



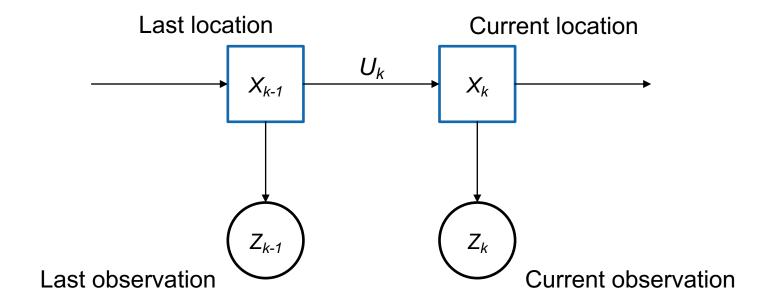
Computer Vision HS 2020 Lab Session 3 - Particle Filter

Zuoyue Li Fri, 9 Oct 2020



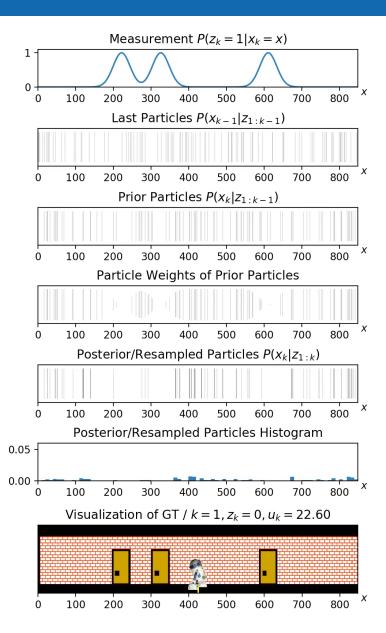
Goal: 1D Localization of a Robot

Hidden Markov Model (HMM)

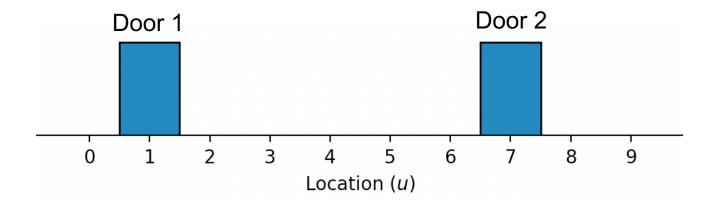


Goal: 1D Localization of a Robot

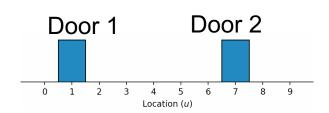
- What is known
 - Current odometry U_k
 How far travelled since last step
 - Door sensor observation Z_k
 Whether the sensor detects a door
- What we need to compute
 - Posterior: the current location distribution based on the observations so far $P(X_k = x \mid Z_{1:k})$
 - Prior: the current location distribution based on the observations until the last step $P(X_k = x \mid Z_{1:k-1})$
 - Alternating update

