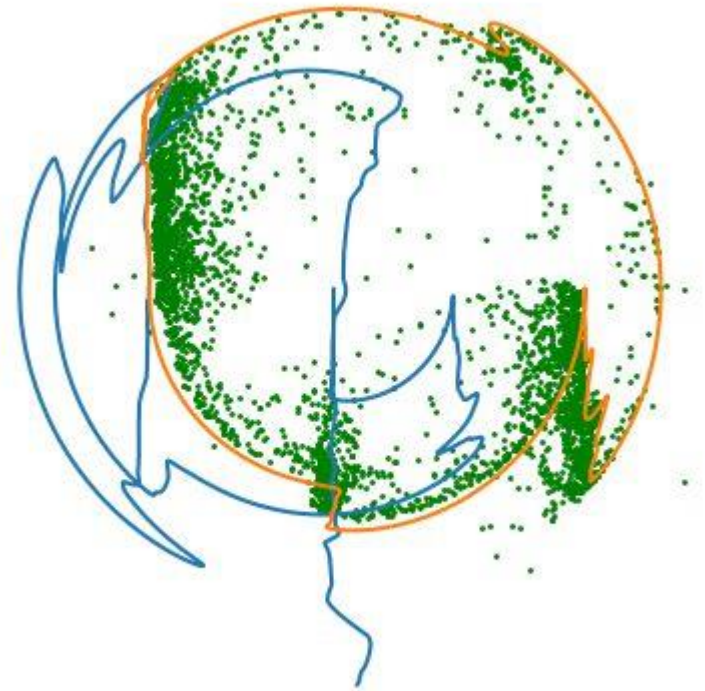
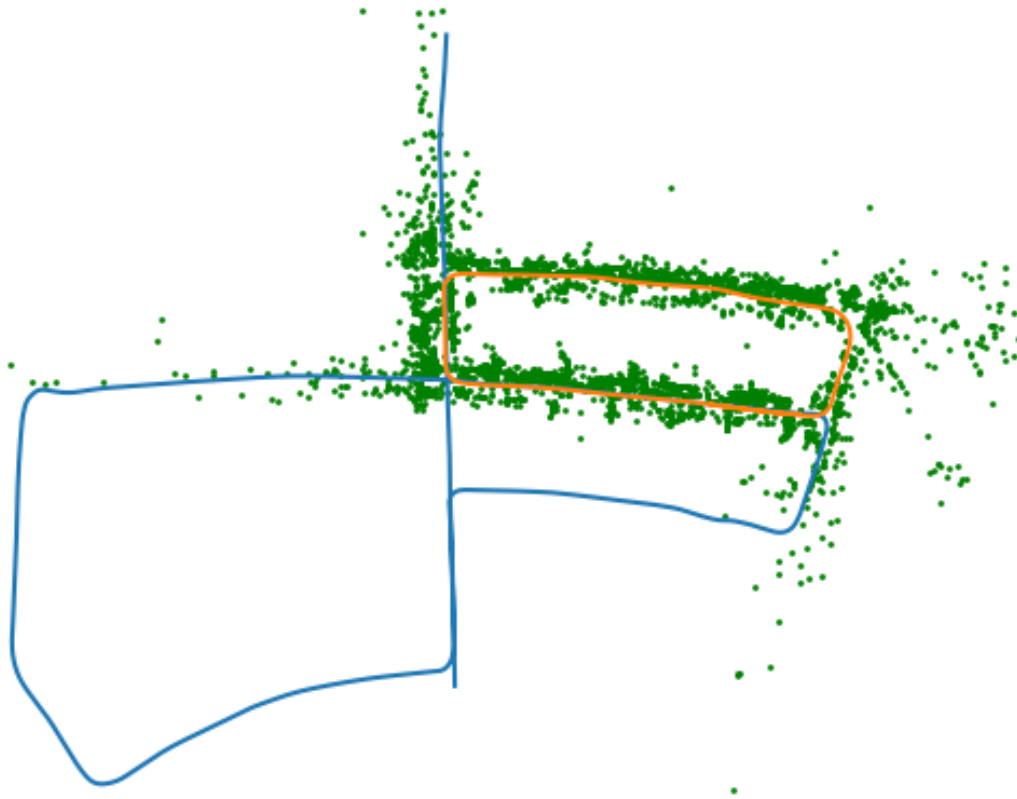


