:n})} = w_{n-1}(x_{1:n-1}) \times \frac{\gamma(x_{1:n})}{\gamma(x_{1:n-1})q(x_n|x_{1:n-1})}$$

Revision on SMC (2)

Top-down:

$$w_n(x_{1:n}) = w_{n-1}(x_{1:n-1}) \frac{\gamma(x_{1:n})}{\gamma(x_{1:n-1}) q(x_n | x_{1:n-1})} \tag{3}$$

Bottom-up:

$$w_n(x_{1:n}) = w_1(x_1) \prod_{j=2}^{n} \frac{\gamma(x_{1:j})}{\gamma(x_{1:j-1}) q(x_j | x_{1:j-1})}$$

The two are equivalent

Just too easy to put it all in an algorithm:

The SIS algorithm:

$$
\begin{aligned}
&\text{At dimension } n = 1\text{: For each particle } i\\
&\quad \text{Sample } x_1^i \sim q_1(x_1)\\
&\quad \text{Compute the weights } w_1^i \propto \frac{\gamma(x_1^i)}{q_1(x_1^i)}\\
&\text{At dimension } n \geq 2\text{: For each particle } i\\
&\quad \text{Sample } x_n^i \sim q_n(x_n | x_{1:n-1}^i)\\
&\quad \text{Compute the weights } w_n^i \propto w_{n-1}^i \frac{\gamma(x_{1:n}^i)}{\gamma(x_{1:n-1}^i) q(x_n^i | x_{1:n-1}^i)}
\end{aligned}
\tag{4}
$$

Particle Filter

Put this in a state-space setting, you have particle filter!
By changing n to t to reflect time sequentiality. In here, we assume that:

$$p(x_{1:t}|y_{1:t}) = \frac{p(x_{1:t}, y_{1:t})}{p(y_{1:t})} = \frac{\gamma_t(x_{1:t})}{\mathcal{Z}}$$

In here, we assume:

$$\begin{aligned}
\gamma_t(x_{1:t}) &= p(x_{1:t}, y_{1:t}) \\
&= p(y_t|x_{1:t}, y_{1:t-1})p(x_t|x_{1:t-1}, y_{1:t-1})\gamma_{t-1}(x_{1:t-1}) \\
&= p(y_t|x_t)p(x_t|x_{t-1})\gamma_{t-1}(x_{1:t-1})
\end{aligned} \tag{5}$$

Particle Filter

Divide by the proposal distribution $q(.)$, and do the same trick, this time, we use:

$$w_t(x_{1:t}) = \frac{\gamma_{(1:t)}}{q_{(1:t)}} = \frac{\gamma_{(1:t-1)}}{q_{(1:t-1)}} \times \frac{p(y_t|x_t)p(x_t|x_{t-1})}{q(x_t|x_{1:t-1})}$$

we can make a "reasonable" assumption that:

$$q(x_t|x_{1:t-1}) \equiv q(x_t|x_{t-1}, y_t) \tag{6}$$

Hence,

$$w_t(x_{1:t}) = w_{t-1}(x_{1:t-1}) \times \frac{p(y_t|x_t)p(x_t|x_{t-1})}{q(x_t|x_{t-1}, y_t)}$$

question is How are we going to choose $q(.)$ **a short answer** Choose $q(.)$ somehow from your dynamic model

Optimal proposal: $q(x_t|x_{k-1}, y_t) = p(x_t|x_{k-1}, y_t)$

Stated in [Doucet 1998], $q(x_t|x_{k-1}, y_t) = p(x_t|x_{k-1}, y_t)$ is optimal,then:

$$\begin{aligned} w_{(1:t)} &\propto w_{(1:t-1)} \times \frac{p(y_t|x_t)p(x_t|x_{t-1})}{p(x_t|x_{t-1}, y_t)} \\ &= w_{(1:t-1)} \times \frac{p(y_t|x_t)p(x_t|x_{t-1})p(y_t|x_{t-1})p(x_{t-1})}{p(y_t|x_t)p(x_t|x_{t-1})p(x_{t-1})} \\ &= w_{(1:t-1)} \times p(y_t|x_{t-1}) \end{aligned}$$

However, $p(y_t|x_{t-1})$ is quite meaningless:

$$w_{(1:t)} \propto w_{(1:t-1)} \times \int_{x_t} p(y_t|x_t)p(x_t|x_{t-1}) \tag{7}$$

Two problem: (1) Difficult to sample from $p(x_t|x_{k-1}, y_t)$ and (2) integral is difficult to perform!

