

SLAM and factorgraphs

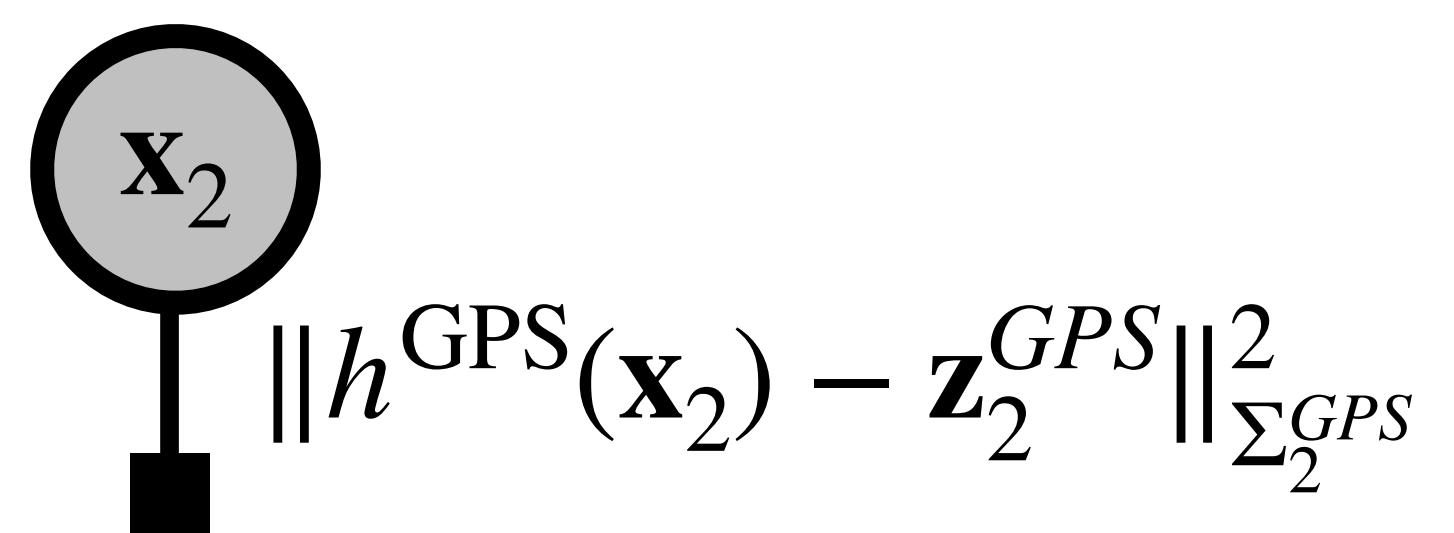
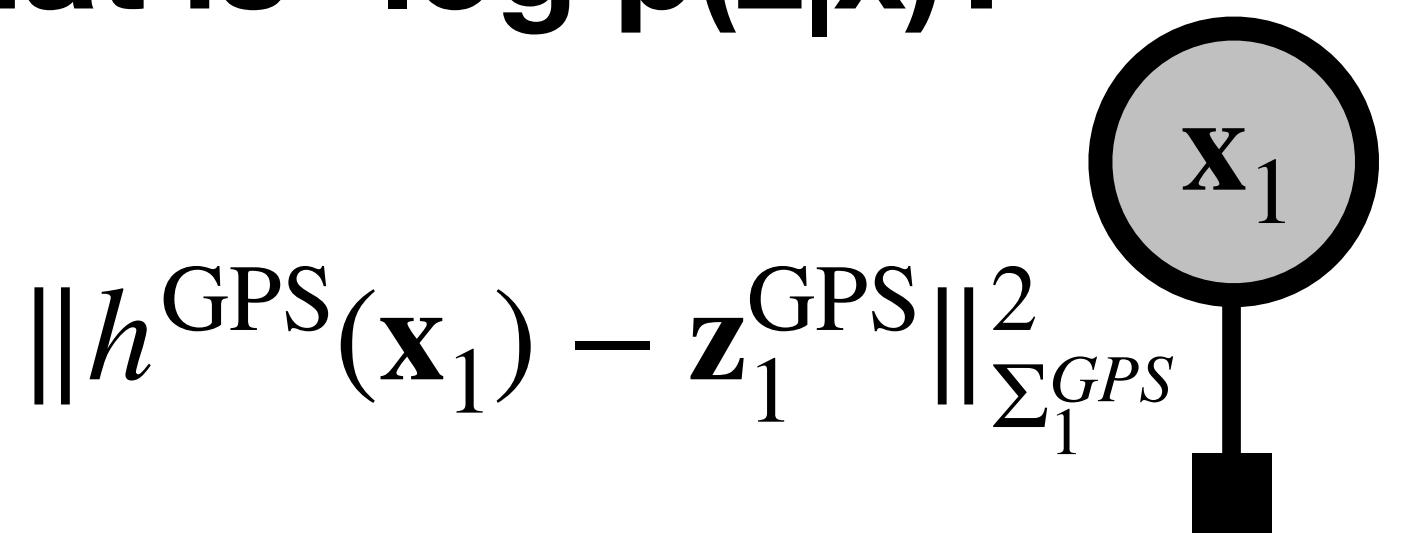
Labs 03

Karel Zimmermann

$$p\left(\underbrace{\begin{bmatrix} z_t^{\text{GPS},x} \\ z_t^{\text{GPS},y} \end{bmatrix}}_{\mathbf{z}_t^{\text{GPS}}} \mid \underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}}_{\mathbf{x}_t}\right) = \mathcal{N}\left(\mathbf{z}_t^{\text{GPS}}; \underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}}_{h^{\text{GPS}}(\mathbf{x}_t)}, \mathbf{Q}_t^{\text{GPS}}\right)$$



what is $-\log p(z|x)$?

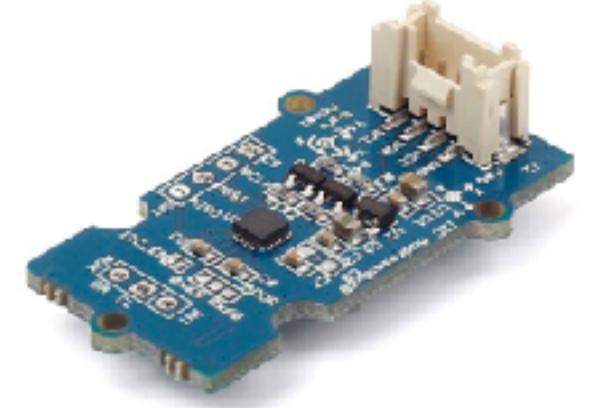


$$p\left(\underbrace{\begin{bmatrix} z_t^{\text{GPS},x} \\ z_t^{\text{GPS},y} \end{bmatrix}}_{\mathbf{z}_t^{\text{GPS}}} \mid \underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}}_{\mathbf{x}_t}\right) = \mathcal{N}\left(\mathbf{z}_t^{\text{GPS}}; \underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}}_{h^{\text{GPS}}(\mathbf{x}_t)}, \mathbf{Q}_t^{\text{GPS}}\right)$$



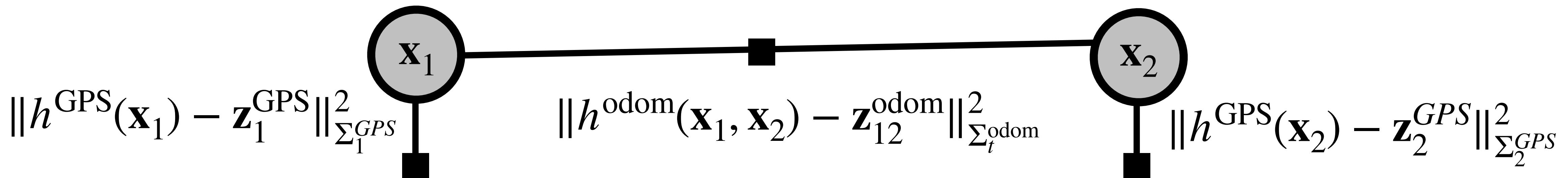
GPS

$$p\left(\underbrace{\begin{bmatrix} z_t^x \\ z_t^y \end{bmatrix}}_{\mathbf{z}_t^{\text{odom}}} \mid \underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}}_{\mathbf{x}_t}, \underbrace{\begin{bmatrix} x_{t+1} \\ y_{t+1} \end{bmatrix}}_{\mathbf{x}_{t+1}}\right) = \mathcal{N}\left(\mathbf{z}_t^{\text{odom}}; \underbrace{\mathbf{x}_{t+1} - \mathbf{x}_t}_{h^{\text{odom}}(\mathbf{x}_t, \mathbf{x}_{t+1})}, \mathbf{Q}_t^{\text{odom}}\right)$$



IMU

what is $-\log p(z_{\text{odom}} \mid \mathbf{x}_1, \mathbf{x}_2)$?

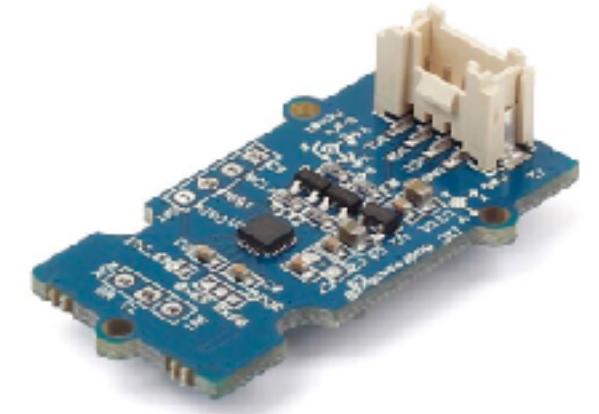


$$p\left(\underbrace{\begin{bmatrix} z_t^{\text{GPS},x} \\ z_t^{\text{GPS},y} \end{bmatrix}}_{\mathbf{z}_t^{\text{GPS}}} \mid \underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}}_{\mathbf{x}_t}\right) = \mathcal{N}\left(\mathbf{z}_t^{\text{GPS}}; \underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}}_{h^{\text{GPS}}(\mathbf{x}_t)}, \mathbf{Q}_t^{\text{GPS}}\right)$$



GPS

$$p\left(\underbrace{\begin{bmatrix} z_t^x \\ z_t^y \end{bmatrix}}_{\mathbf{z}_t^{\text{odom}}} \mid \underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}, \begin{bmatrix} x_{t+1} \\ y_{t+1} \end{bmatrix}}_{h^{\text{odom}}(\mathbf{x}_t, \mathbf{x}_{t+1})}\right) = \mathcal{N}\left(\mathbf{z}_t^{\text{odom}}; \underbrace{\mathbf{x}_{t+1} - \mathbf{x}_t}_{h^{\text{odom}}(\mathbf{x}_t, \mathbf{x}_{t+1})}, \mathbf{Q}_t^{\text{odom}}\right)$$