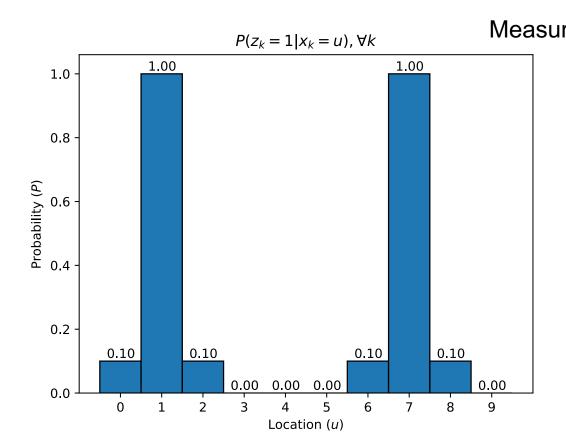


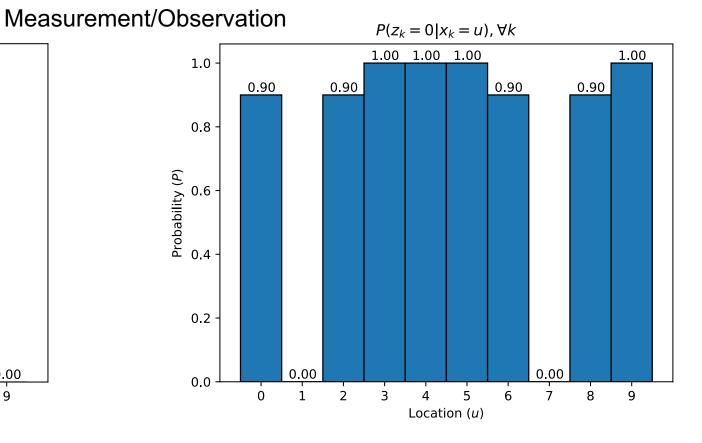








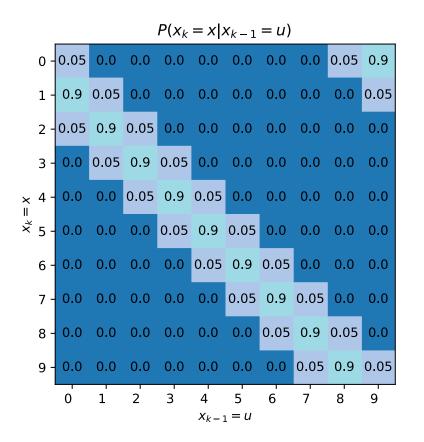






Transition Matrix

P(Remain in the same place) = 0.05 P(Go to the right location) = 0.9 P(Skip the next one) = 0.05



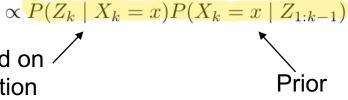


Compute posterior using prior

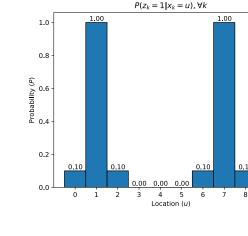
Split conditions
$$P(X_k = x \mid Z_{1:k}) = P(X_k = x \mid Z_k, Z_{1:k-1})$$

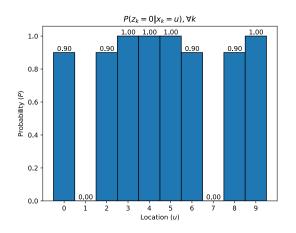
Bayes' theorem $= \frac{P(Z_k \mid X_k = x, Z_{1:k-1})P(X_k = x \mid Z_{1:k-1})}{P(Z_k \mid Z_{1:k-1})}$
Conditional independence $= \frac{P(Z_k \mid X_k = x)P(X_k = x \mid Z_{1:k-1})}{P(Z_k \mid Z_{1:k-1})}$

Measurement based on the current observation



Element-wise product







Compute prior using the last posterior

Marginal distribution
$$P(X_k = x \mid Z_{1:k-1}) = \sum_{u} P(X_k = x, X_{k-1} = u \mid Z_{1:k-1})$$

Conditional distribution

Conditional independence

$$= \sum_{u} P(X_k = x \mid X_{k-1} = u, Z_{1:k-1}) P(X_{k-1} = u \mid Z_{1:k-1})$$