Main talk: sub-optimal methods

In this talk, I will present two “popular” sub-optimal sampling methods first:

- Bootstrap Particle Filter
- Auxiliary Particle Filter

Bootstrap Particle Filter

Sometimes calling it Condensational Filter. (Famous Michael Isard)
Let $q(x_t|x_{k-1}, y_t) = p(x_t|x_{k-1})$, i.e., y_t does not participate in the proposal $q(.)$

$$
\begin{aligned}
w_{(1:t)} &\propto w_{(1:t-1)} \times \frac{p(y_t|x_t)p(x_t|x_{t-1})}{p(x_t|x_{t-1})} \\
&= w_{(1:t-1)} \times p(y_t|x_t)
\end{aligned}
\tag{8}
$$

- particles x_t^i are sampled from $p(.|x_{t-1})$, but are weighted by $p(y_t|x_t^i)$
- the danger is that x_t^i may receive close to zero weight if $p(y_t|x_t^i)$ is very small.

The Condensational Filter algorithm:

$$
\begin{aligned}
&\text{At time } t \\
&\text{For each particle } i: \\
&\qquad \text{Sample } x_t^i \sim p(x_t | x_{t-1}^i) \qquad \big(\text{Or } x_1^i \sim p(x_1) \text{ when } t = 1\big) \\
&\qquad \text{Compute the weights } w_t^i \propto \pi_{t-1}^i p(y_t | x_t^i) \\
&\text{normalize weights } \pi_t^i = \frac{w_t^i}{\sum_{i=1}^N w_t^i}
\end{aligned}
\tag{9}
$$

Problem particle degeneracy occurs very quickly.
Solution break those big particle into smaller ones, from the "re-sampling" step. To determine if "big particles" exist, check effective particle size.
BTW re-sampling does not solve particle degeneracy problem altogether.

Introducing Re-Sampling

Re-sampling sometimes can be considered as jointly "sample" an index i^j to indicate which $x_{t-1}^{i^j}$ generated x_t^i, and x_t^i itself.

$$\begin{aligned} & x_t^i \sim q(x_t | x_{t-1}^i, y_t) \\ & \text{ becomes:} \\ & j \sim \pi_{t-1}(x_{1:t-1}) \\ & x_t^i \sim q(x_t | x_{t-1}^{i^j}, y_t) \end{aligned} \tag{10}$$

For each particle i at time t, you get (x_t^i, i^j).

Introducing Re-Sampling

Substituting N of the (x_t^i, i^j) into the following:

$$w_t(x_{1:t}) \propto \pi_{t-1}(x_{1:t-1}) \times \frac{p(y_t|x_t)p(x_t|x_{t-1})}{q(x_t|x_{t-1}, y_t)}$$

$$\begin{aligned} w_t^i(x_{1:t}) &\propto \pi_{(t-1)}^{i^j} \times \frac{p(y_t|x_t^i)p(x_t^i|x_{t-1}^{i^j})}{\pi_{(t-1)}^{i^j} q(x_t^i|x_{t-1}^{i^j}, y_t)} \\ &= \frac{p(y_t|x_t^i)p(x_t^i|x_{t-1}^{i^j})}{q(x_t^i|x_{t-1}^{i^j}, y_t)} \end{aligned}$$

In the bootstrap filter:

$$w_t^i(x_{1:t}) \propto p(y_t|x_t^i)$$

The Condensational Filter algorithm:

At time t

For each i:

$$
\begin{aligned}
&\text{Sample } j \sim \pi_{t-1}(x_{1:t-1}) && - \text{choose an an ancestor} \\
&\text{Sample } x_t^i \sim p(x_t | x_{t-1}^{i^j}) && \big(\text{Or } x_1^i \sim p(x_1) \text{ when } t = 1\big) \\
&\text{Compute the weights } w_t^i \propto p(y_t | x_t^i)
\end{aligned}
\tag{11}
$$