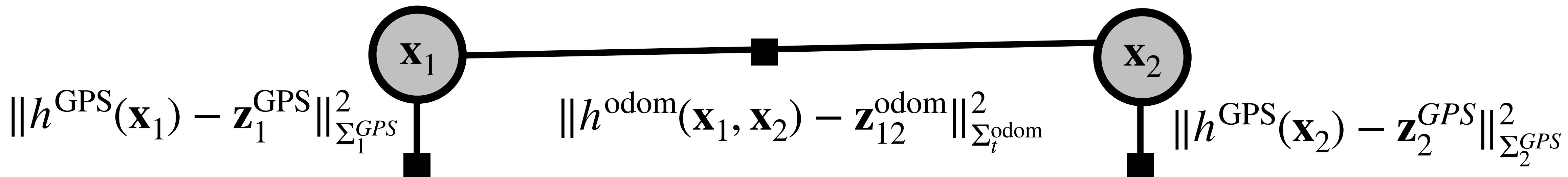
IMU

$$p\left(\underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}}_{\mathbf{x}_t} \mid \underbrace{\begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix}}_{\mathbf{x}_{t-1}}, \underbrace{\begin{bmatrix} v_t \\ \omega_t \end{bmatrix}}_{\mathbf{u}_t}, \underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}}_{\mathbf{x}_t}, \underbrace{\begin{bmatrix} x_{t+1} \\ y_{t+1} \end{bmatrix}}_{h^{\text{odom}}(\mathbf{x}_t, \mathbf{x}_{t+1})}, \underbrace{\begin{bmatrix} x_{t-1} + v_t \Delta t \cos(\omega_t) \\ y_{t-1} + v_t \Delta t \sin(\omega_t) - \frac{1}{2} g \Delta t^2 \end{bmatrix}}_{g(\mathbf{x}_{t-1}, \mathbf{u}_t)}, \mathbf{R}_t\right) = \mathcal{N}\left(\mathbf{x}_t; \underbrace{\begin{bmatrix} x_{t-1} + v_t \Delta t \cos(\omega_t) \\ y_{t-1} + v_t \Delta t \sin(\omega_t) - \frac{1}{2} g \Delta t^2 \end{bmatrix}}_{g(\mathbf{x}_{t-1}, \mathbf{u}_t)}, \mathbf{R}_t\right)$$



motion
model

what is $-\log p(\mathbf{x}_2 \mid \mathbf{x}_1, \mathbf{u}_{12})$?

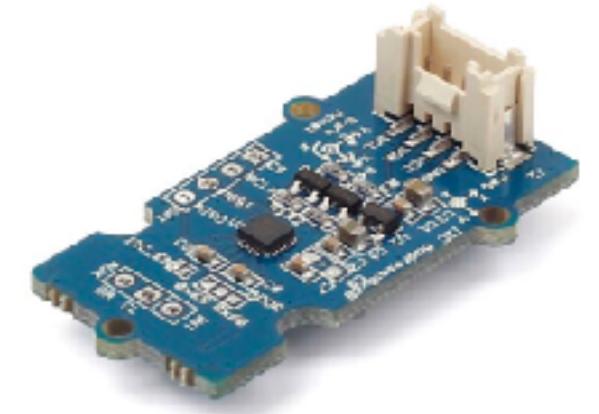


$$p\left(\underbrace{\begin{bmatrix} z_t^{\text{GPS},x} \\ z_t^{\text{GPS},y} \end{bmatrix}}_{\mathbf{z}_t^{\text{GPS}}} \mid \underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}}_{\mathbf{x}_t}\right) = \mathcal{N}\left(\mathbf{z}_t^{\text{GPS}}; \underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}}_{h^{\text{GPS}}(\mathbf{x}_t)}, \mathbf{Q}_t^{\text{GPS}}\right)$$



GPS

$$p\left(\underbrace{\begin{bmatrix} z_t^x \\ z_t^y \end{bmatrix}}_{\mathbf{z}_t^{\text{odom}}} \mid \underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}, \begin{bmatrix} x_{t+1} \\ y_{t+1} \end{bmatrix}}_{h^{\text{odom}}(\mathbf{x}_t, \mathbf{x}_{t+1})}\right) = \mathcal{N}\left(\mathbf{z}_t^{\text{odom}}; \underbrace{\mathbf{x}_{t+1} - \mathbf{x}_t}_{h^{\text{odom}}(\mathbf{x}_t, \mathbf{x}_{t+1})}, \mathbf{Q}_t^{\text{odom}}\right)$$



IMU

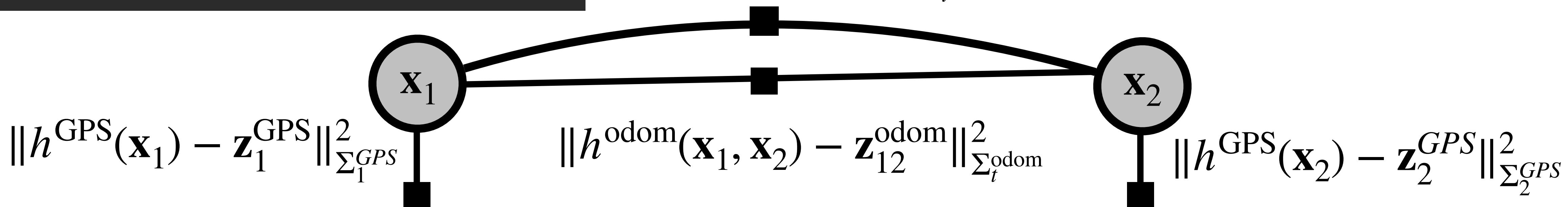
$$p\left(\underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}}_{\mathbf{x}_t} \mid \underbrace{\begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix}}_{\mathbf{x}_{t-1}}, \underbrace{\begin{bmatrix} v_t \\ \omega_t \end{bmatrix}}_{\mathbf{u}_t}, \underbrace{\begin{bmatrix} x_{t-1} + v_t \Delta t \cos(\omega_t) \\ y_{t-1} + v_t \Delta t \sin(\omega_t) - \frac{1}{2} g \Delta t^2 \end{bmatrix}}_{g(\mathbf{x}_{t-1}, \mathbf{u}_t)}\right) = \mathcal{N}\left(\mathbf{x}_t; \underbrace{\begin{bmatrix} x_{t-1} + v_t \Delta t \cos(\omega_t) \\ y_{t-1} + v_t \Delta t \sin(\omega_t) - \frac{1}{2} g \Delta t^2 \end{bmatrix}}_{g(\mathbf{x}_{t-1}, \mathbf{u}_t)}, \mathbf{R}_t\right)$$