$$= \sum_{u} P(X_k = x \mid X_{k-1} = u) P(X_{k-1} = u \mid Z_{1:k-1})$$

Transition matrix

Last Posterior

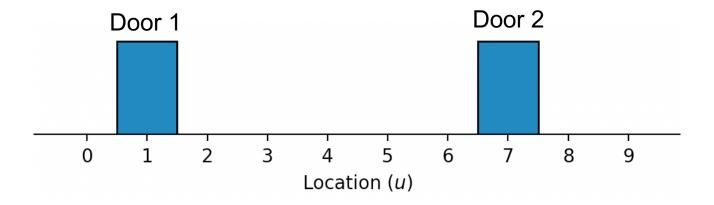
$$P(AB) = P(A|B)P(B)$$

Matrix product

 $P(x_k = x | x_{k-1} = u)$

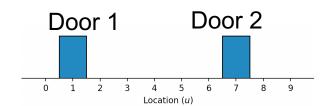


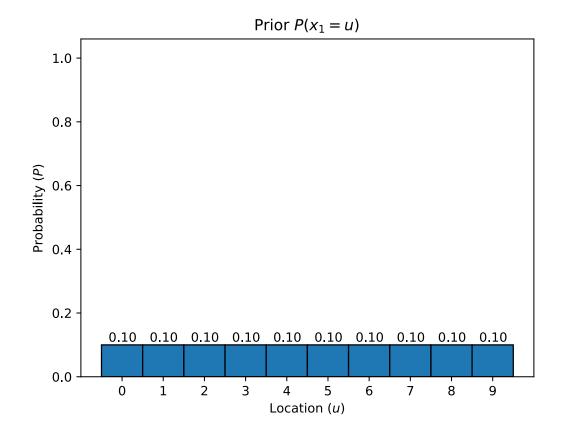
- Door sensor observation: [0, 1, 0, 0, 0, 1]
- Guess what may be the starting location and the current location?





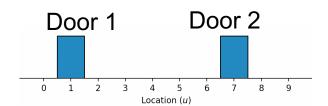
• Observation: [0, 1, 0, 0, 0, 1]

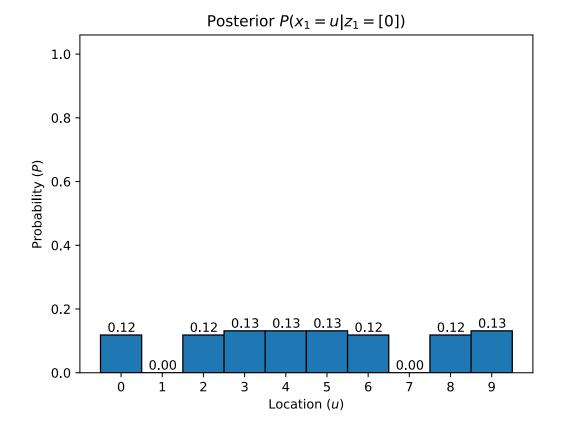






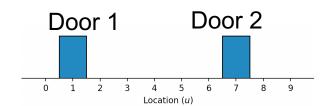
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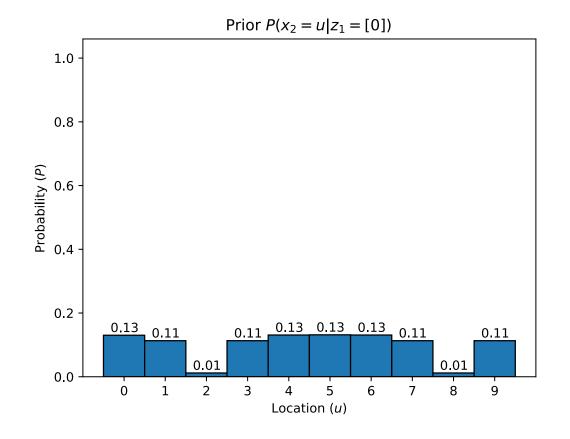






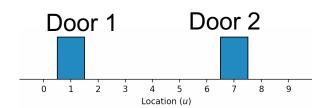
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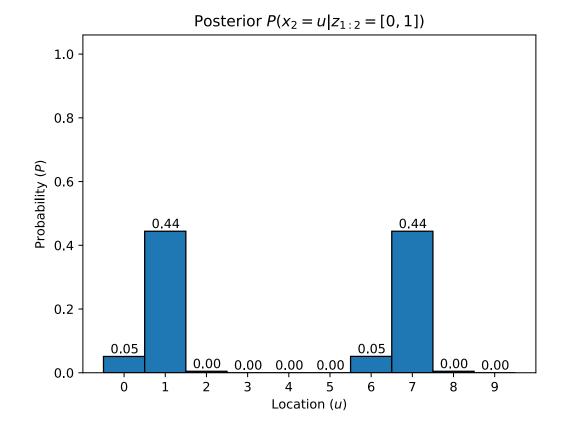