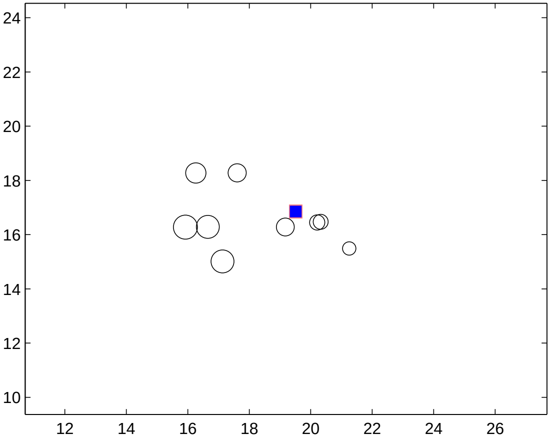
normalize weights $\pi_t^i = \dfrac{w_t^i}{\sum_{i=1}^N w_t^i}$

A little demo

- $p(x_t|x_{t-1}) = \mathcal{N}(Ax_{t-1} + B, Q)$
- $p(y_t|x_t) = \mathcal{N}(x_t, R)$

This is just for demo purpose, you can compute $p(x_t|y_{1:t})$ exactly using Kalman Filter!

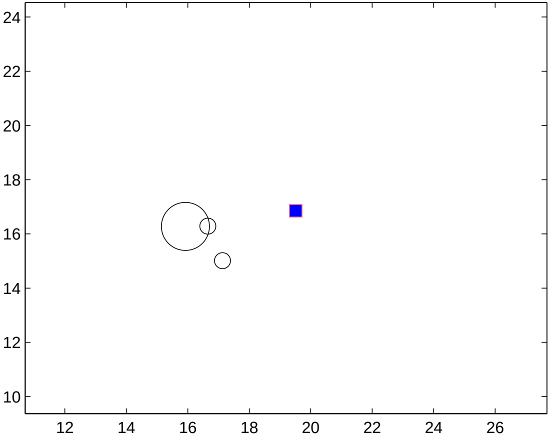
Representation for $p(x_{t-1}|y_{1:t-1})$



- Circles are weighted particle representation of $p(x_{t-1}|y_{1:t-1})$
- The blue square is y_t

Re-sampling

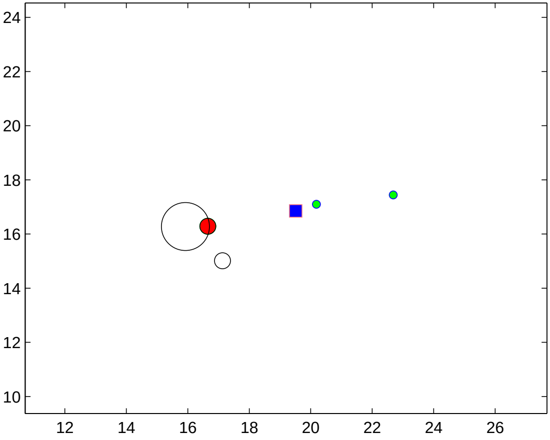
To sample $j \sim \pi_{t-1}(x_{1:t-1})$:



- Size of the circle indicates the number of times $x^{i^j}_{t-1}$ was selected.