motion
model

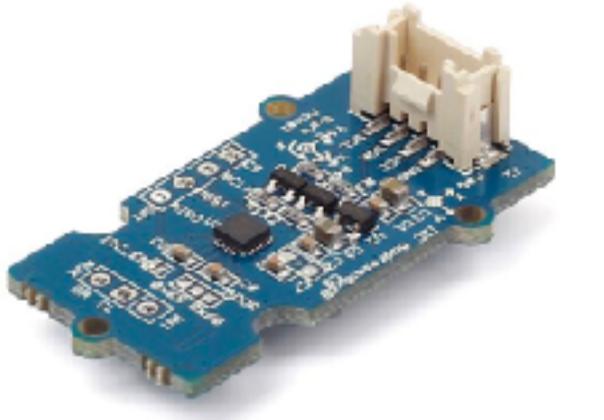
loss = # <----- TODO FILL IN

$$\|g(\mathbf{x}_1, \mathbf{u}_{12}) - \mathbf{x}_2\|_{\Sigma_t^g}^2$$





GPS

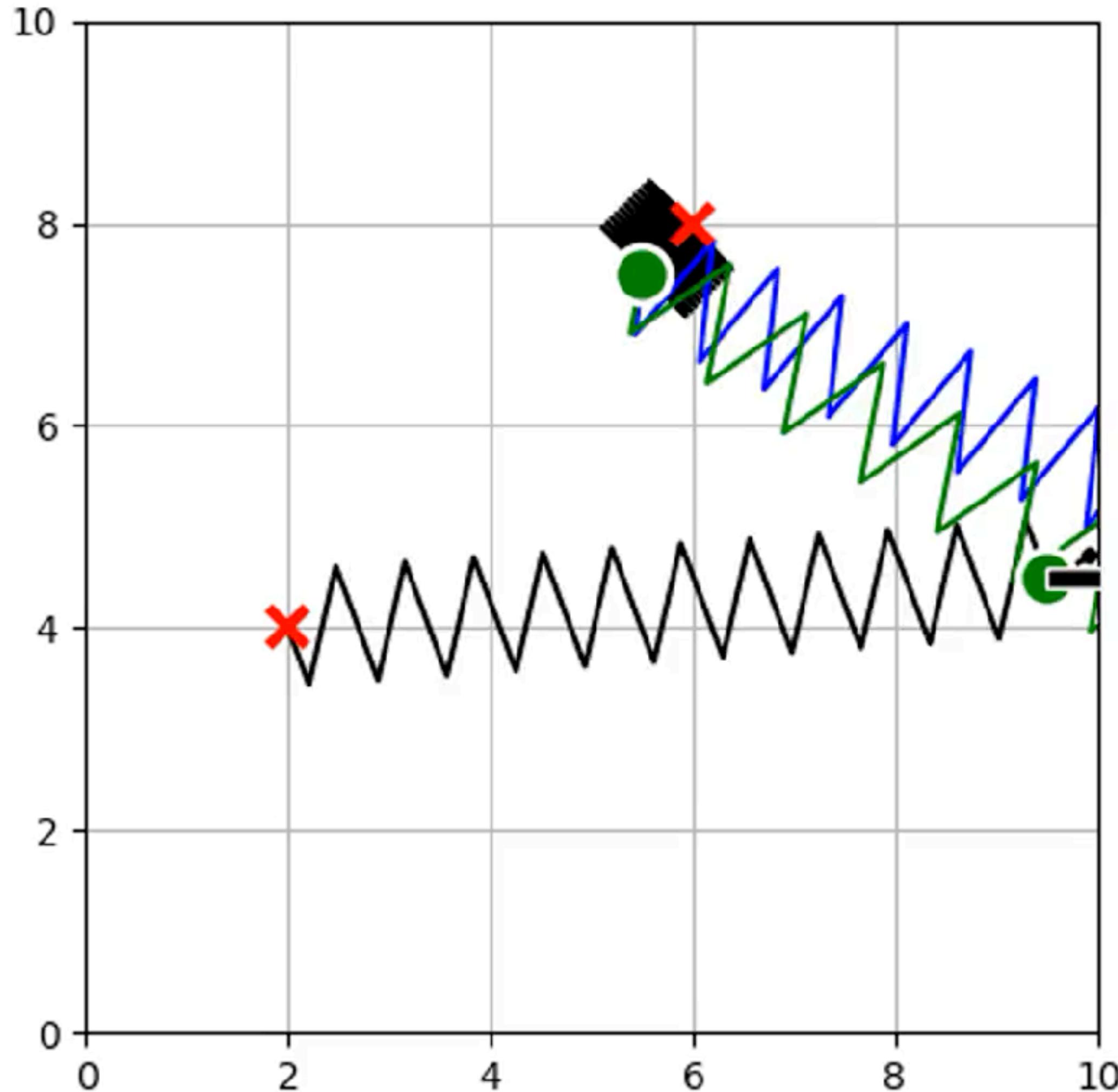


IMU



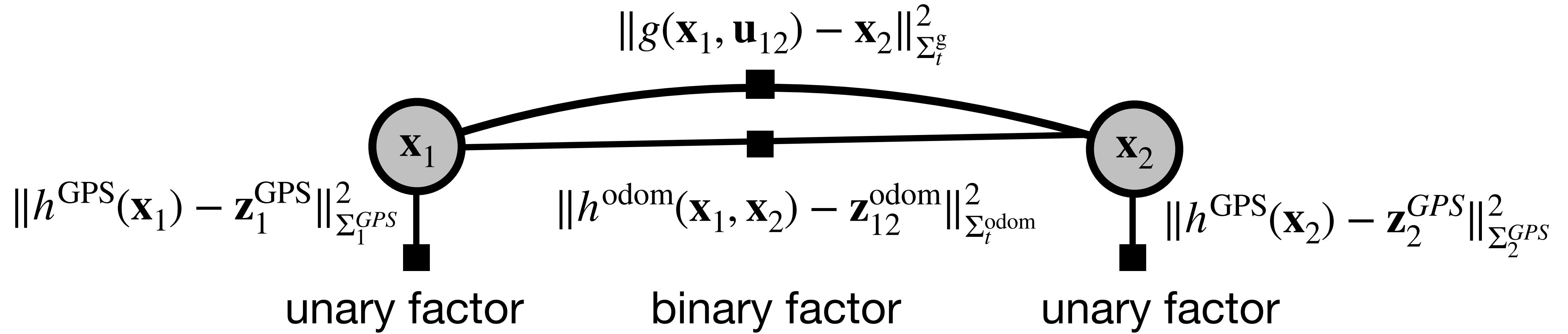
+ motion model

$$\mathbf{x}_1^*, \mathbf{x}_2^* = \arg \min_{\mathbf{x}_1, \mathbf{x}_2} \|\mathbf{x}_1 - \mathbf{z}_1^{GPS}\|_{\Sigma_1^{GPS}}^2 + \|\mathbf{x}_2 - \mathbf{z}_2^{GPS}\|_{\Sigma_2^{GPS}}^2 + \|\mathbf{x}_2 - \mathbf{x}_1 - \mathbf{z}_{12}^{odom}\|_{\Sigma_t^{odom}}^2 + \|g(\mathbf{x}_1, \mathbf{u}_2) - \mathbf{x}_2\|_{\Sigma_t^g}^2$$



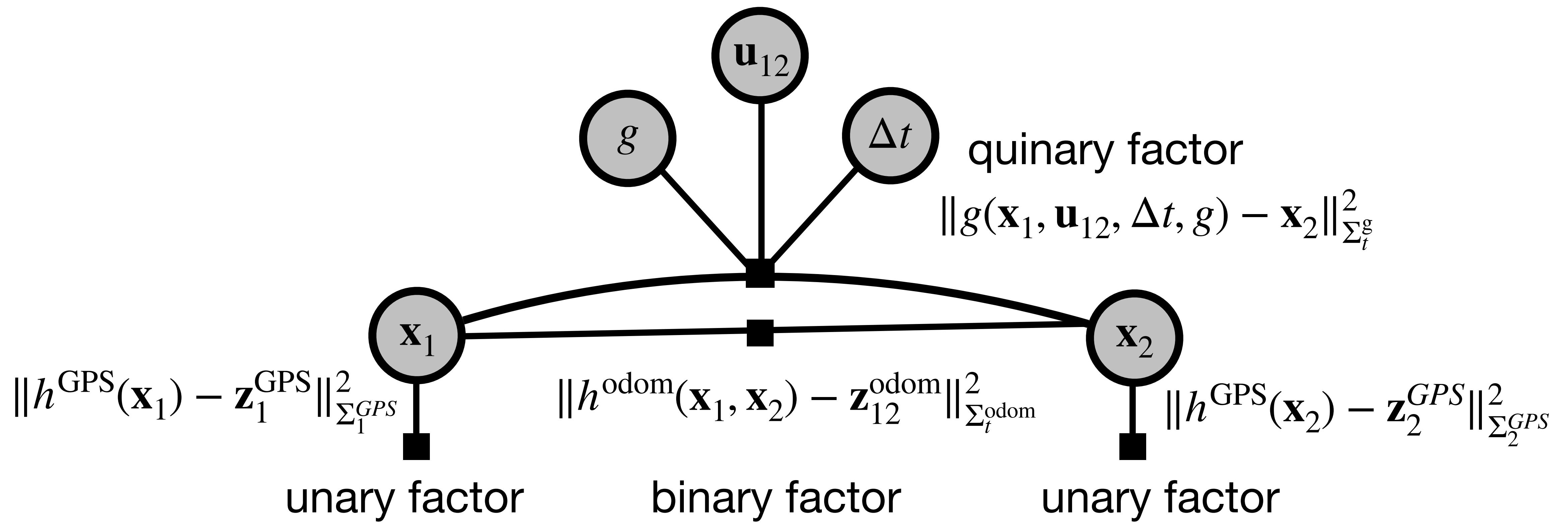
- \mathbf{x}_t ... robot poses
- ✖ \mathbf{z}_t^{GPS} ... GPS measurement
- \mathbf{z}_t^{odom} ... odometry measurements
- \mathcal{W} $\sum_t \|\mathbf{x}_t - \mathbf{z}_t^{GPS}\|_{\Sigma_t^{GPS}}^2$... GPS loss
- \mathcal{W} $\|\mathbf{x}_2 + \mathbf{z}_{12}^{odom} - \mathbf{x}_2\|_{\Sigma_t^{odom}}^2$... odom loss
- \mathcal{W} $\|g(\mathbf{x}_1, \mathbf{u}_2) - \mathbf{x}_2\|_{\Sigma_t^g}^2$... motion loss

What if the control, gravity and time are also unknown?



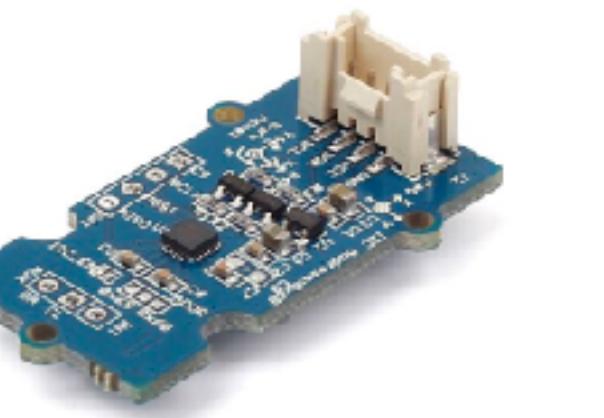
What if the control, gravity and time are also unknown?

```
opt = torch.optim.Adam([x1, x2, ..... ], lr=0.5)
```





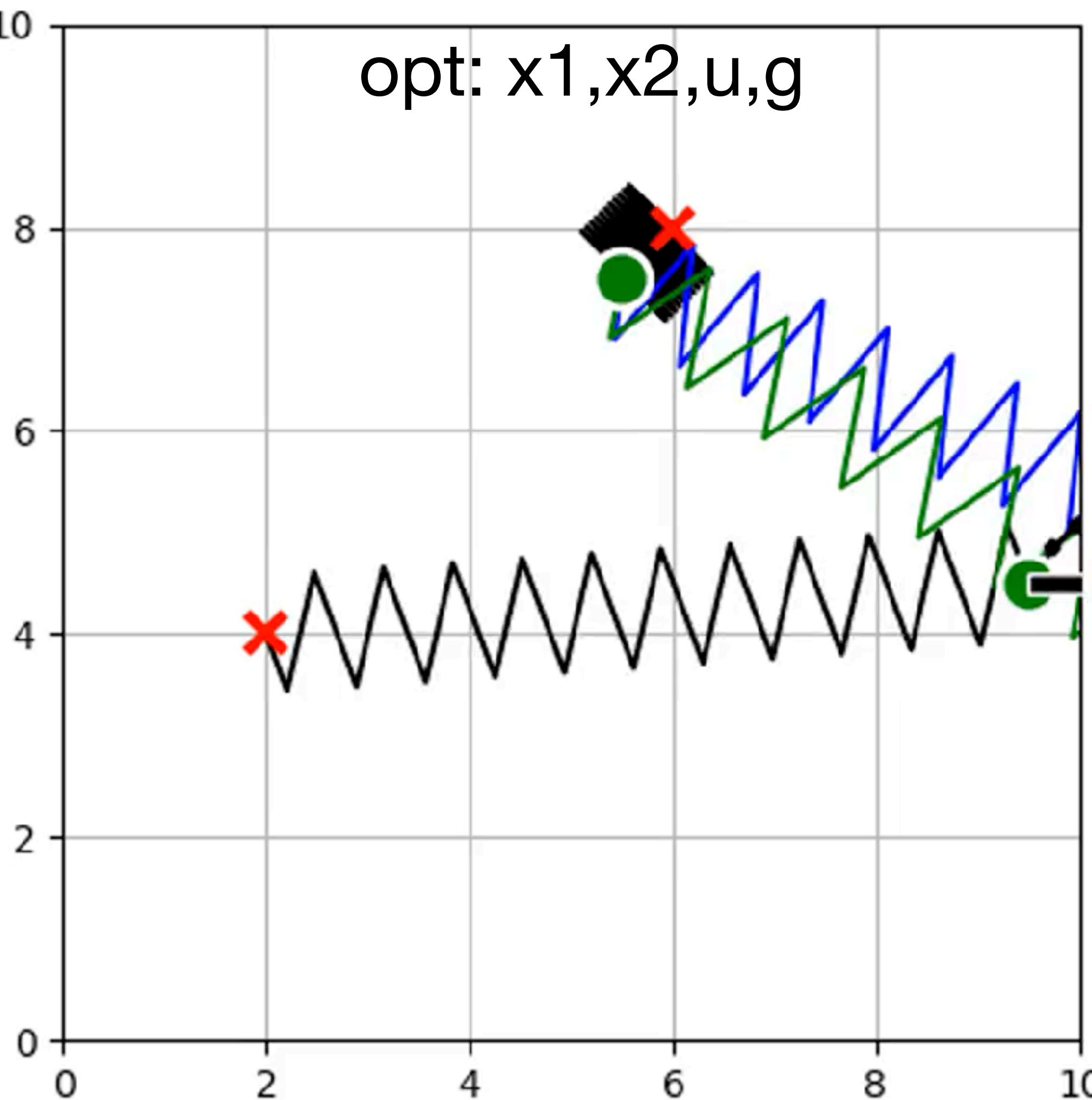
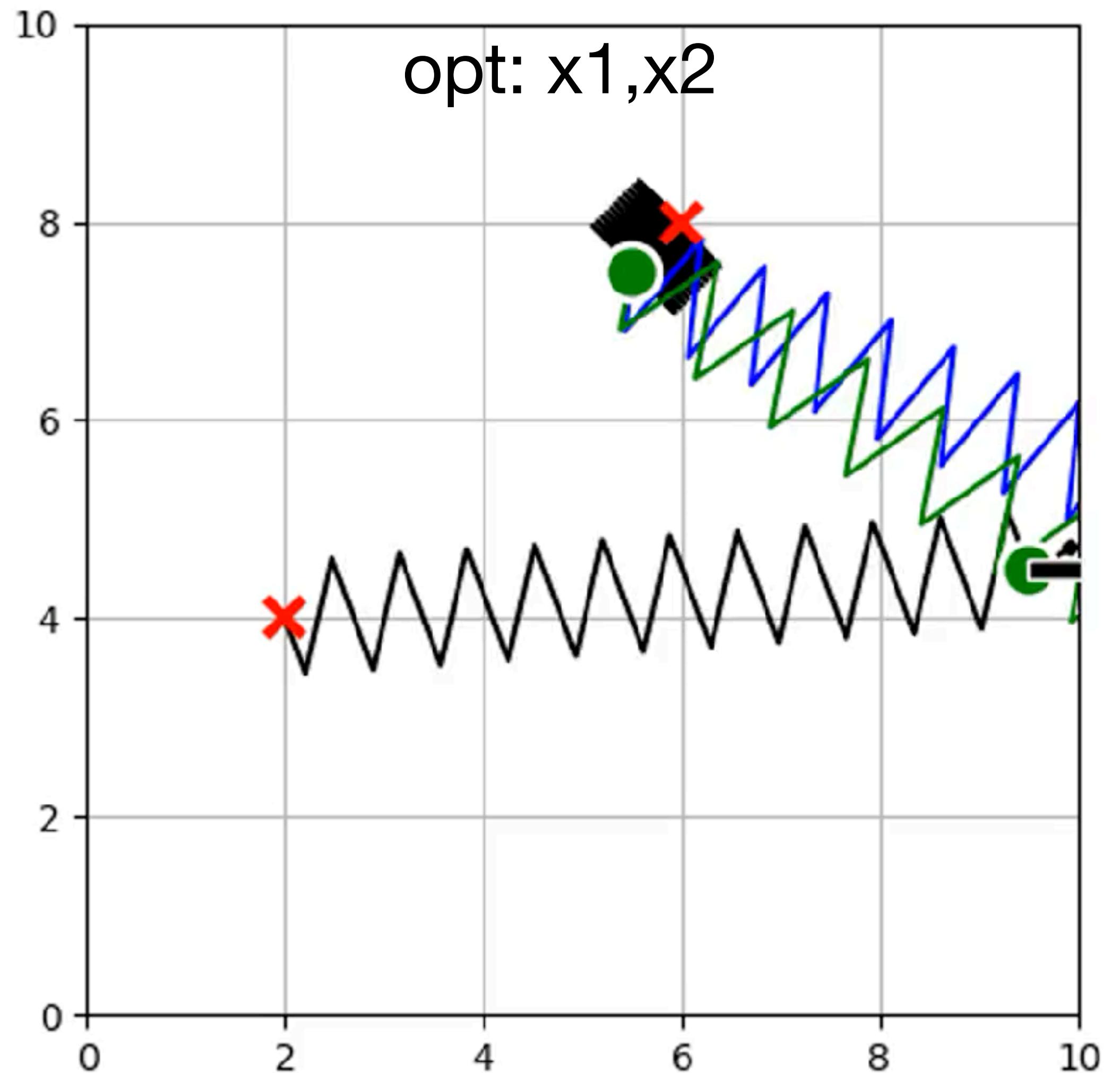
GPS