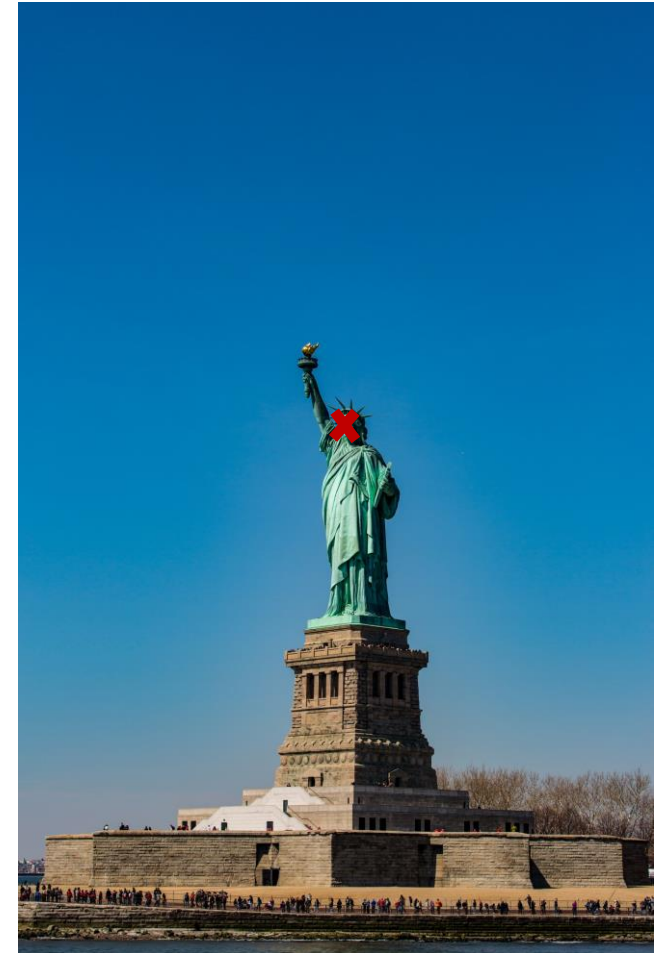
# Bundle Adjustment

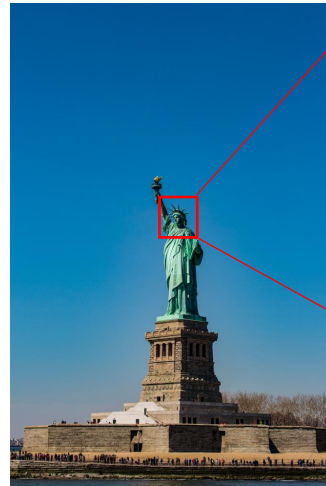
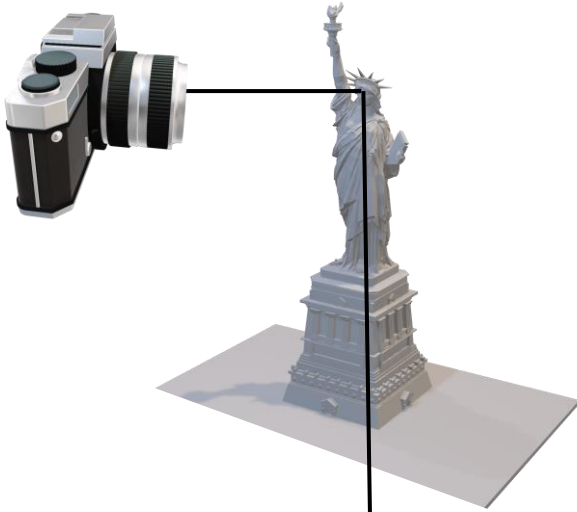
David Arnon