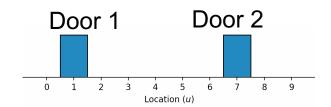
• Observation: [0, 1, 0, 0, 0, 1]

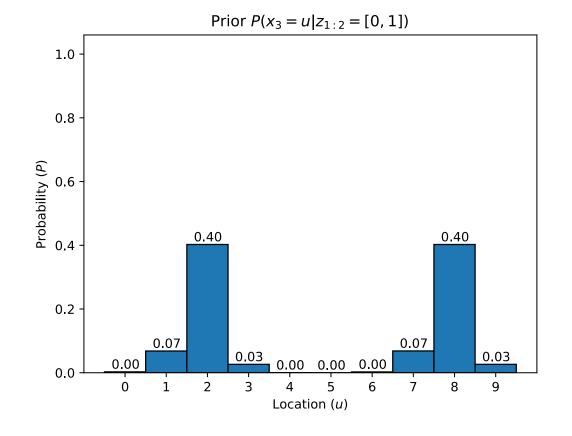






• Observation: [0, 1, 0, 0, 0, 1]

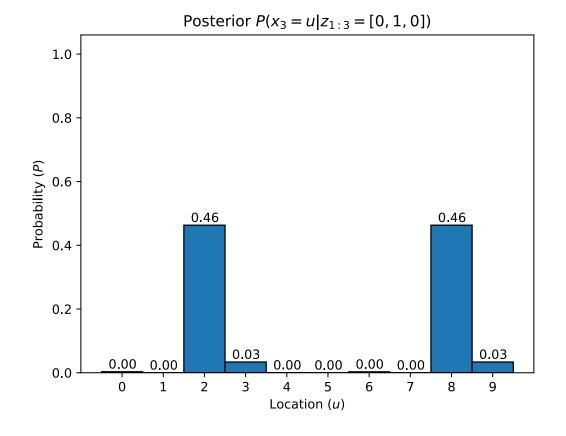






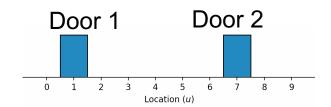
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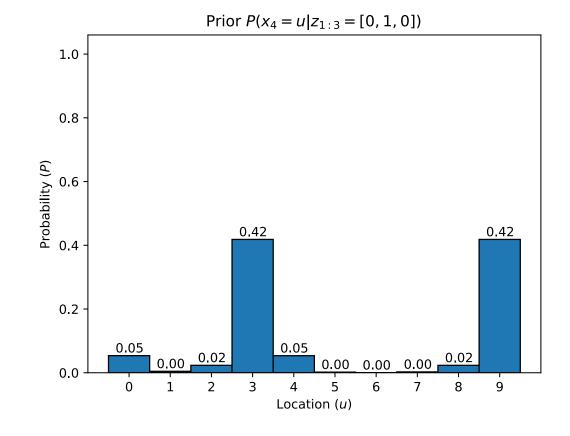






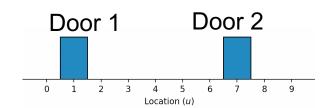
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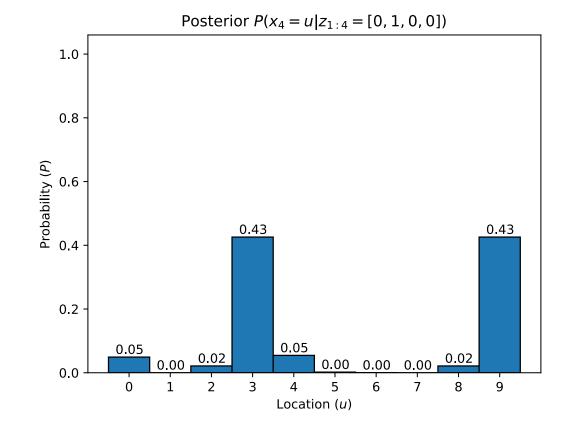