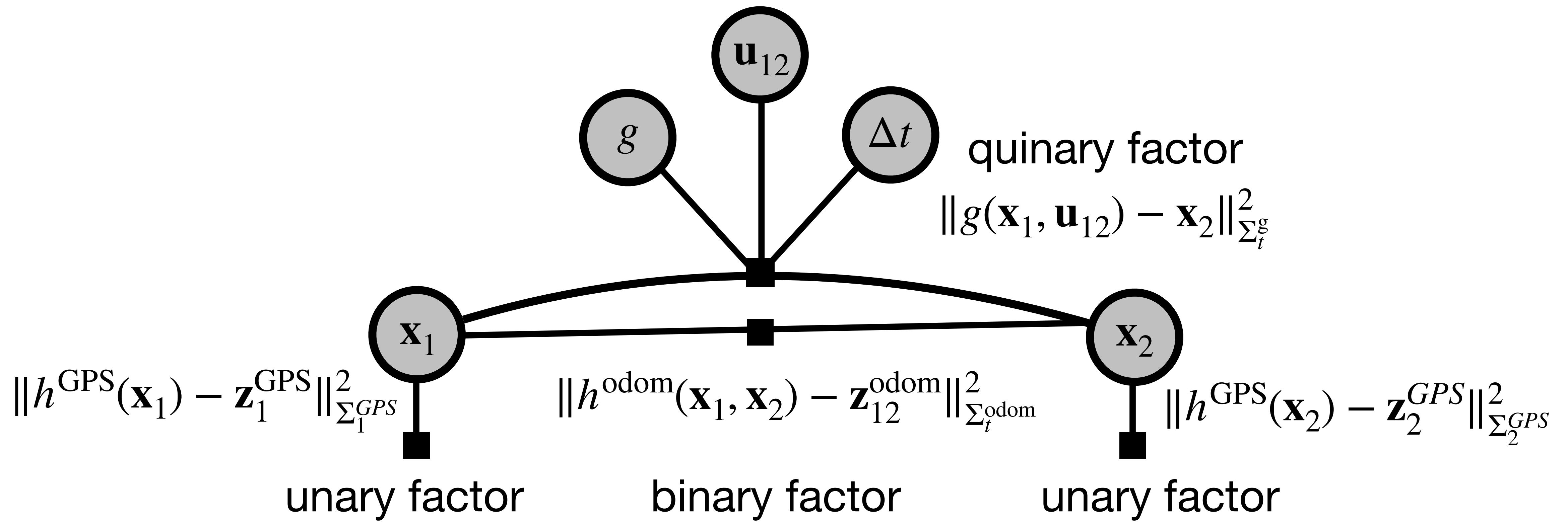
IMU

• motion
model

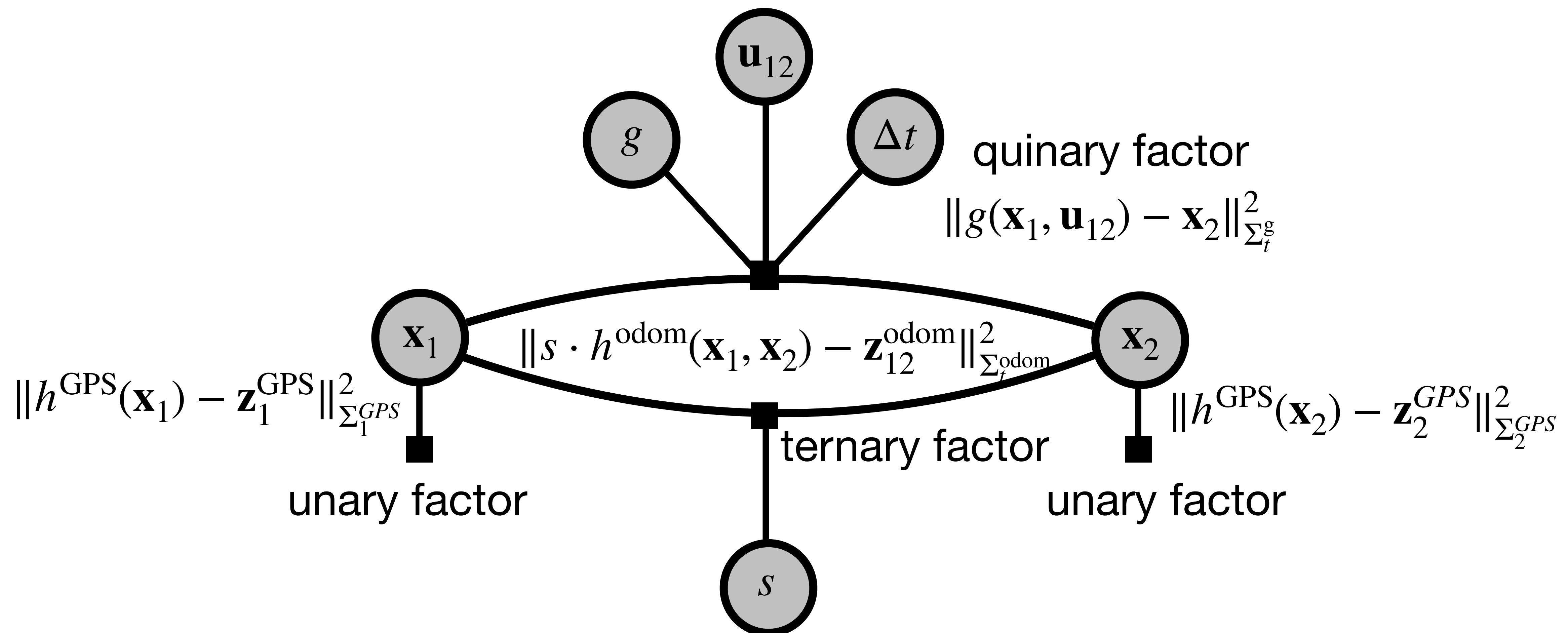
$$\mathbf{x}_1^*, \mathbf{x}_2^* = \arg \min_{\mathbf{x}_1, \mathbf{x}_2} \|\mathbf{x}_1 - \mathbf{z}_1^{GPS}\|_{\Sigma_1^{GPS}}^2 + \|\mathbf{x}_2 - \mathbf{z}_2^{GPS}\|_{\Sigma_2^{GPS}}^2 + \|\mathbf{x}_2 + \mathbf{z}_{12}^{odom} - \mathbf{x}_2\|_{\Sigma_t^{odom}}^2 + \|g(\mathbf{x}_1, \mathbf{u}_2) - \mathbf{x}_2\|_{\Sigma_t^g}^2$$



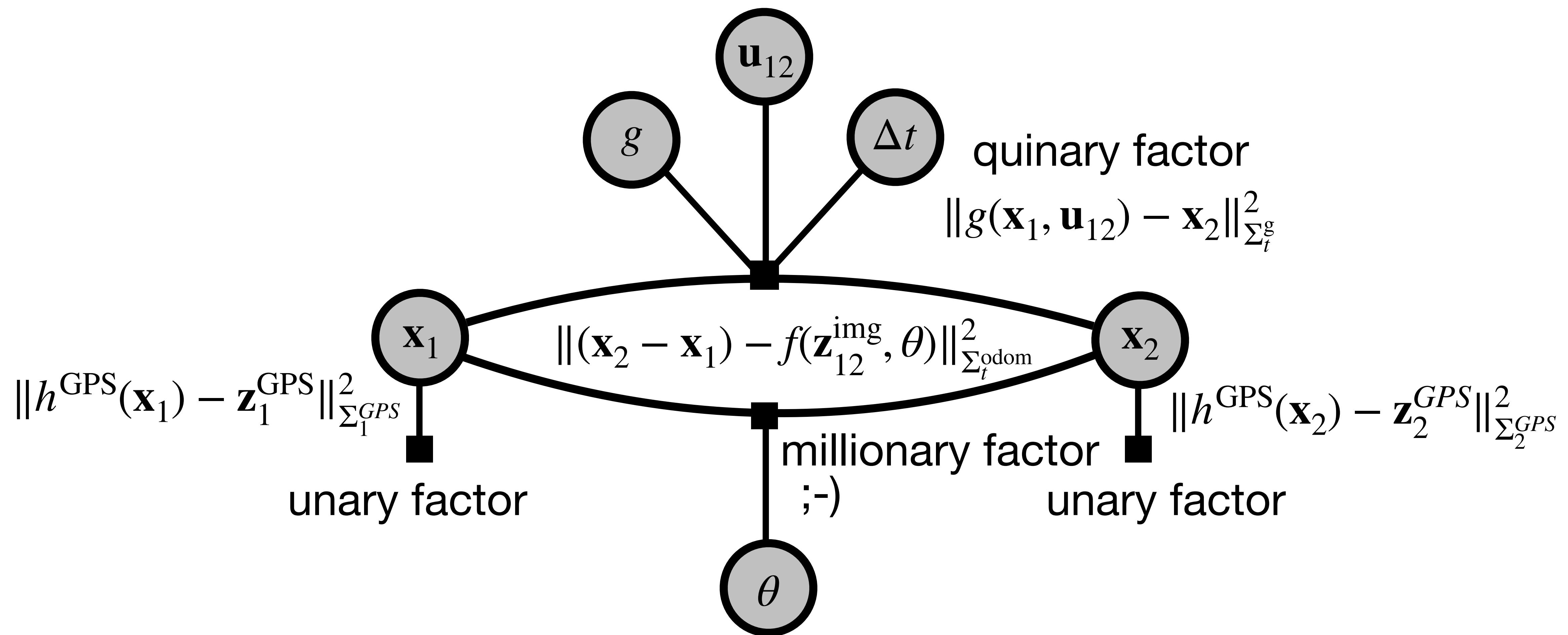
What if the scale of odometry measurement is unknown?

