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Your Answers:

1 1 / 1 point

Assume that we have measurements $\mathbf{y}_k, k = 1 \dots K$, and that we use a smoother with a state-space model to compute $\hat{\mathbf{x}}_{k|K}$ and $\mathbf{P}_{k|K}$. What is in general true about the densities involved in smoothing:

- [x] Uncertainty about $\hat{\mathbf{x}}_{k+1|K}$ is less than or equal to the uncertainty about $\hat{\mathbf{x}}_{k+1|k}$.
- [x] $\mathbf{P}_{K|K}$ is the smoothing and the filtering posterior covariance at time $k = K$.
- [ ] Uncertainty about $\hat{\mathbf{x}}_{k+1|k}$ is less than or equal to the uncertainty about $\hat{\mathbf{x}}_{k|k}$.
- [ ] Uncertainty about $\hat{\mathbf{x}}_{k|k}$ is less than or equal to the uncertainty about $\hat{\mathbf{x}}_{k|K}$.

2 1 / 1 point

Which of the following is required (to compute or to have) to do one step of backward smoothing, that is, to compute $\hat{\mathbf{x}}_{k|K}$ and $\mathbf{P}_{k|K}$?

- [ ] $\mathbf{y}_k$, the measurement at time k.
- [x] The process model.
- [ ] $\mathbf{P}_{k+1|k+1}$
- [ ] The measurement model.
- [x] $\mathbf{P}_{k+1|K}$.

3 1 / 1 point

Which of the following is correct regarding general Gaussian smoothers? Check all that apply.

- [x] We approximate $\mathbf{x}_k, \mathbf{x}_{k+1}|\mathbf{y}_{1:k}$ as jointly Gaussian using moment matching.
- [ ] We must approximate $\hat{\mathbf{x}}_{k+1|k}, \mathbf{P}_{k+1|k}$ and $\mathbf{P}_{k,k+1|k}$ using the same moment matching technique.
- [ ] $\hat{\mathbf{x}}_{k+1|k}$ and $\mathbf{P}_{k+1|k}$ must be recomputed during the backward recursions.
- [x] If both the motion and the measurement model are linear and Gaussian, we do not need to introduce any new approximations during the backward recursions.

4 1 / 1 point

With the particle filters we approximate the posterior as $p(\mathbf{x}_k|\mathbf{y}_{1:k}) \approx \sum_{i=1}^N w_k^{(i)} \delta(\mathbf{x}_k - \mathbf{x}_k^{(i)})$. Which of the following statements regarding this approximation are true?

- [ ] $\mathbf{x}_k$ can take any value in $[\min_i(\mathbf{x}_k^{(i)}), \max_i(\mathbf{x}_k^{(i)})]$.
- [x] It follows that, $\mathbb{E}\{\mathbf{x}_k|\mathbf{y}_{1:k}\} \approx \sum_{i=1}^N w_k^{(i)} \mathbf{x}_k^{(i)}$.
- [x] We can view this as a discrete distribution, where $P\{\mathbf{x}_k = \mathbf{x}_k^{(i)}|\mathbf{y}_{1:k}\} = w_k^{(i)}$.
- [x] We can get arbitrary fine approximation by just increasing the number of particles, N.

5 1 / 1 point

What of the following is true about the SIS (Sequential Importance Sampling) particle filter?

- [x] It can approximate multi-modal state distributions.
- [x] It eventually degenerates to just a few particles with significant weights.
- [ ] It is a special case of a sigma-point filter.
- [ ] It outputs strictly Gaussian posterior distribution approximations.

6 1 / 1 point

Assume you want to compute the mean of a function $g(\mathbf{x})$ where $\mathbf{x}$ is distributed according to $p(\mathbf{x})$, which cannot be sampled from. To compute an approximate mean, you use importance sampling with a proposal density $q(\mathbf{x})$ and the normalised weights $w^{(i)}$. What of the following is true?