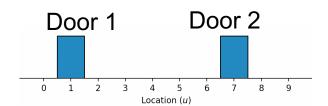
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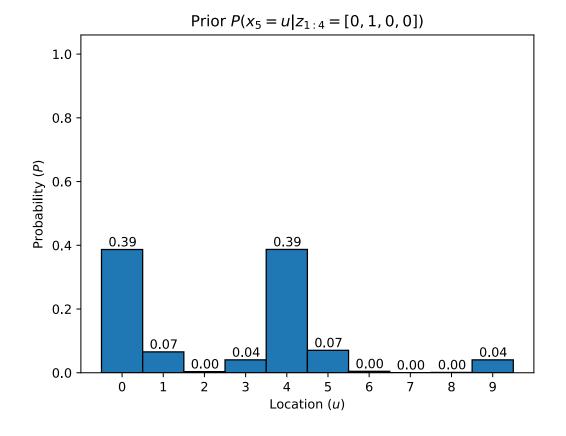






Observation: [0, 1, 0, 0, 0, 1]

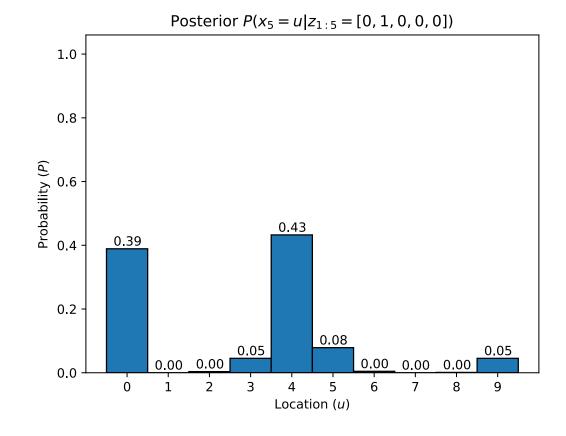






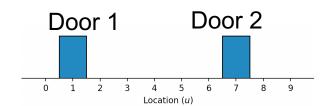
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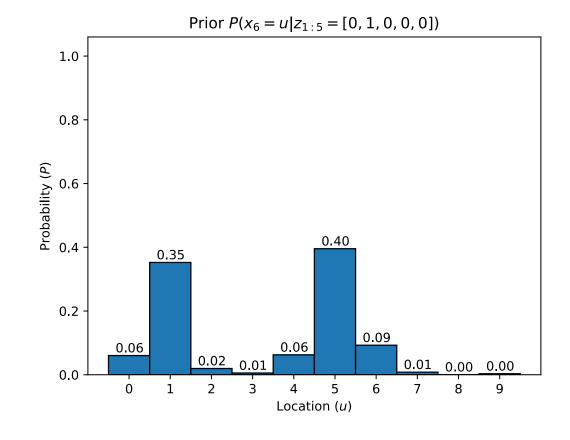






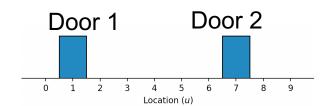
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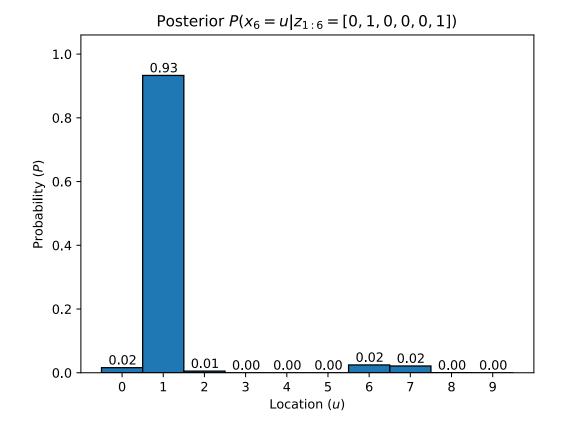