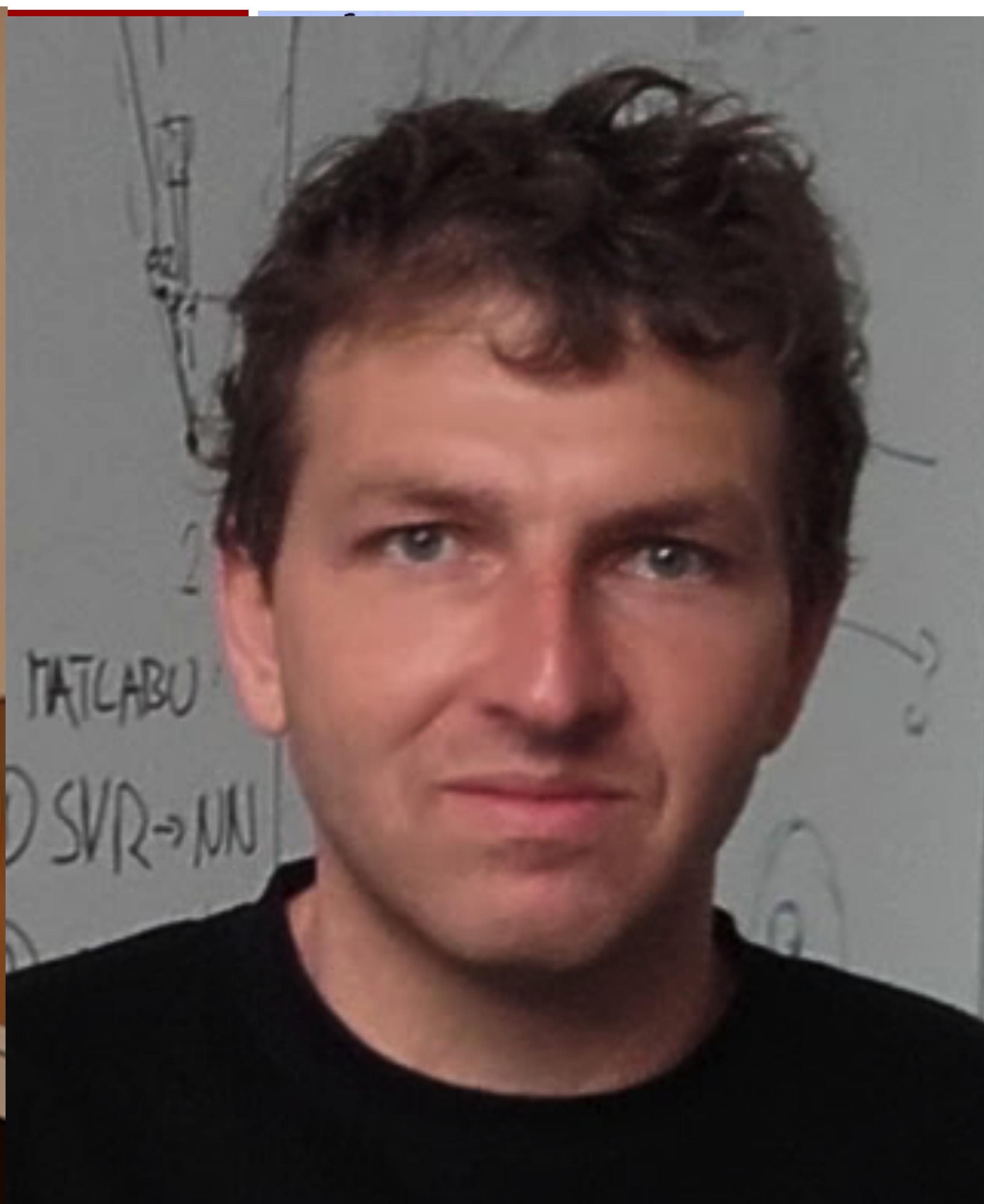


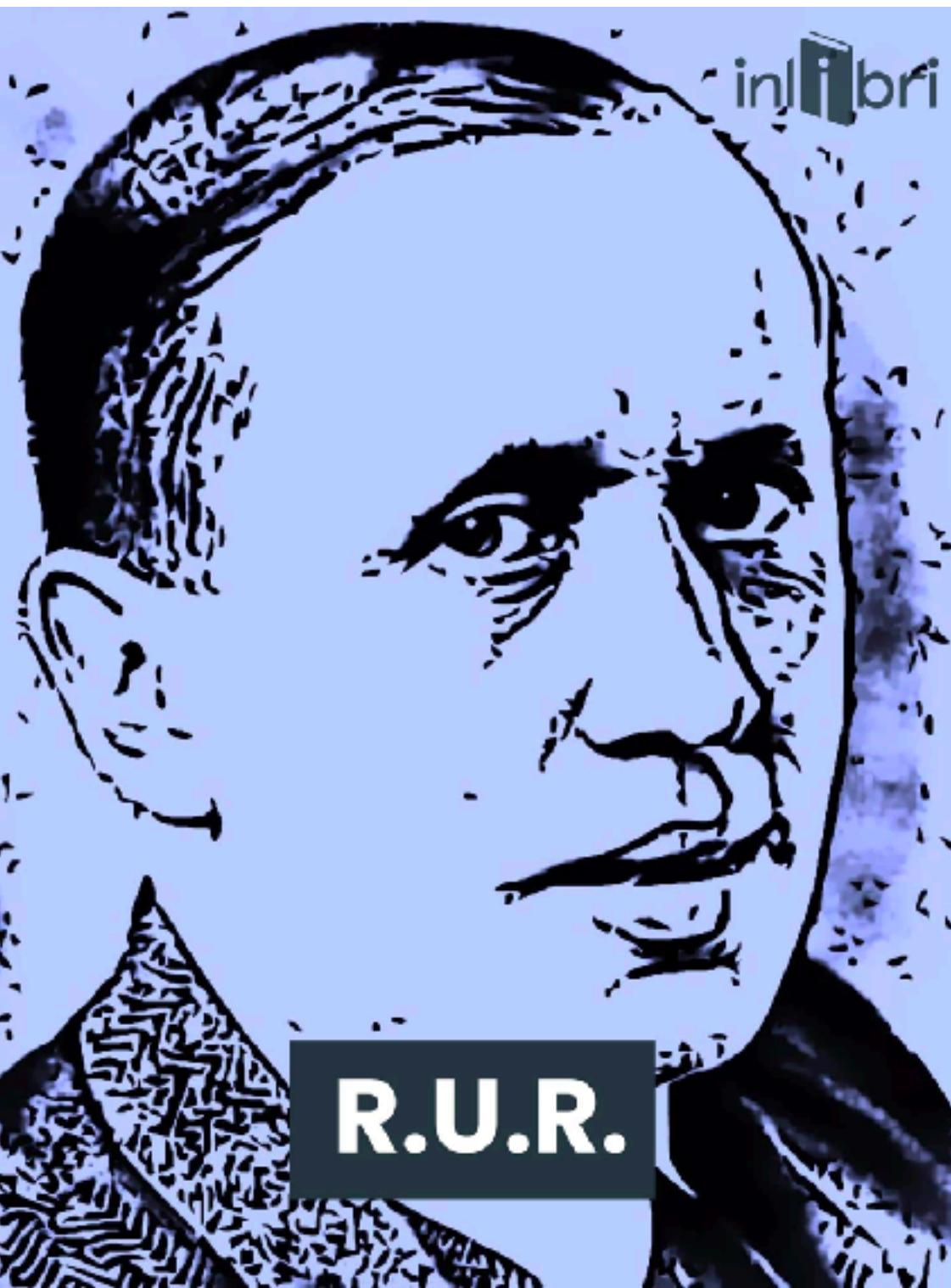
What if the scale of odometry measurement is unknown?
 What if the measurement is blurred image and I want to learn deep odometry predictor, which transform image to odometry vector?



What if the scale of odometry measurement is unknown?
 What if the measurement is blurred image and I want to learn deep odometry predictor, which transform image to odometry vector?







Where does the image come from? Theatre play “Rossum's Universal Robots” 1920
R.U.R. challenge: bonus task (max 3points)

- Come up with an original sci-fi postapocalyptic universe (image diffusion model)
- Unique law of physics (e.g. variable gravity even negative, speed of light = 60km/h)
- Unique sensor with non-linear measurement function (e.g. $z = \sin(x)$)
- Unique state estimation problem (describe + draw corresponding factorgraph)
- Implement two state example in pytorch
- Upload to BRUTE

Localization in SE(2)

Pose of the house transformed from rcf to wcf:

$$\mathbf{z}^w = \begin{bmatrix} z_x^w \\ z_y^w \\ z_\theta^w \end{bmatrix} = \begin{bmatrix} \cos \theta_t & -\sin \theta_t & 0 \\ \sin \theta_t & \cos \theta_t & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} z_x^r \\ z_y^r \\ z_\theta^r \end{bmatrix} + \begin{bmatrix} x_t \\ y_t \\ \theta_t \end{bmatrix} = \begin{bmatrix} R(\theta_t) & \mathbf{0} \\ \mathbf{0}^\top & 1 \end{bmatrix} \mathbf{z}^r + \mathbf{x}_t = T(\mathbf{z}^r, \mathbf{x}_t) \dots \text{r2w}(\mathbf{z}^r, \mathbf{x}_t)$$

Pose of the house transformed from wcf to rcf:

$$\mathbf{z}^r = \begin{bmatrix} R(\theta_t)^\top & \mathbf{0} \\ \mathbf{0}^\top & 1 \end{bmatrix} (\mathbf{z}^w - \mathbf{x}_t) = T^{-1}(\mathbf{z}^w, \mathbf{x}_t) \dots \text{w2r}(\mathbf{z}^w, \mathbf{x}_t)$$