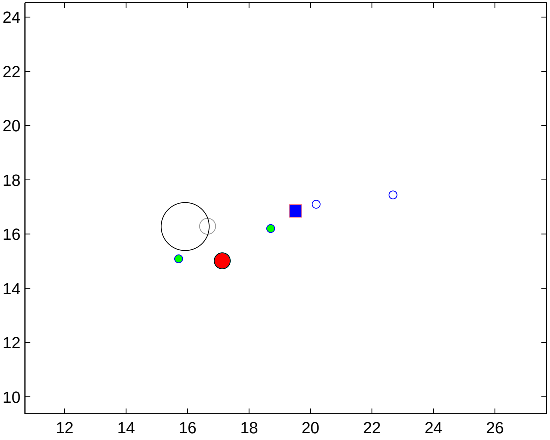
Transition demos

Sample $x_t^i \sim p(x_t | x_{t-1}^{i^j}) : \forall i^j = 1$



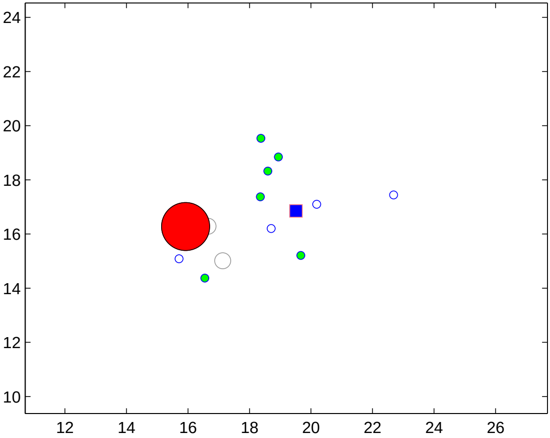
Transition demos

Sample $x_t^i \sim p(x_t | x_{t-1}^{i^j}) : \forall i^j = 2$



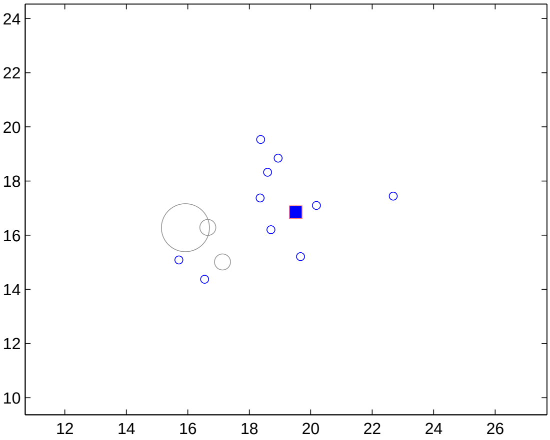
Transition demos

Sample $x_t^i \sim p(x_t | x_{t-1}^{i^j}) : \forall i^j = 3$



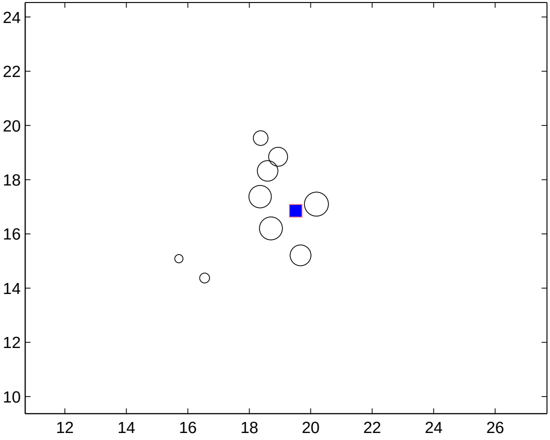
Transition demos

Here are the complete $\{x_t^i\}_1^N$ sampled.



After re-weighting

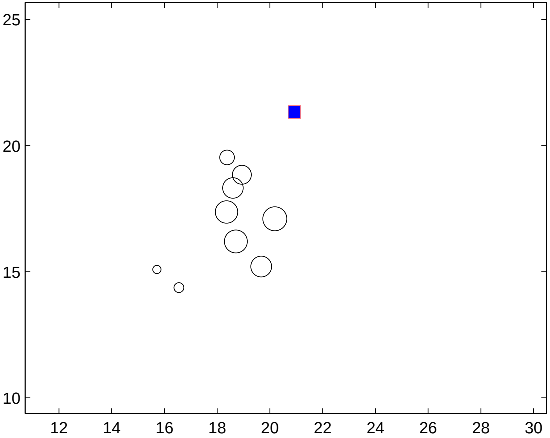
Compute the weights $w_t^i \propto p(y_t | x_t^i)$:



The above is the representation for $p(x_t | y_{1:t})$ Note that weights are in log

Next t

So the recursion will repeat:



The above is the representation for $p(x_{t-1}|y_{1:t-1})$ in the next t:

Some cool things you can do just with Bootstrap Filter

For example, A Coupled two-states dynamic model:
To estimate $p(x^1_{1:t}, x^2_{1:t} | y^1_{1:t}, y^2_{1:t})$

$$
\begin{aligned}
& w^i_t(x^1_{1:t}, x^2_{1:t}) \propto \\
& = \frac{g_1(y^1_t | x^1_t) g_2(y^2_t | x^2_t) f_1(x^1_t | x^1_{t-1}, x^2_{t-1}) f_2(x^2_t | x^1_{t-1}, x^2_{t-1})}{q^1(x^1_t | y^1_t, x^1_{t-1}, x^2_{t-1}) q^2(x^2_t | y^2_t, x^1_{t-1}, x^2_{t-1})} \\
& \quad w^i_{t-1}(x^1_{1:t-1}, x^2_{1:t-1})
\end{aligned} \tag{12}
$$