• Observation: [0, 1, 0, 0, 0, 1]

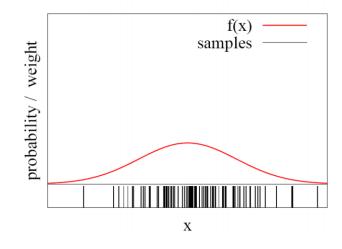


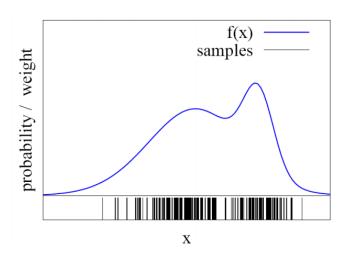




Why Particles?

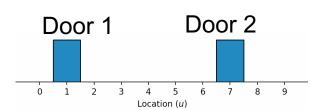
- Unable to traverse the full domain
 - Continuous distribution
 - High-dimensional discrete space
- Use particles for function approximation

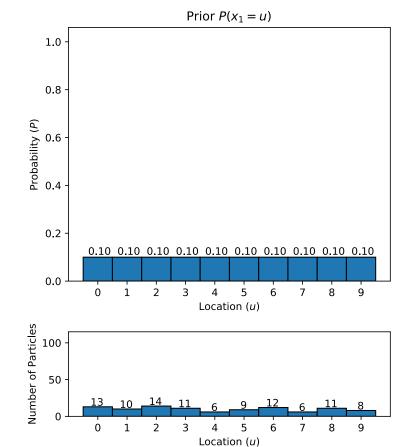




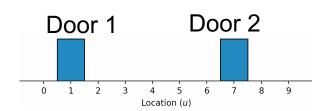


Observation: [0, 1, 0, 0, 0, 1]









Observation: [0, 1, 0, 0, 0, 1]

Compute posterior using prior

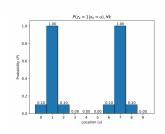
$$\begin{array}{ll} \text{Split conditions} & P(X_k = x \mid Z_{1:k}) = P(X_k = x \mid Z_k, Z_{1:k-1}) \\ \text{Bayes' theorem} & = \frac{P(Z_k \mid X_k = x, Z_{1:k-1}) P(X_k = x \mid Z_{1:k-1})}{P(Z_k \mid Z_{1:k-1})} \\ \text{Conditional independence} & = \frac{P(Z_k \mid X_k = x) P(X_k = x \mid Z_{1:k-1})}{P(Z_k \mid Z_{1:k-1})} \\ & \propto P(Z_k \mid X_k = x) P(X_k = x \mid Z_{1:k-1}) \\ \end{array}$$

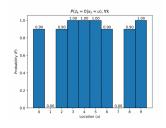
Measurement based on / the current observation