# KITTI



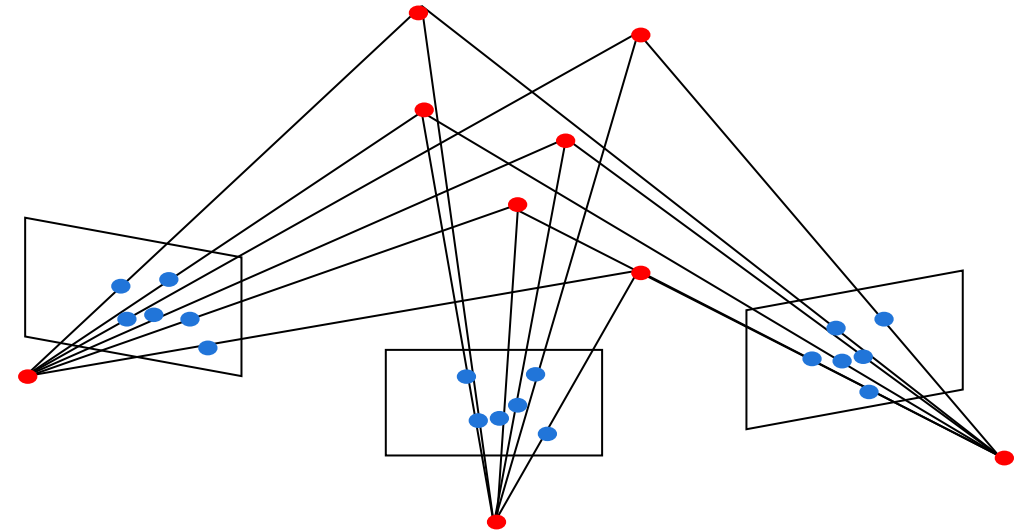
# Triangulation



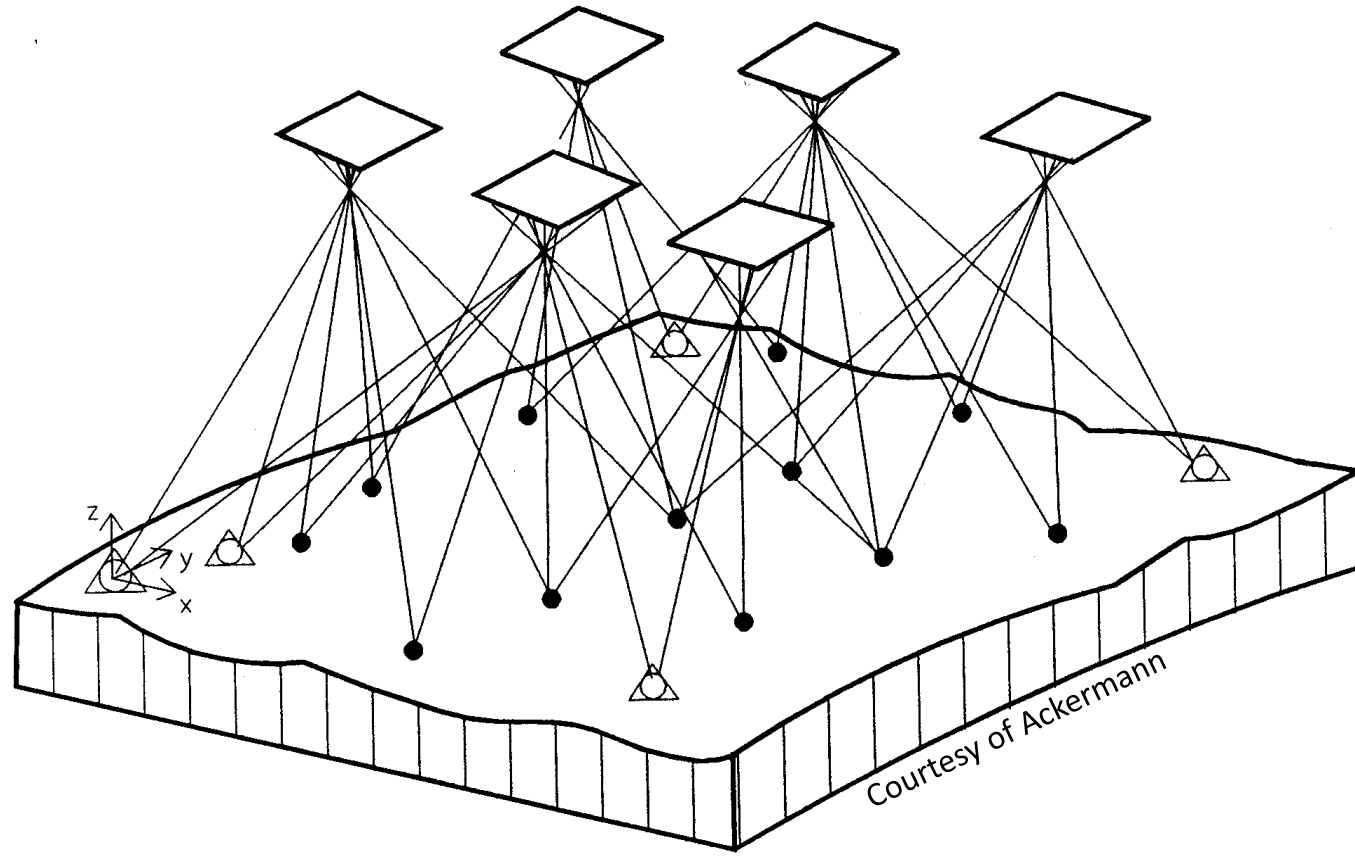


# Bundle Adjustment

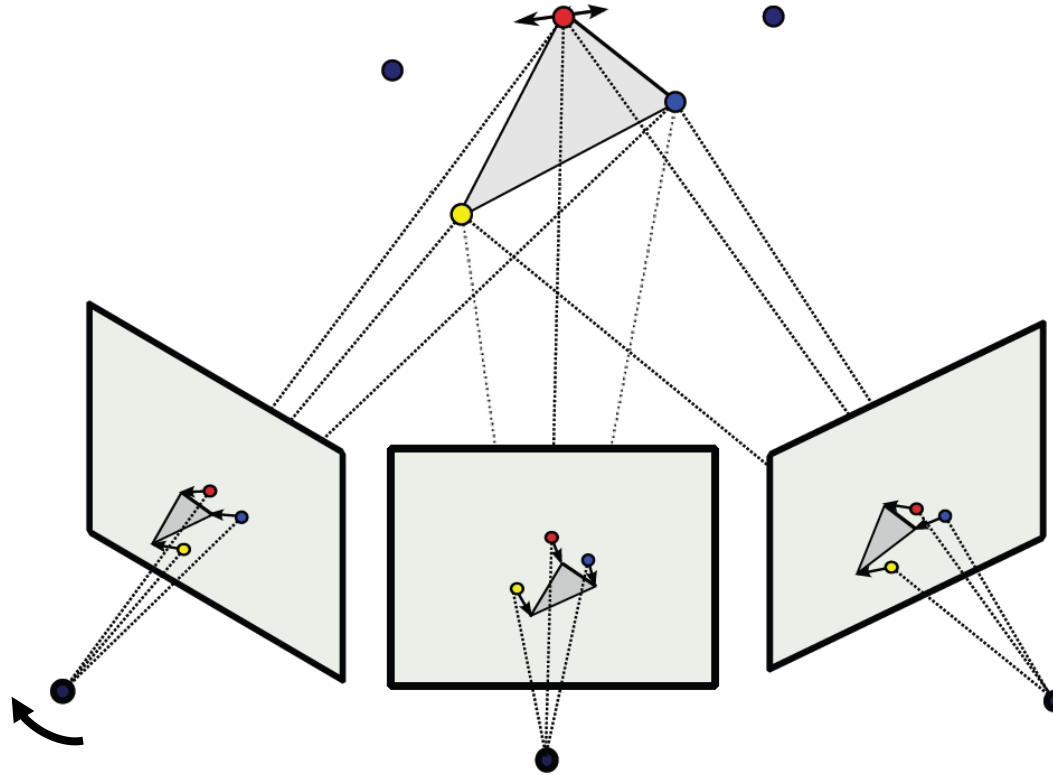
- Refines a visual reconstruction to produce jointly optimal 3D structure (world) and viewing parameters (cameras)
- '*bundle*' refers to the bundle of light rays leaving each 3D feature and converging on each camera center.
- Developed in the field of photogrammetry in the 1950's