Sampler for Coupled dynamic model

(leaving out the case of $t = 1$, and re-sampling step)

$$
\begin{aligned}
&\text{At time } t\text{:}\\
&\text{Sample } x_t^{1,(i)} \sim f_1(x_t^1 | x_{t-1}^{1,(i)}, x_{t-1}^{2,(i)})\\
&\text{Sample } x_t^{2,(i)} \sim f_2(x_t^2 | x_{t-1}^{1,(i)}, x_{t-1}^{2,(i)})\\
&\text{Compute the weights } w_t^{1,(i)} \propto \pi_{t-1}^{1,(i)} g_1(y_t^{1,(i)} | x_t^{1,(i)})\\
&\text{Compute the normalized weights } \pi_t^{1,(i)}\\
&\text{Compute the weights } w_t^{2,(i)} \propto \pi_{t-1}^{2,(i)} g_2(y_t^{2,(i)} | x_t^{2,(i)})\\
&\text{Compute the normalized weights } \pi_t^{2,(i)}
\end{aligned}
\tag{13}
$$

Auxiliary Particle Filter

- **idea**: Let y_t also participates in the proposal.
- **how**: In bootstrap sampling, x_t^i is more likely to be generated from $x_{t-1}^{i^j}$ when the value of $\pi_{t-1}^{i^j}$ is high. **Then** , how about let's also give preference to those $x_{t-1}^{i^j}$ where their proposed $x^i \sim x_{t-1}^{i^j}$ can be weighted higher by $p(y_t|x^i)$ as well?
- **in my word**: Have a bit of scouting before sampling!

Auxiliary Particle Filter algorithm

$$\mu_t^i = \mathrm{E}_{x_t}[x_t | x_{t-1}^i], \text{ OR: } \mu_t^i \sim p(x_t | x_{t-1}^i) \tag{14}$$

At time t, for each particle i:

$$\begin{aligned}
&\text{Calculate } \mu_t^i \\
&\text{Compute the weights } w_t^i \propto p(y_t | \mu_t^i)\pi_{t-1}^i \\
&\text{Normalize } w_t^i \\
&\text{Sample } i^j \sim \{w_t^i\} \\
&\text{Sample } x_t^i \sim p(x_t | x_{t-1}^{i^j}) \\
&\text{Assign } w_t^i \propto \frac{p(y_t | x_t^i)}{p(y_t | \mu_t^{i_j})} \\
&\text{Normalize } w_t^i \to \pi_t^i
\end{aligned} \tag{15}$$

Why $w_t^i \propto \frac{p(y_t|x_t^i)}{p(y_t|\mu_t^{i^j})}$? The proposal

Looking at the proposal:

$$q(x_t^i, i^j|.) = \underbrace{q(x_t^i|i^j, x_{t-1}, y_{1:t})}_{\text{2: choose } x_t} \underbrace{q(i^j|x_{t-1}, y_{1:t})}_{\text{1: choose the index}} \tag{16}$$

From the algorithm of the previous page:

$$\begin{aligned} &\text{1st Step: choose the index: } q(i^j|x_{t-1}, y_{1:t}) \propto p(y_t|\mu_t^{i^j})\pi_{t-1}^{i^j} \\ &\text{2nd Step: choose the } x_t\text{: } q(x_t^i|i^j, x_{t-1}, y_{1:t}) \equiv p(x_t^i|x_{t-1}^{i^j}) \end{aligned} \tag{17}$$

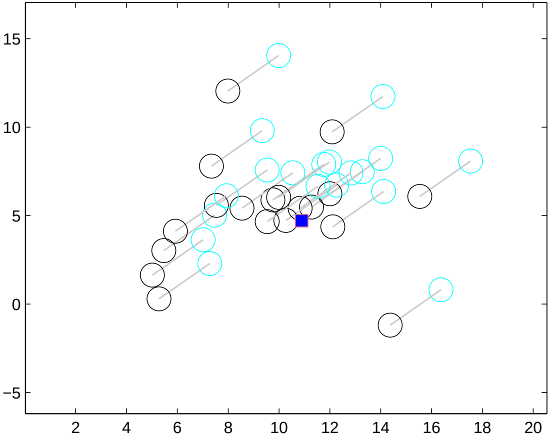
Why $w_t^i \propto \frac{p(y_t|x_t^i)}{p(y_t|\mu_t^{i^j})}$?