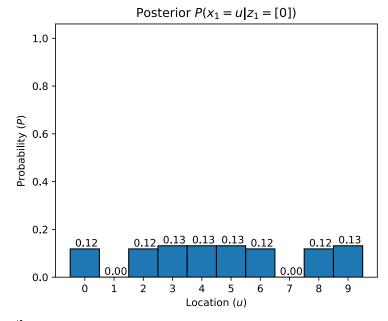


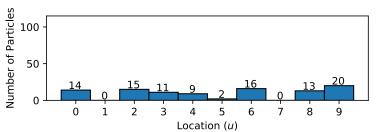
Element-wise production

$$P(A|B) = \frac{P(AB)}{P(B)} = \frac{P(B|A)P(A)}{P(B)}$$

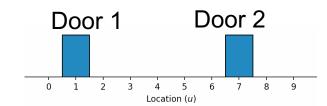








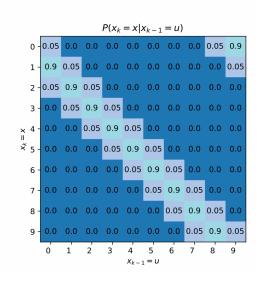


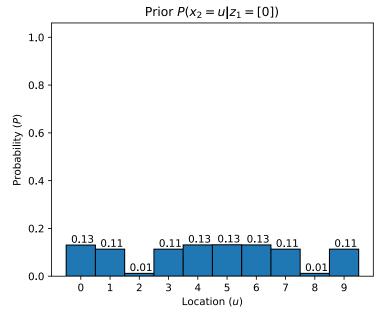


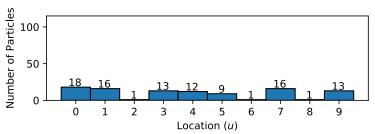
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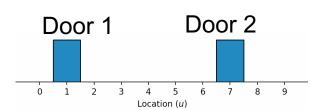


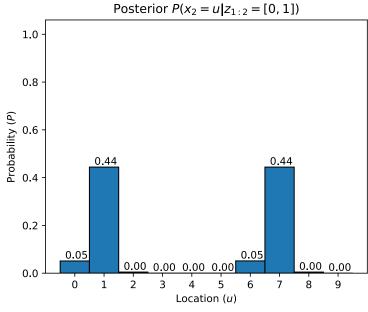


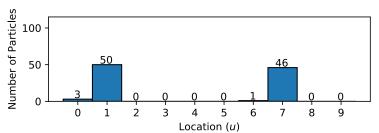




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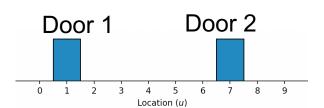


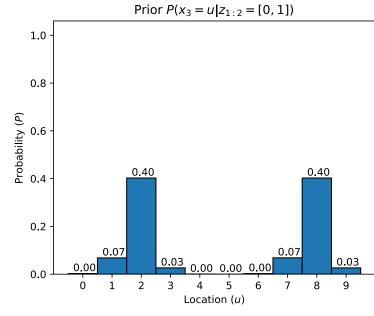


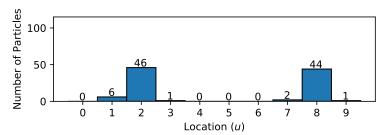




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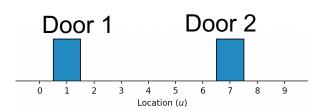


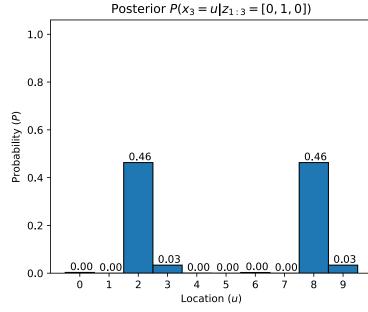


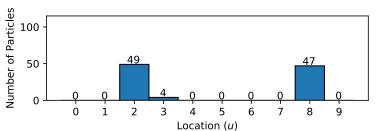




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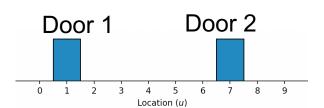


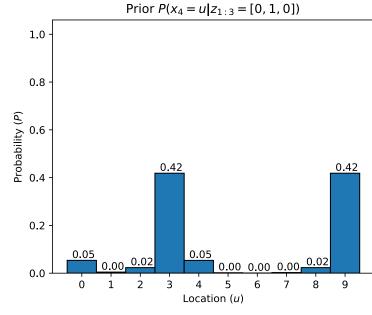


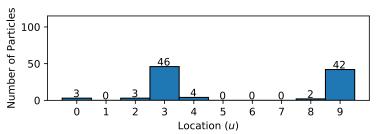




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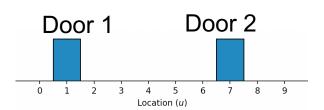