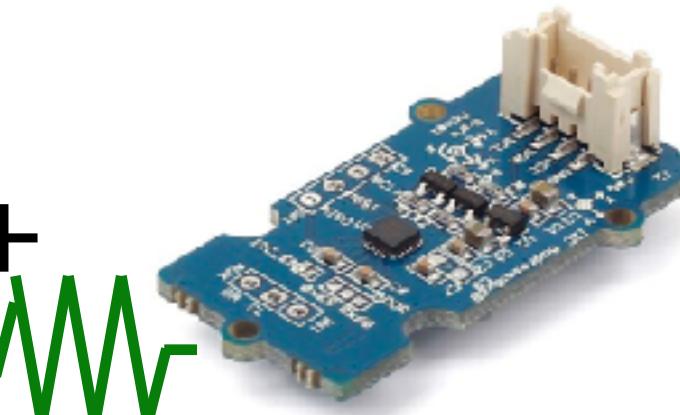
```
def r2w(z_r, x):
    z_w = torch.zeros(3)
    R = torch.vstack((torch.hstack((torch.cos(x[2]), -torch.sin(x[2]))), ...
                      z_w[0:2] = R @ z_r[0:2] + x[0:2]
    z_w[2] = z_r[2] + x[2]
    return z_w
```

```
def w2r(z_w, x):
    z_r = torch.zeros(3)
    R = torch.vstack((torch.hstack((torch.cos(x[2]), -torch.sin(x[2]))), ...
                      z_r[0:2] = R.t() @ (z_w[0:2] - x[0:2])
    z_r[2] = z_w[2] - x[2]
    return z_r
```



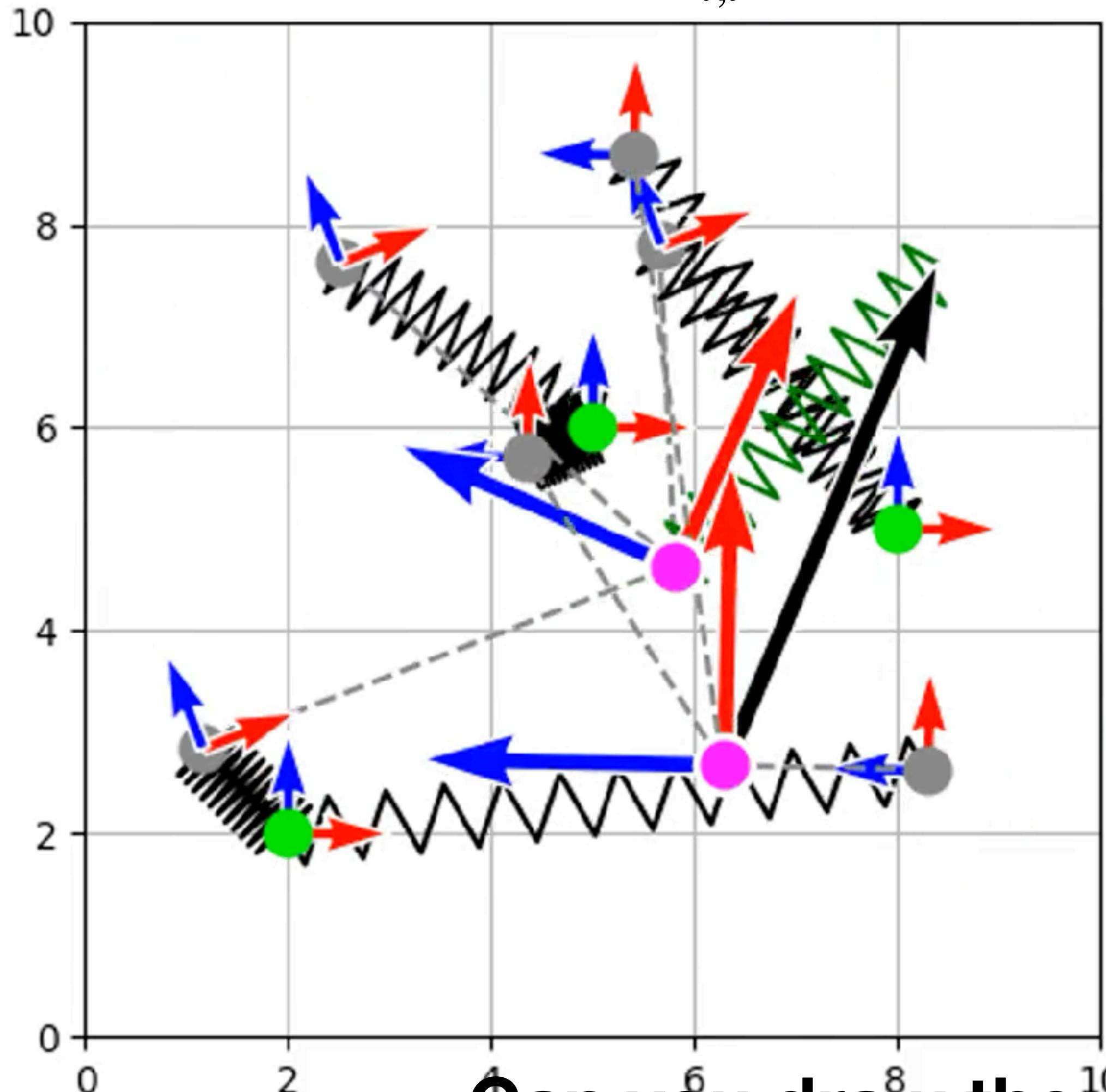
Localization

3D marker detector (RGBD camera)



Odometry (IMU)

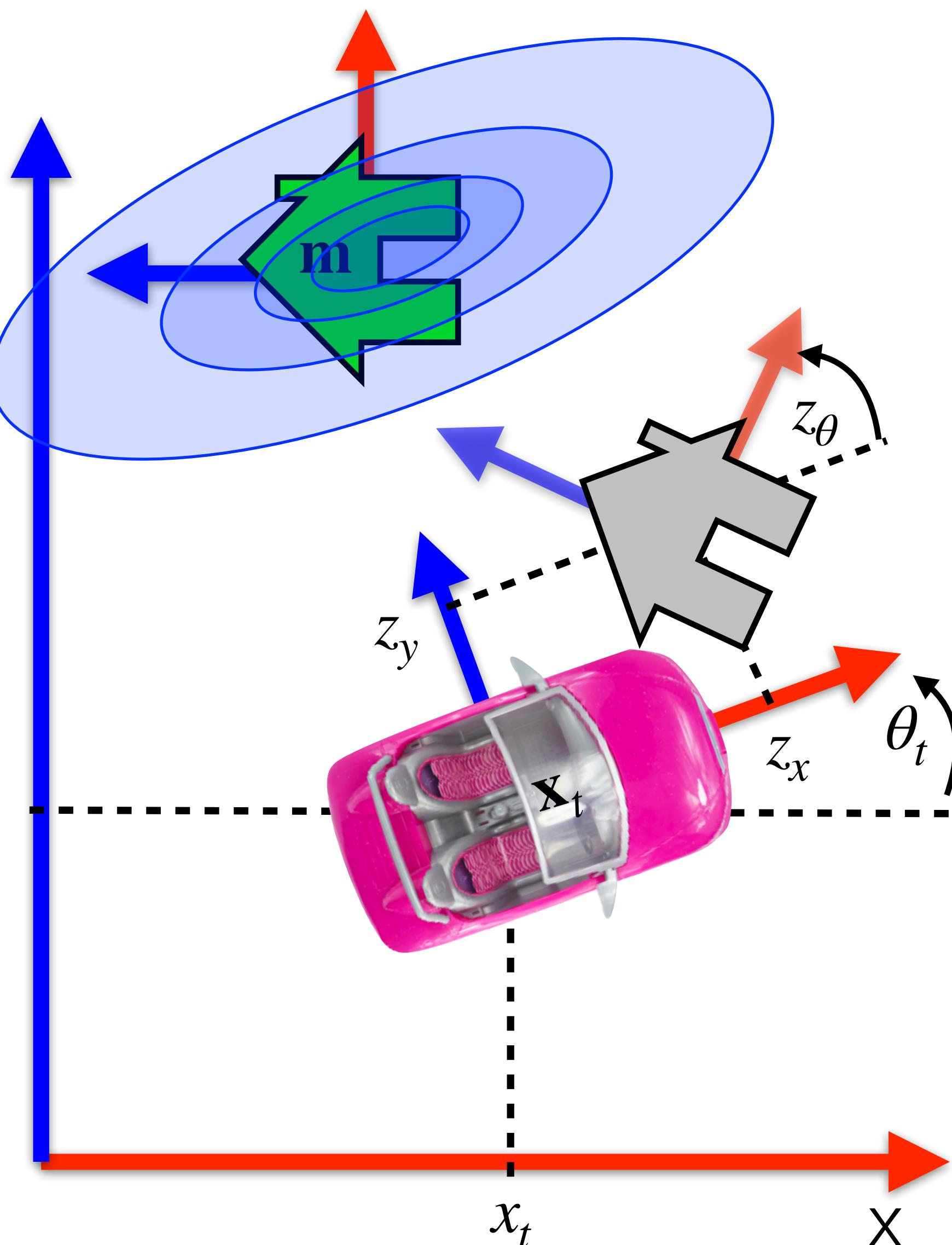
$$\mathbf{x}_1^*, \mathbf{x}_2^* = \arg \min_{\mathbf{x}_1, \mathbf{x}_2} \sum_{i,t} \|\mathbf{w2r}(\mathbf{m}_i, \mathbf{x}_t) - \mathbf{z}_t^{\mathbf{m}_i}\|^2 + \|\mathbf{w2r}(\mathbf{x}_2, \mathbf{x}_1) - \mathbf{z}_{12}^{odom}\|^2$$



- \mathbf{x}_t ... robot poses
- \mathbf{m}_i ... known marker positions
- $\mathbf{z}_t^{\mathbf{m}_i}$... marker measurements
- ↑ local coordinate frame
- odometry
- W $\sum_{i,t} \|\mathbf{w2r}(\mathbf{m}_i, \mathbf{x}_t) - \mathbf{z}_t^{\mathbf{m}_i}\|^2$... marker loss
- W $\|\mathbf{w2r}(\mathbf{x}_2, \mathbf{x}_1) - \mathbf{z}_{12}^{odom}\|^2$... odom loss

Can you draw the corresponding factorgraph?