# Bundle Adjustment

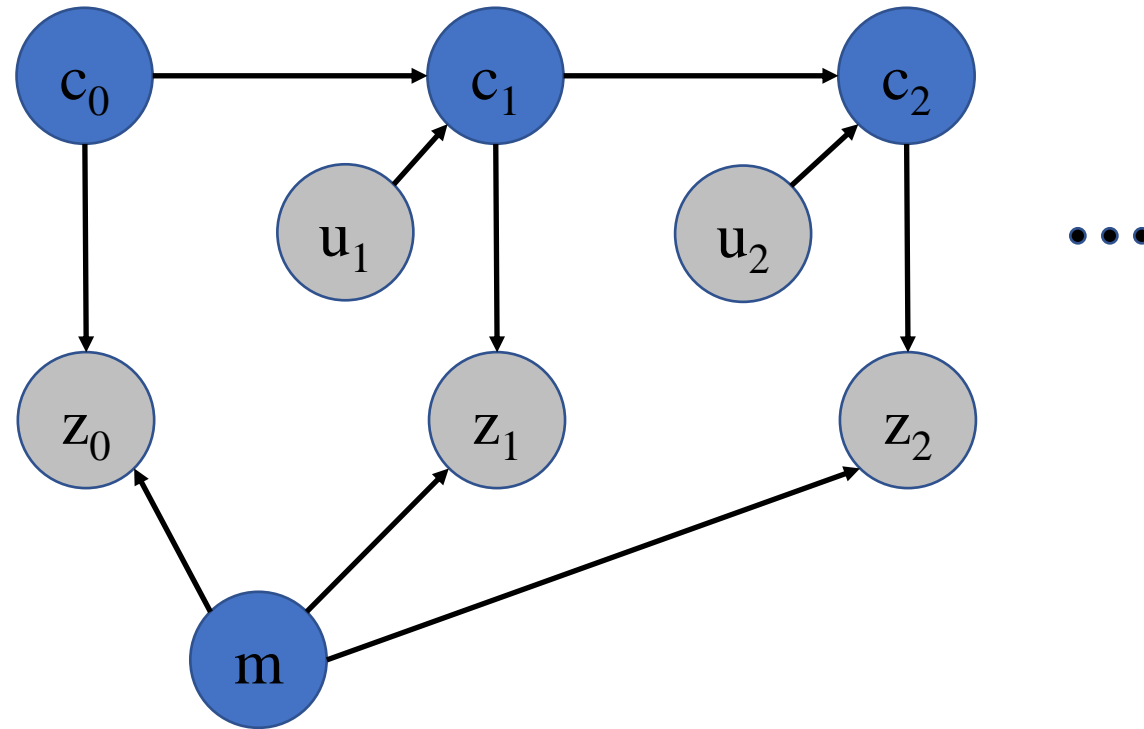


# Bundle Adjustment



# Slam

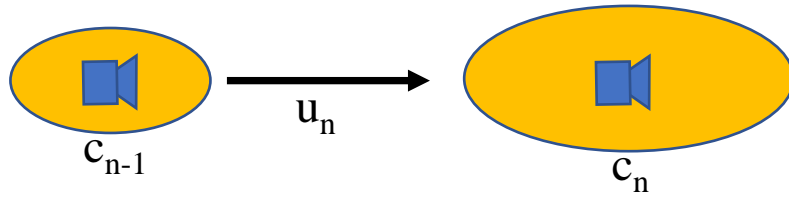
- Graphical Model



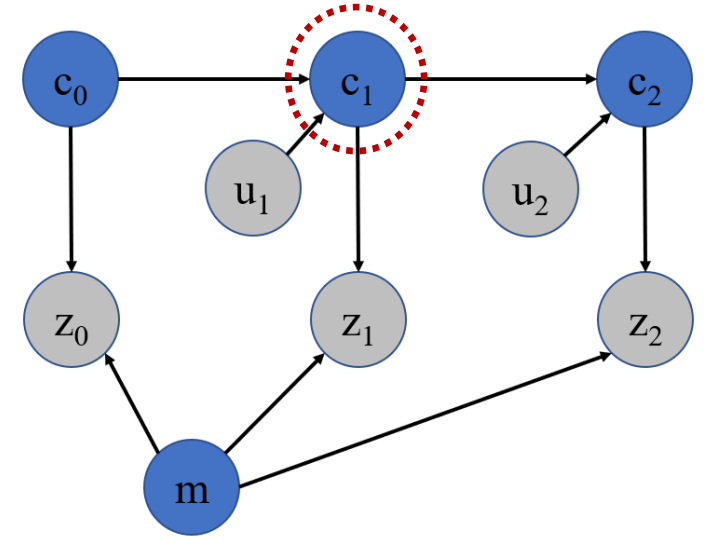