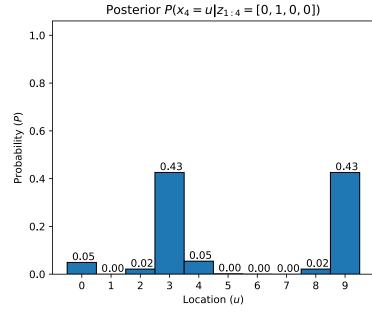


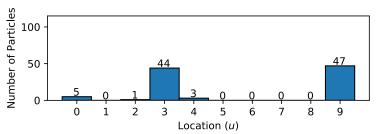




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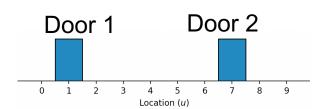


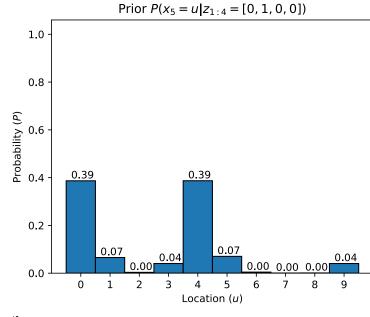


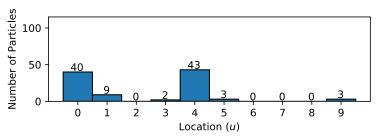




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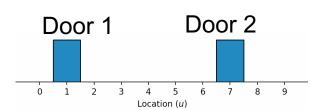


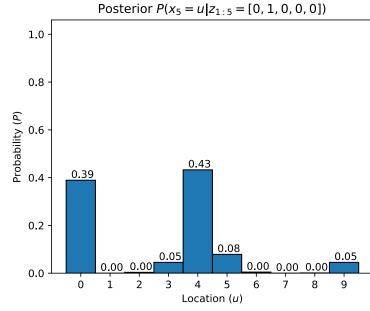


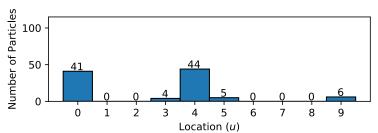




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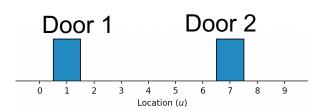


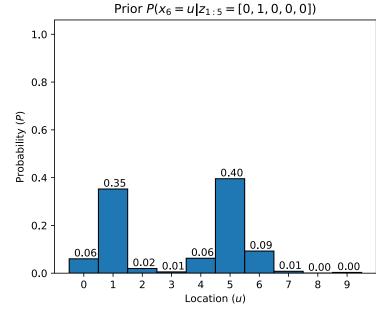


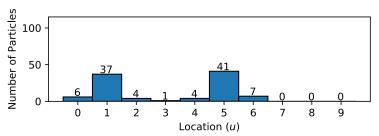




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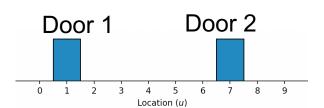


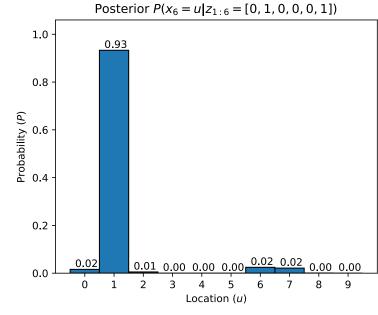


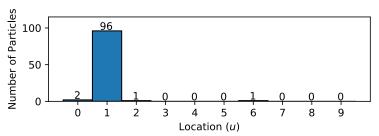




Observation: [0, 1, 0, 0, 0, 1]









Thank you!