Marker detector in EKF SLAM



$$p\left(\underbrace{\begin{bmatrix} z_t^{m,x} \\ z_t^{m,y} \\ z_t^{m,\theta} \\ z_t \end{bmatrix}}_{\mathbf{z}_t^m} \mid \underbrace{\begin{bmatrix} x_t \\ y_t \\ \theta_t \end{bmatrix}}_{\mathbf{x}_t}\right) = \mathcal{N}\left(\mathbf{z}_t^m; \underbrace{w2r(\mathbf{m}, \mathbf{x}_t)}_{h^m(\mathbf{x}_t)}, Q_t^m\right)$$

$$p\left(\underbrace{\begin{bmatrix} z_t^{\text{odom},x} \\ z_t^{\text{odom},y} \\ z_t^{\text{odom},\theta} \end{bmatrix}}_{\mathbf{z}_t^{\text{odom}}} \mid \underbrace{\begin{bmatrix} x_t \\ y_t \\ \theta_t \end{bmatrix}}_{\mathbf{x}_t}\right) = \mathcal{N}\left(\mathbf{z}_t^{\text{odom}}; \underbrace{w2r(\mathbf{m}, \mathbf{x}_t)}_{h^{\text{odom}}(\mathbf{x}_t)}, Q_t^{\text{odom}}\right)$$

Graphical representation of the EKF SLAM update loop:

```

    graph LR
        X1((X1)) ---|z12| X2((X2))
        X2 ---|z12| X1
        X1 ---|z12| Z12[ ]
        X2 ---|z12| Z12
    
```

Cost functions:

$$\sum_{i=1}^3 \|w2r(\mathbf{m}_i, \mathbf{x}_1) - \mathbf{z}_1^{\mathbf{m}_i}\|^2$$

$$\sum_{i=1}^3 \|w2r(\mathbf{m}_i, \mathbf{x}_2) - \mathbf{z}_2^{\mathbf{m}_i}\|^2$$

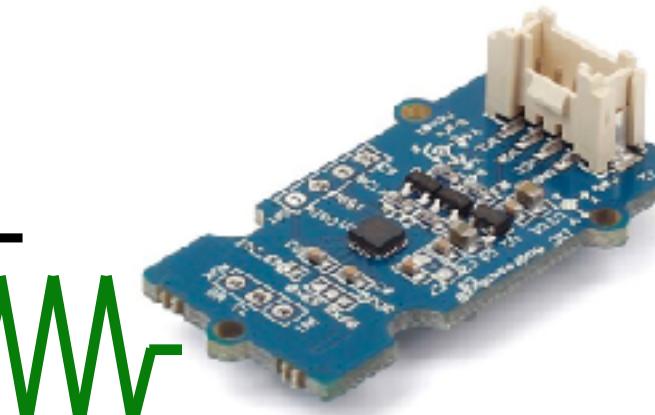
$$\|w2r(\mathbf{x}_2, \mathbf{x}_1) - \mathbf{z}_{12}^{\text{odom}}\|^2$$

SLAM in $\text{SE}(2)$



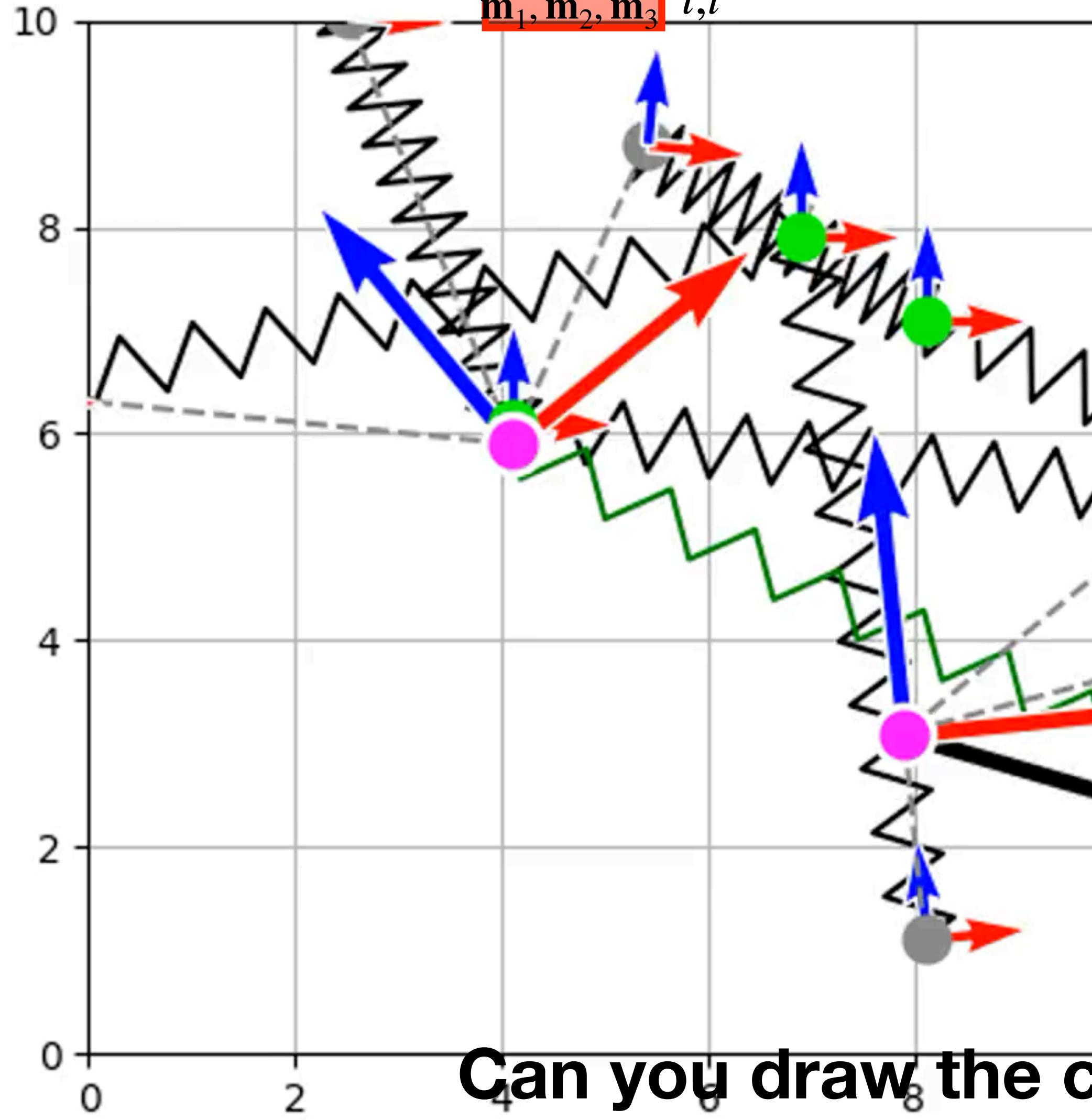
3D marker detector (RGBD camera)

SLAM



Odometry (IMU)

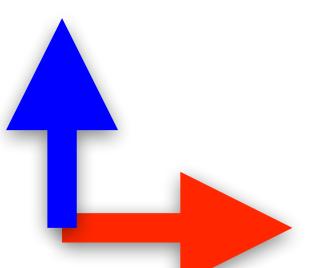
$$\mathbf{x}_1^*, \mathbf{x}_2^* = \arg \min_{\substack{\mathbf{x}_1, \mathbf{x}_2 \\ \mathbf{m}_1, \mathbf{m}_2, \mathbf{m}_3}} \sum_{i,t} \| \text{w2r}(\mathbf{m}_i, \mathbf{x}_t) - \mathbf{z}_t^{\mathbf{m}_i} \|^2 + \| \text{w2r}(\mathbf{x}_2, \mathbf{x}_1) - \mathbf{z}_{12}^{odom} \|^2$$



- \mathbf{x}_t ... robot poses
 - \mathbf{m}_i ... known marker positions
 - $\mathbf{z}_t^{\mathbf{m}_i}$... marker measurements

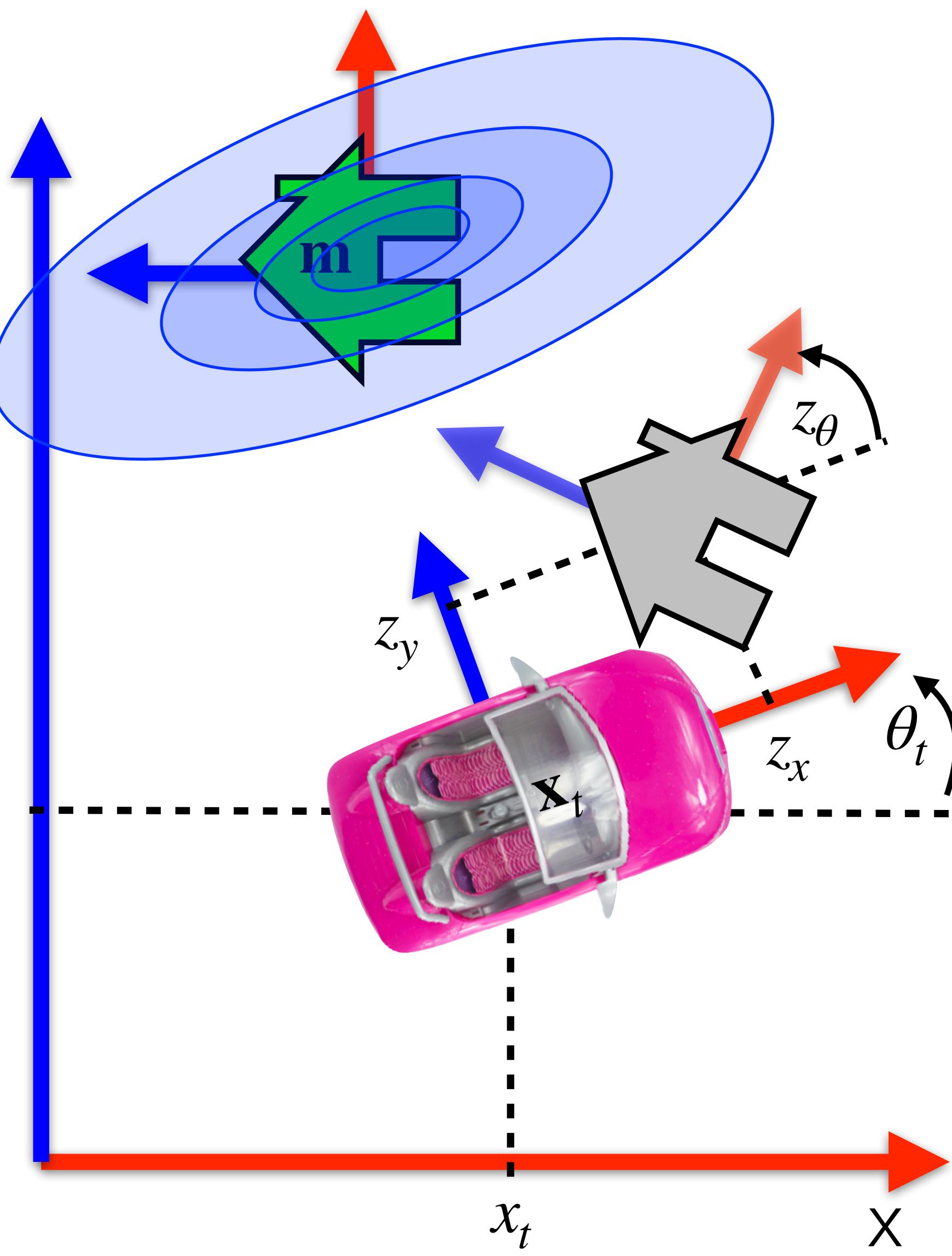
-  $\sum_{i,t} \|\mathbf{w2r}(\mathbf{m}_i, \mathbf{x}_t) - \mathbf{z}_t^{\mathbf{m}_i}\|^2$... marker loss