- [ ] $p(\mathbf{x})$ is approximated by the samples $\mathbf{x}^{(i)}$ as $p(\mathbf{x}) \approx \frac{1}{N} \sum_{i=1}^N \delta(\mathbf{x} - \mathbf{x}^{(i)})$.
- [x] The mean of any function $g(\mathbf{x})$ is approximated as $\mathbb{E}_{p(\mathbf{x})}[g(\mathbf{x})] \approx \sum_{i=1}^N g(\mathbf{x}^{(i)}) w^{(i)}$.
- [x] You must evaluate the densities $p(\mathbf{x}^{(i)})$ and $q(\mathbf{x}^{(i)})$ for each sample in order to compute the mean of $g(\mathbf{x})$ by importance sampling.
- [ ] The proposal density $q(\mathbf{x})$ must be proportional to $p(\mathbf{x})$.
- [ ] Samples $\mathbf{x}^{(i)}$ are drawn from $g(\mathbf{x})$.

7 1 / 1 point

Now you also want to compute the covariance of $g(\mathbf{x})$. What of the following is true?

- [ ] The proposal density $q(\mathbf{x})$ must have similar support as $g(\mathbf{x})$.
- [x] When approximating the covariance of $g(\mathbf{x})$ using importance sampling, one **can** reuse the samples $\mathbf{x}^{(i)}$ and weights $w^{(i)}$ from when approximating $\mathbb{E}_{p(\mathbf{x})}[g(\mathbf{x})]$ with importance sampling.
- [ ] Covariance of any function $g(\mathbf{x})$ can be approximated using importance sampling as $Cov(g(\mathbf{x})) = \sum_{i=1}^N Cov(g(\mathbf{x}^{(i)})) w^{(i)}$.
- [x] Covariance of any function $g(\mathbf{x})$ can be approximated using importance sampling as $Cov(g(\mathbf{x})) \approx \sum_{i=1}^N (g(\mathbf{x}^{(i)}) - \mu_g)(g(\mathbf{x}^{(i)}) - \mu_g)^T w^{(i)}$, where $\mu_g \approx \mathbb{E}_{p(\mathbf{x})}[g(\mathbf{x})]$.

8 1 / 1 point

Which of the following is true about the SIR (Sequential Importance Resampling) particle filter?

- [x] The bootstrap filter is a typical variation of SIR.
- [x] Its performance depends on the quality of the importance distribtution.
- [ ] The number of samples reduces after resampling.
- [x] It solves the degeneracy problem.
- [ ] It should be performed at every time step.

9 1 / 1 point

Which of the following statements regarding resampling are true?

- [x] By resampling we focus our particles to high probability areas so they are not wasted in improbable states.
- [x] By resampling we make an approximation of our particle approximation of $p(\mathbf{x}_k|\mathbf{y}_{1:k})$.
- [ ] By resampling we get a more accurate approximation of $p(\mathbf{x}_k|\mathbf{y}_{1:k})$ than what we had before we resampled.
- [ ] By resampling we move the particles in a similar manner as we do in the measurement update of a Gaussian filter.

10 1 / 1 point

Resampling can sometimes result in lack of diversity. Consider the following toy example: There are two rooms, and the robot is unsure about which room it is in. The non-informative sensor shows equal probability of being in either room. We start with N particles equally distributed between the two rooms. How are particles distributed after a sufficiently long time if resampling is done at each time step?

- ( ) Each room will have the same number of particles.
- (•) The particles will converge to one of the two rooms.
- ( ) We don't know. It depends on the distribution of last time step.

11 1 / 1 point

Let u_k denote the arbitrary latent variable, x_k denote the state, and y_k denote the measurement. Which of the following is true about the Rao-Blackwellized particle filter?

- [ ] Full posterior distribution at step k is factored as $p(u_{0:k}, x_{0:k}|y_{1:k}) = p(u_{0:k}|x_{0:k}, y_{1:k}) p(x_{0:k}|y_{1:k})$.
- [x] Full posterior distribution at step k is factored as $p(u_{0:k}, x_{0:k}|y_{1:k}) = p(x_{0:k}|u_{0:k}, y_{1:k}) p(u_{0:k}|y_{1:k})$.
- [x] They enable us to handle higher dimensions than the conventional particles filters
- [x] Compared to the conventional particle filters, the number of particles used can be reduced to achieve comparative results.