$$p(c_{0:2}, m \mid u_{1:2}, z_{0:2})$$



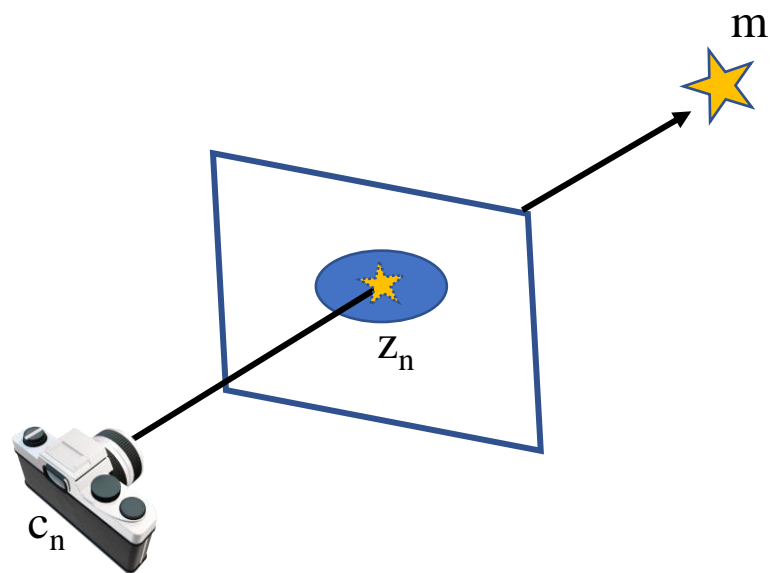
# Motion Model



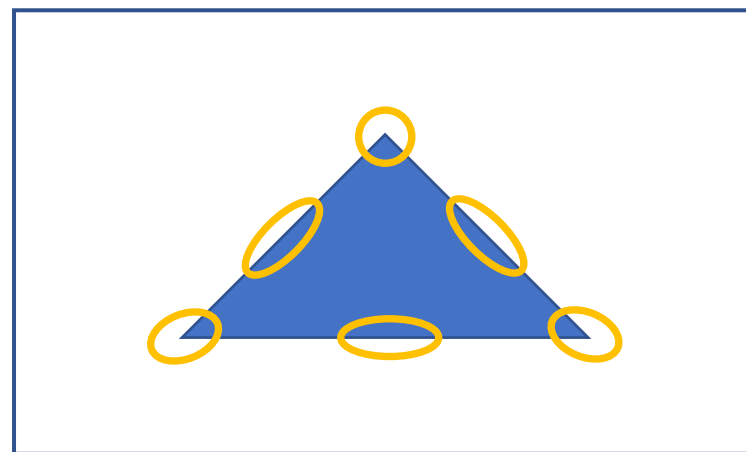
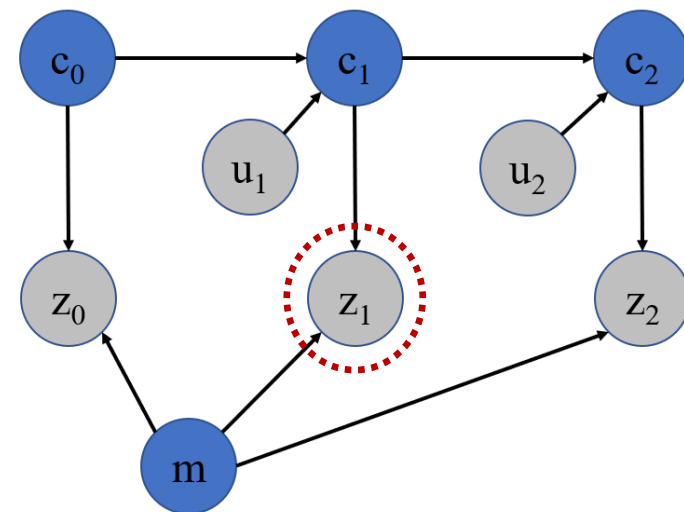
$$p(c_n | c_{n-1}, u_n)$$



