Probabilistic SLAM: \[ P(x_k, m | Z_{0:k}, U_{0:k}, x_0) \]
Probabilistic SLAM: \[ P(x_k, m|Z_{0:k}, U_{0:k}, x_0) \]

State history: \[ X_{0:k} = \{x_0, x_1, \ldots, x_k\} \]

Control history: \[ U_{0:k} = \{u_1, u_2, \ldots, u_k\} \]

Set of all landmarks: \[ m = \{m_1, m_2, \ldots, m_n\} \]

Observation history: \[ Z_{0:k} = \{z_1, z_2, \ldots, z_k\} \]
Bayesian SLAM
Start with knowledge of:

\[ P(x_{k-1}, m|Z_{0:k-1}, U_{0:k-1}, x_0) \]

And new control and observation at time \( k \):

\[ u_k \]

\[ z_k \]
Start with knowledge of:

\[ P(x_{k-1}, m|Z_{0:k-1}, U_{0:k-1}, x_0) \]

And new control and observation at time \( k \):

\[ u_k \quad z_k \]

Use Bayes Theorem to update estimation of \( x_k, m \):

\[ P(x_{k}, m|Z_{0:k}, U_{0:k}, x_0) \]
Start with knowledge of:
\[ P(x_{k-1}, m|Z_{0:k-1}, U_{0:k-1}, x_0) \]

And new control and observation at time \( k \):
\( u_k \), \( z_k \)

Use Bayes Theorem to update estimation of \( x_k, m \):
\[ P(x_k, m|Z_{0:k}, U_{0:k}, x_0) \]

Assuming we know:

Sensor Model:
\[ P(z_k|x_k, m) \]

Motion Model:
\[ P(x_k|x_{k-1}, u_k) \]
Time Update:

\[ P(x_k, m|Z_{0:k-1}, U_{0:k}, x_0) = \int P(x_k|x_{k-1}, u_k) \times P(x_{k-1}, m|Z_{0:k-1}, U_{0:k-1}, x_0) \, dx_{k-1} \]
Measurement Update:

\[ P(x_k, m|Z_{0:k}, U_{0:k}, x_0) \]

\[ = \frac{P(z_k|x_k, m)P(x_k, m|Z_{0:k-1}, U_{0:k}, x_0)}{P(z_k|Z_{0:k-1}, U_{0:k})} \]