-  $\|\mathbf{w2r}(\mathbf{x}_2, \mathbf{x}_1) - \mathbf{z}_{12}^{odom}\|^2$... odom loss

 local coordinate frame

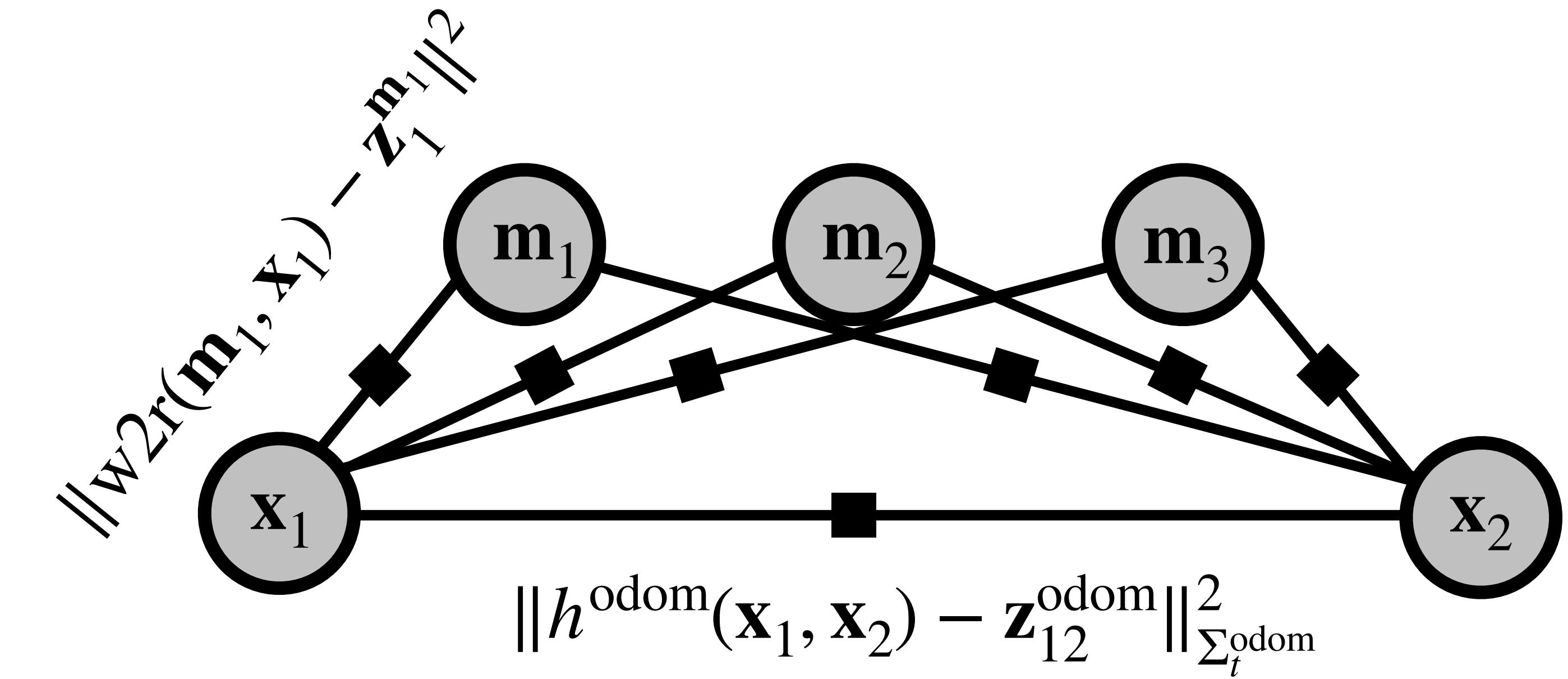
 odometry
corresponding factorgraph?

Marker detector in EKF SLAM



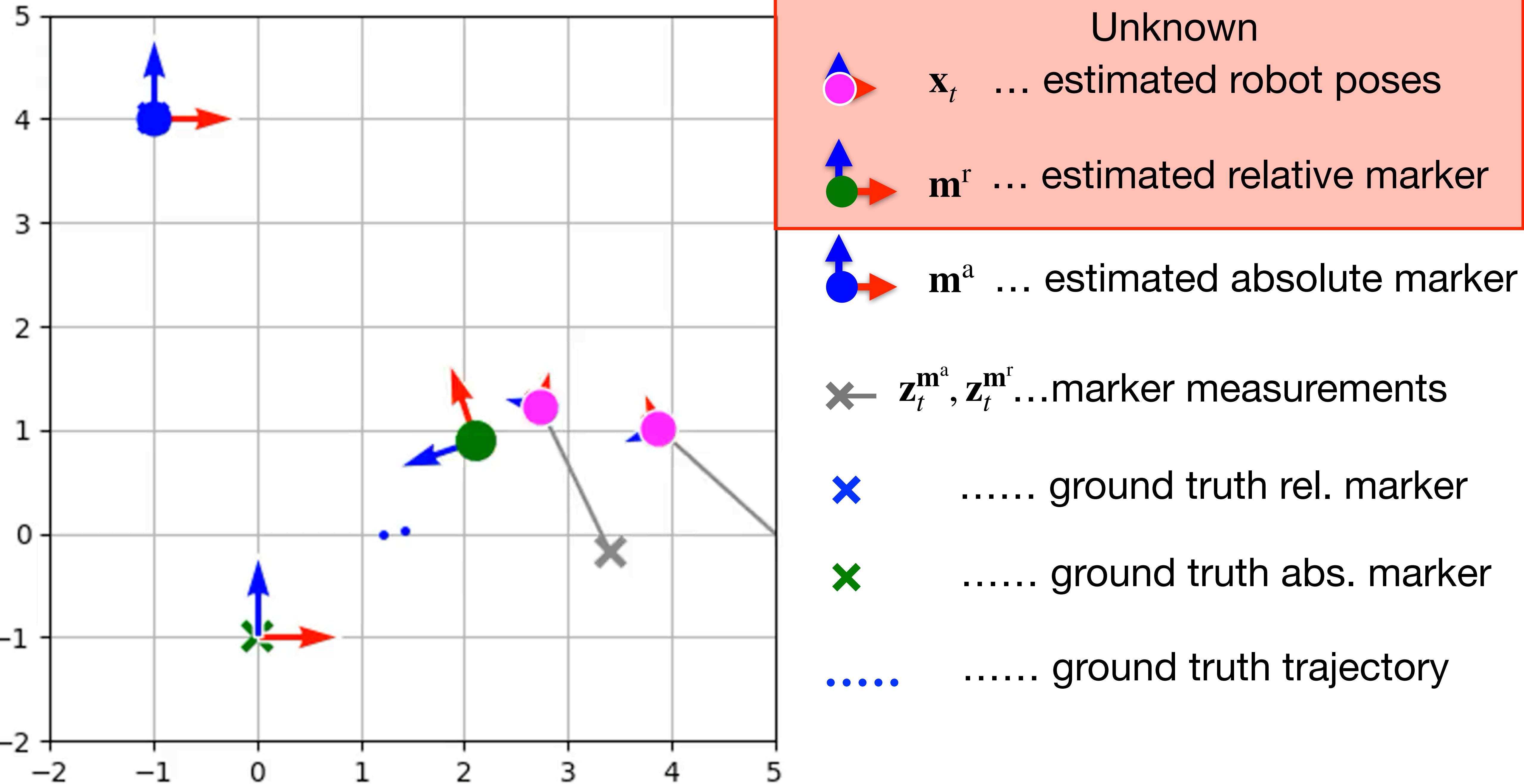
$$p\left(\underbrace{\begin{bmatrix} z_t^x \\ z_t^y \\ z_t^\theta \end{bmatrix}}_{\mathbf{z}_t^m} \mid \underbrace{\begin{bmatrix} x_t \\ y_t \\ \theta_t \end{bmatrix}}_{\mathbf{x}_t}, \underbrace{\begin{bmatrix} m^x \\ m^y \\ m^\theta \end{bmatrix}}_{\mathbf{m}}\right) = \mathcal{N}\left(\mathbf{z}_t^m; \underbrace{w2r(\mathbf{m}, \mathbf{x}_t)}_{h^m(\mathbf{x}_t)}, Q_t^m\right)$$

```
loss = ..... # <----- TODO FILL IN
```

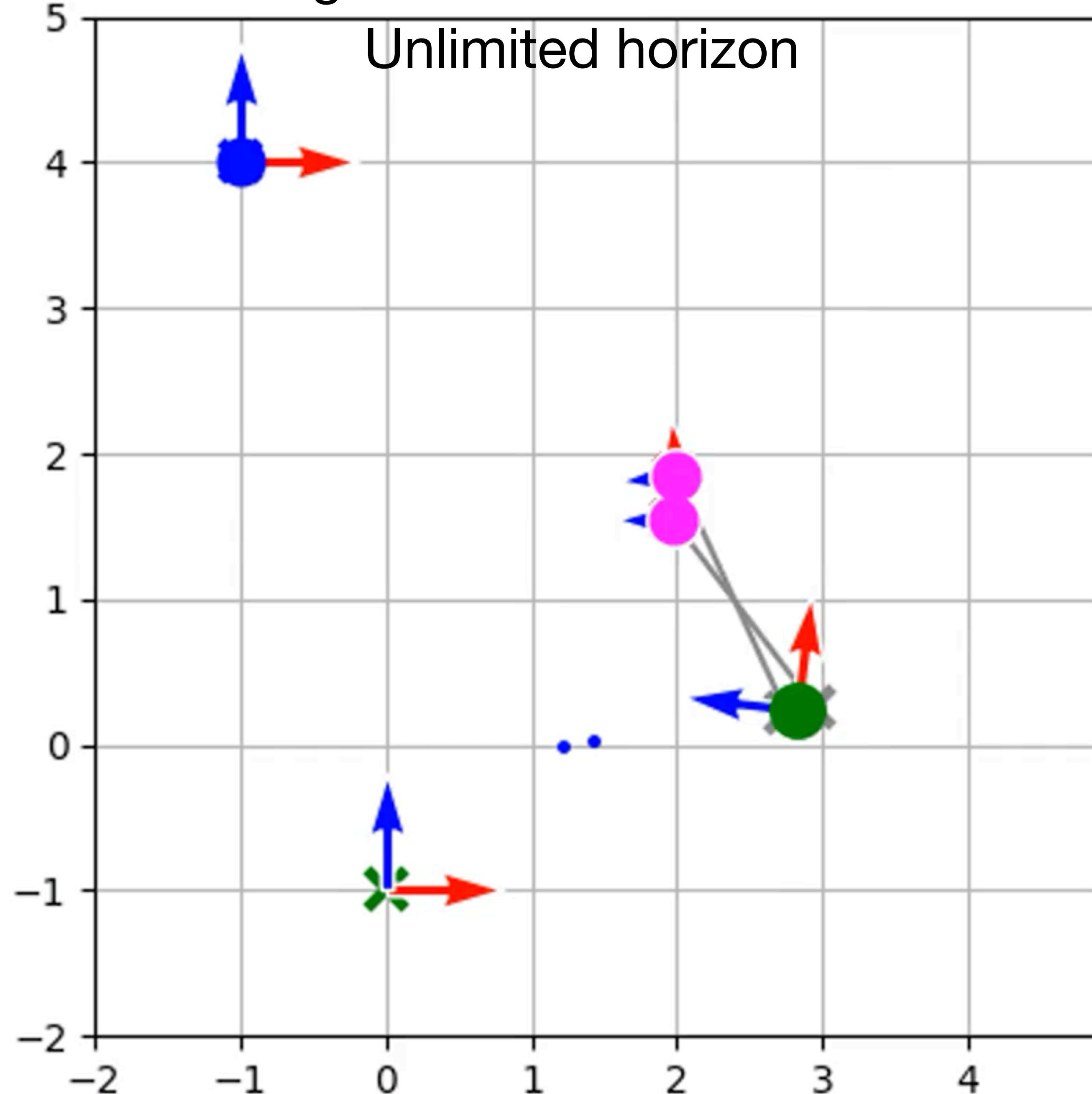


SLAM in $SE(2)$ with successively coming measurements
Combining absolute and relative markers

Combining absolute and relative markers



Combining absolute and relative markers



Combining absolute and relative markers