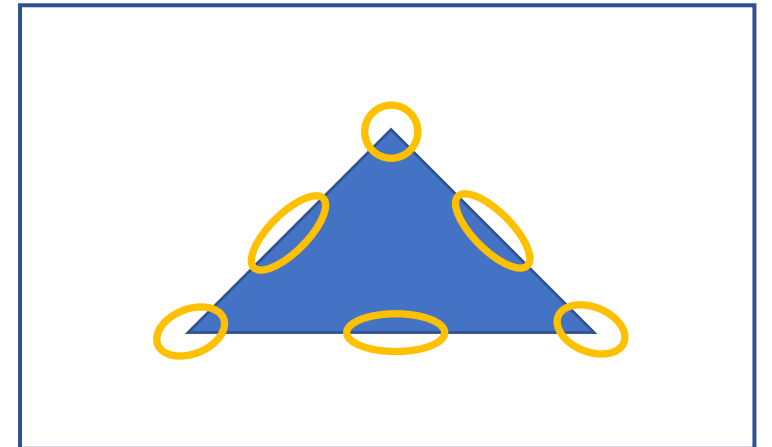
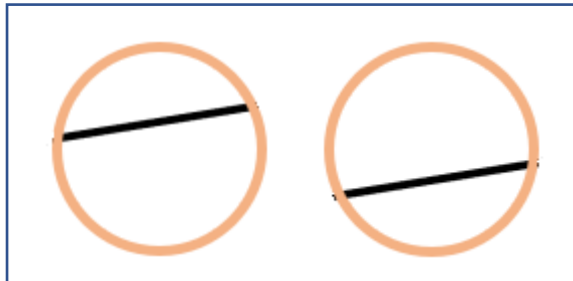
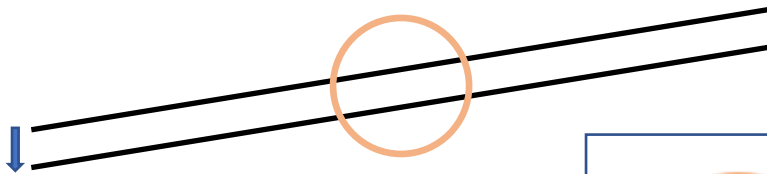
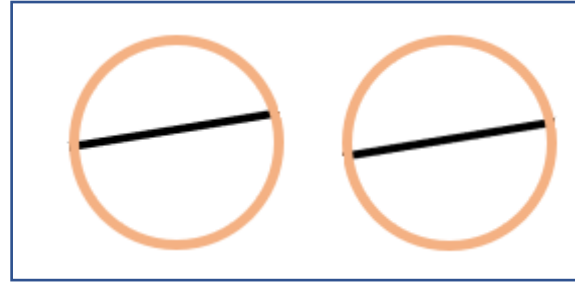
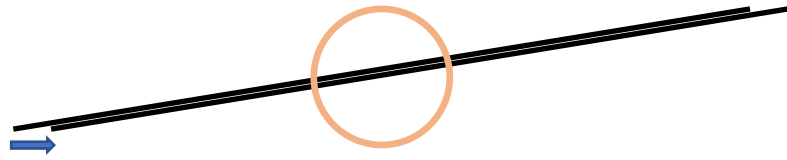
# Measurement Model



