There is lead poisoning in Philly.

Also, SEPTA workers on strike.

Taking more samples means nicer graphs.

The Particle Filter

Idea: Continuous state spaces are too big to run Bayes filters on. Instead of discretizing, represent distribution as collection of samples.

\[ P(x) \]
Once again we have a motion model & a measurement model:

\[ P(x' | x, u) \quad P(z | x) \]

This time, \( x \) is continuous so motion model is a PDF (usually \( z \) is also)

Bayes filter evaluates both distributions

Particle filter samples the motion model

Evaluates the measurement model

Draw random \#`s to simulate noisy motion of the robot

Start with \( n \) particles drawn from some initial distribution

\[ P = \{ x_1, x_2, \ldots, x_n \} \]

Motion update: update the set of particles to:

\[ p' = \{ x'_1, x'_2, \ldots, x'_n \} \quad \text{with each} \quad x'_i \quad \text{sampled from} \quad P(x'_i | x_i, u) \]
MEASUREMENT UPDATE: OBSERVE $z$ THEN

COMPUTE FOR EACH $x_i'$:

$$w_i = \pi \cdot p(z|x_i')$$

**Weight comes from evaluating** MEASUREMENT MODEL PDF $p(z|x_i')$.

**So in effect, $w_i$ is the probability** that $x_i'$ is a "good particle".

**Good particles align well with sensor measurements.**

Now resample, assemble $P = \{x_1', \ldots, x_n\}$ by sampling with replacement each $x_i'$ from $P'$ with probability $w_i$.

**Go back to (1)** (This is $O(n)$ by the way)

$$Z = \begin{bmatrix} Z_1 \\ Z_2 \\ Z_3 \\ Z_4 \end{bmatrix}$$

$$p(z|x) = \prod_{j=1}^{n} p(z_j|x_j)$$

$$p(z_j|x_j) = \pi e^{-\frac{(z_j - 1)^2}{2\sigma^2}}$$