Substituting N of the (x^i, i^j) into the following:

$$w_t(x_{1:t}) \propto \pi_{t-1}(x_{1:t-1}) \times \frac{p(y_t|x_t)p(x_t|x_{t-1})}{q(x_t|x_{t-1}, y_t)}$$

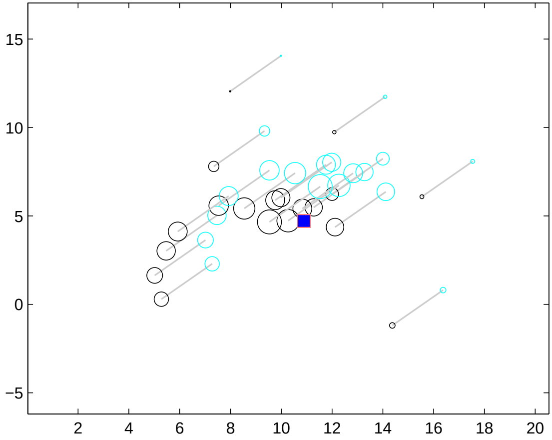
$$\begin{aligned} w_t^i(x_{1:t}) &\propto \pi_{t-1}^{i^j} \times \frac{p(y_t|x_t^i)p(x_t|x_{t-1}^{i^j})}{p(y_t|\mu_t^{i^j})\pi_{t-1}^{i^j} p(x_t^i|x_{t-1}^{i^j})} \\ &= \frac{p(y_t|x_t^i)}{p(y_t|\mu_t^{i^j})} \end{aligned}$$

Representation for $p(x_{t-1}|y_{1:t-1})$ and μ_t^i

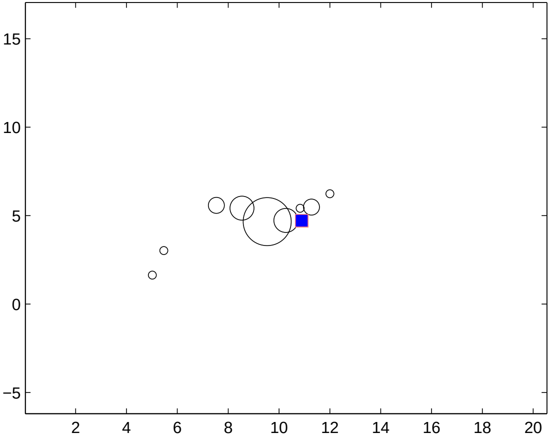


- Light blue circles are μ_t^i for each x_{t-1}^i

New weights: $\propto p(y_t|\mu_t^i)\pi_{t-1}^i$

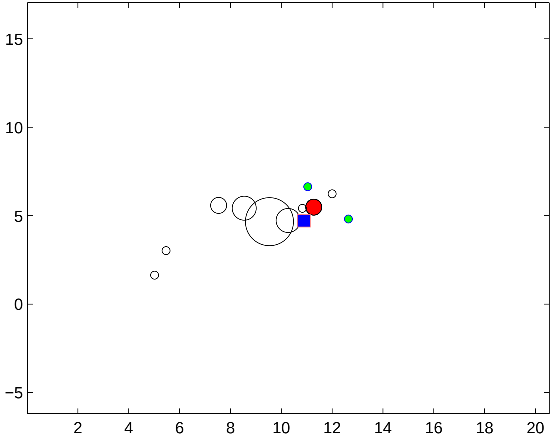


Re-sampling

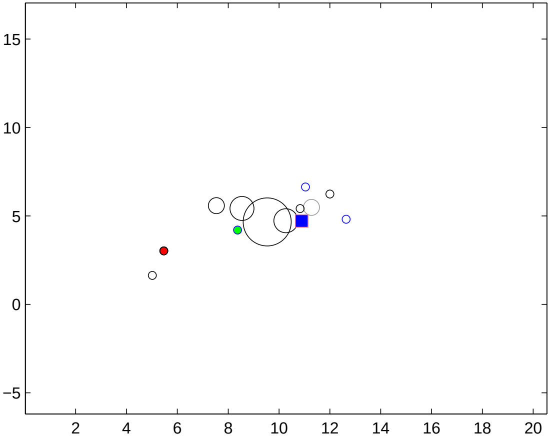


- Size of the circle indicates the number of times $x_{t-1}^{i^j}$ was selected.