$$p(z_n | c_n, m)$$

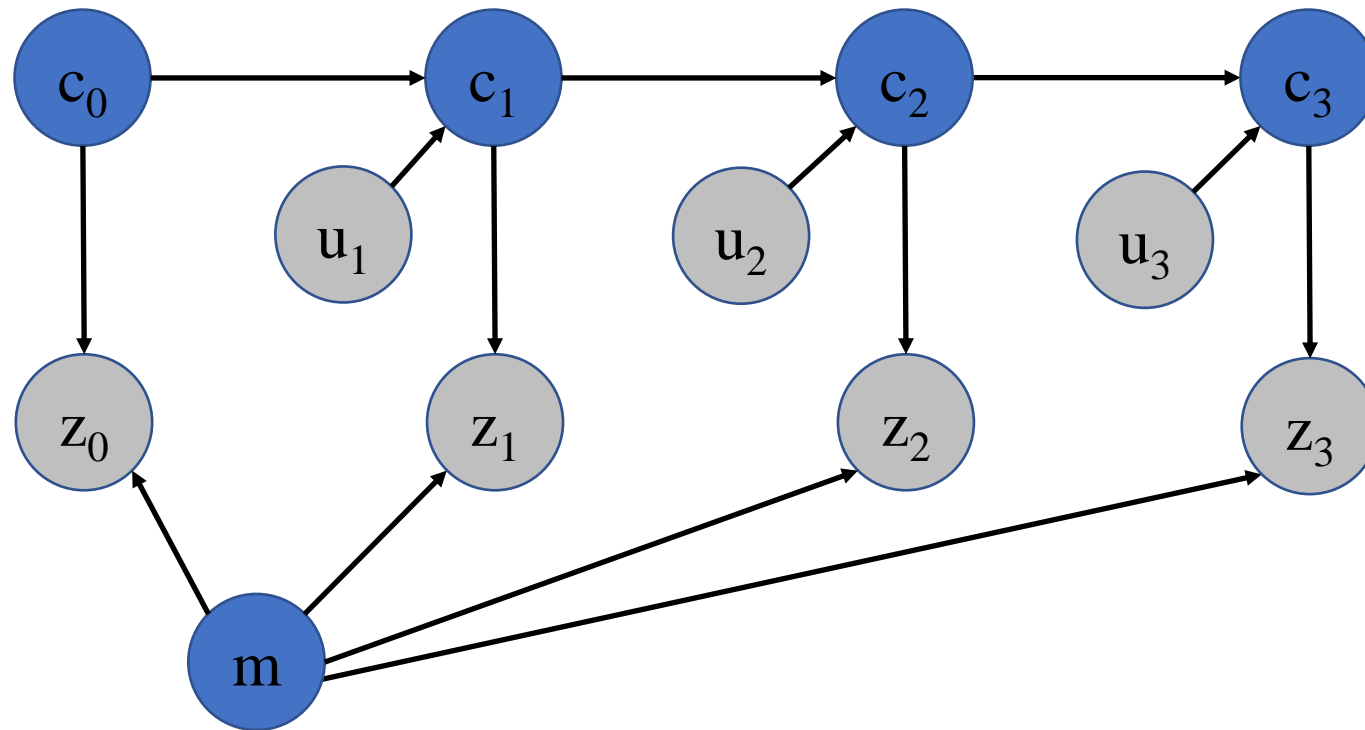


# Measurement Model



# Graphical Model

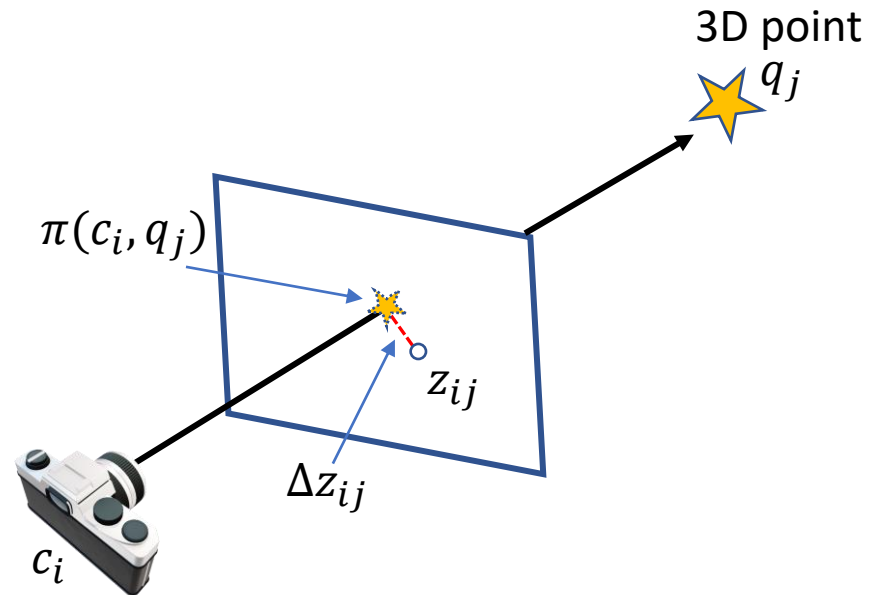
- Bundle Adjustment



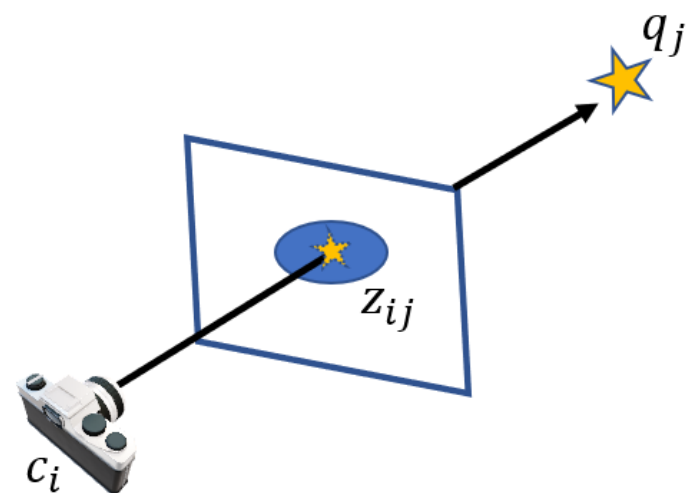
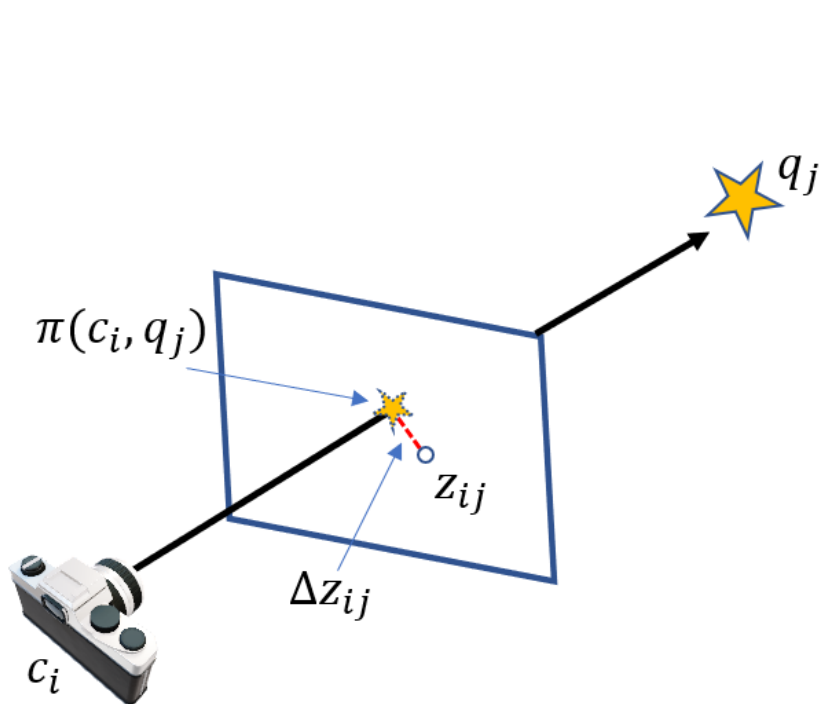
$$p(c_{0:3}, m \mid \cancel{u_{1:3}}, z_{0:3})$$