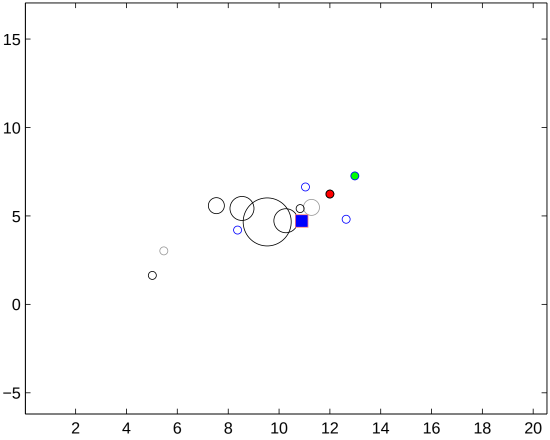
Transition demos



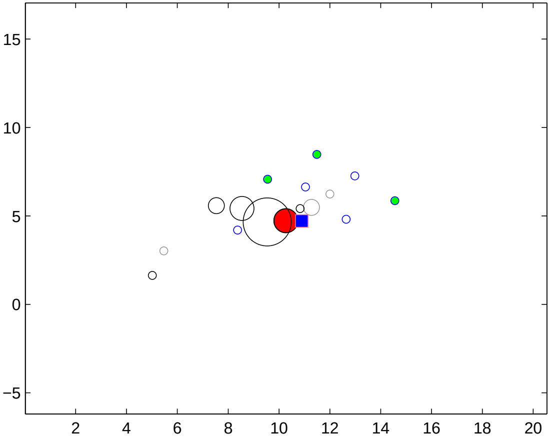
Transition demos



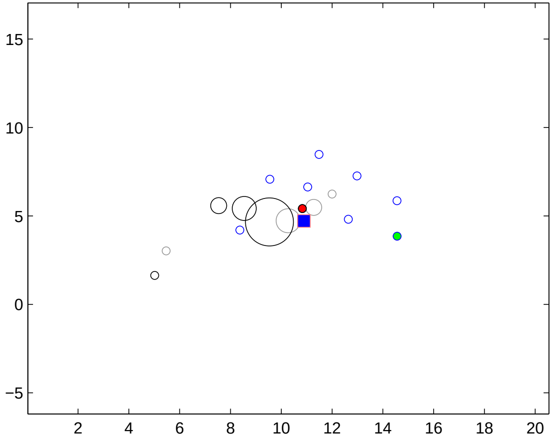
Transition demos



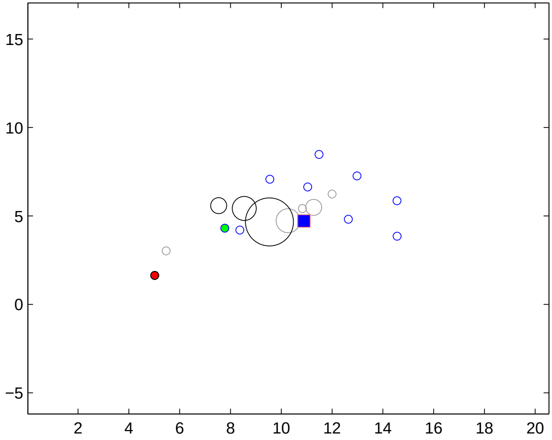
Transition demos



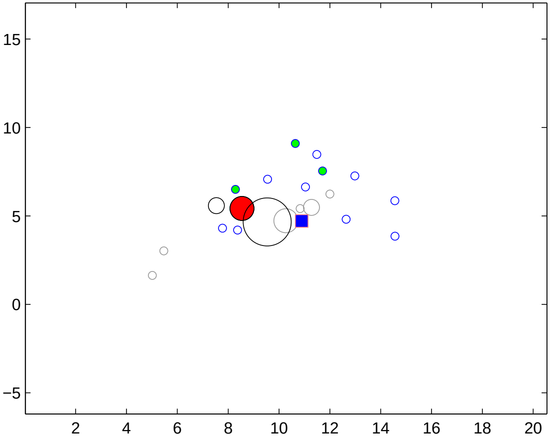
Transition demos



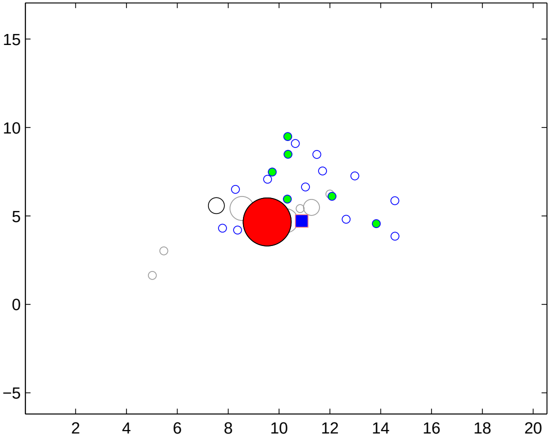
Transition demos



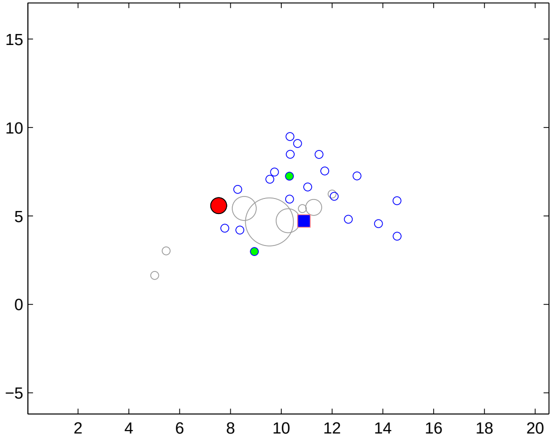
Transition demos



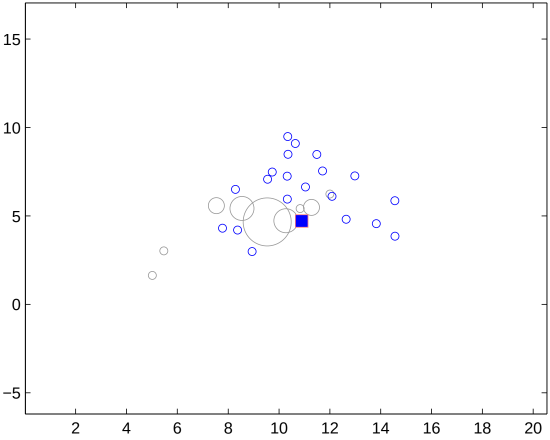
Transition demos



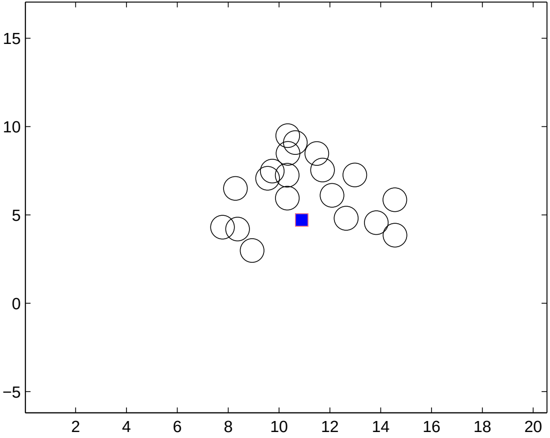
Transition demos



Transition demos

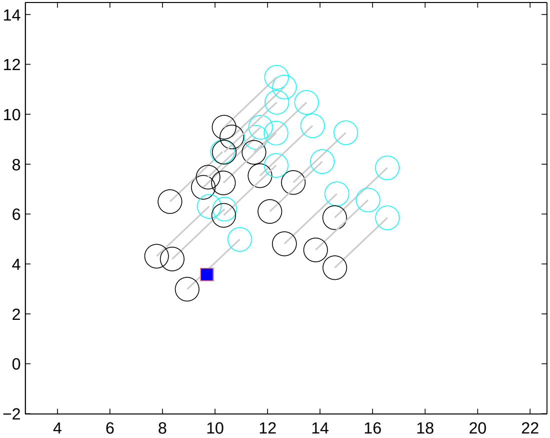


After re-weighting



The above is the representation for $p(x_t|y_{1:t})$ Note that weights are in log scale..

Next t



The above is the representation for $p(x_{t-1}|y_{1:t-1})$ in the next t:

References and a set of good place to study sampling

- Christopher Bishop's textbook Pattern Recognition and Machine Learning - include a whole chapter on sampling
- The BUGS project: (http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/contents.shtml)
- For PhD student, Gary Walsh has a great lecture notes on MCMC tutorial, very gentle, called "Markov Chain Monte Carlo and Gibbs Sampling Lecture Notes for EEB 581"
- For SMC stuff, see Doucet and Johansen, "A Tutorial on Particle Filtering and Smoothing: Fifteen years later"
- Arulampalam, M.S. and Maskell, S. and Gordon, N. and Clapp, T, A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking, IEEE Transactions on Signal Processing, 2002
- Pitt, M.K.; Shephard, N. (1999). "Filtering Via Simulation: Auxiliary Particle Filters". Journal of the American Statistical Association (American Statistical Association) 94 (446): 590591