# Probabilistic Formulation

- Reprojection error:  $\Delta z_{ij} \doteq \pi(c_i, q_j) - z_{ij}$



# Measurement Model



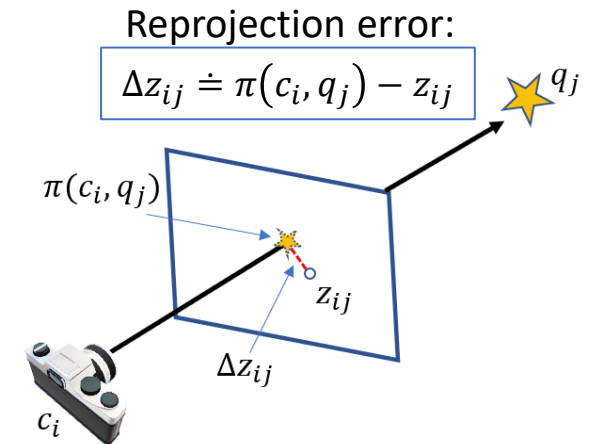
$$p(z_{ij}|c_i, q_j) \sim N(\pi(c_i, q_j), \Sigma)$$

$$z_{ij} = \pi(c_i, q_j) + w, \quad w \sim N(0, \Sigma)$$

# Bayes

- $p(z_{ij}|c_i, q_j) \sim N(\pi(c_i, q_j), \Sigma)$
- $p(c_i, q_j|z_{ij}) = \frac{1}{p(z_{ij})} p(z_{ij}|c_i, q_j) p(c_i, q_j)$
- $p(c_i, q_j|z_{ij}) \propto p(z_{ij}|c_i, q_j) p(c_i, q_j)$
- $p(c_i, q_j|z_{ij}) \propto p(z_{ij}|c_i, q_j)$
- $p(c_i, q_j|z_{ij}) \propto \exp\left(-\frac{1}{2} \|z_{ij} - \pi(c_i, q_j)\|_{\Sigma}^2\right)$
- $p(c_i, q_j|z_{ij}) \propto \exp\left(-\frac{1}{2} \|\Delta z_{ij}\|_{\Sigma}^2\right)$

$$N_{\mu, \Sigma}(z) \propto \exp\left(-\frac{1}{2} \|z - \mu\|_{\Sigma}^2\right)$$



# Bundle Adjustment

- $\operatorname{argmax}_{C,Q} [p(C, Q|Z)]$
- $\operatorname{argmax}_{C,Q} [p(Z|C, Q)]$
- $\operatorname{argmax}_{C,Q} [\prod_{c_i} \prod_{j \in M_i} p(z_{ij}|c_i, q_j)]$
- $\operatorname{argmax}_{C,Q} \left[ \prod_{c_i} \prod_{j \in M_i} \exp \left( -\frac{1}{2} \|\Delta z_{ij}\|_{\Sigma}^2 \right) \right]$
- $\operatorname{argmax}_{C,Q} \left[ \sum_{c_i} \sum_{j \in M_i} -\frac{1}{2} \|\Delta z_{ij}\|_{\Sigma}^2 \right]$
- $\operatorname{argmin}_{C,Q} \left[ \sum_{c_i} \sum_{j \in M_i} \|\Delta z_{ij}\|_{\Sigma}^2 \right]$
- $\operatorname{argmin}_{C,Q} \left[ \sum_{c_i} \sum_{j \in M_i} \|\Sigma^{-1/2} \Delta z_{ij}\|^2 \right]$

$$\Delta z_{ij} \doteq \pi(c_i, q_j) - z_{ij}$$

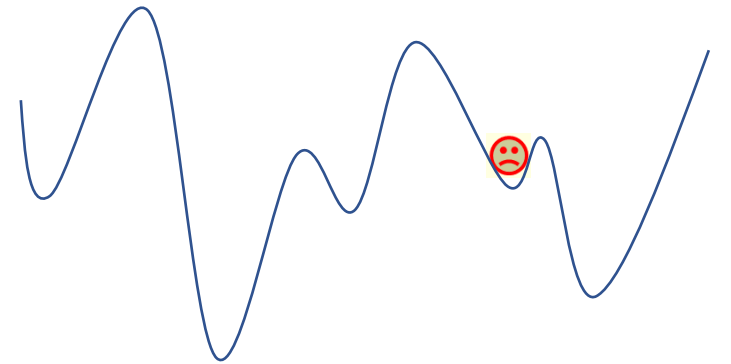
$$\Sigma^{1/2} = \operatorname{chol}(\Sigma)$$

$$\begin{aligned} \Sigma &= (\Sigma^{1/2})(\Sigma^{1/2})^T \\ \Sigma^{-1} &= \Sigma^{-1/2 T} \Sigma^{-1/2} \end{aligned}$$

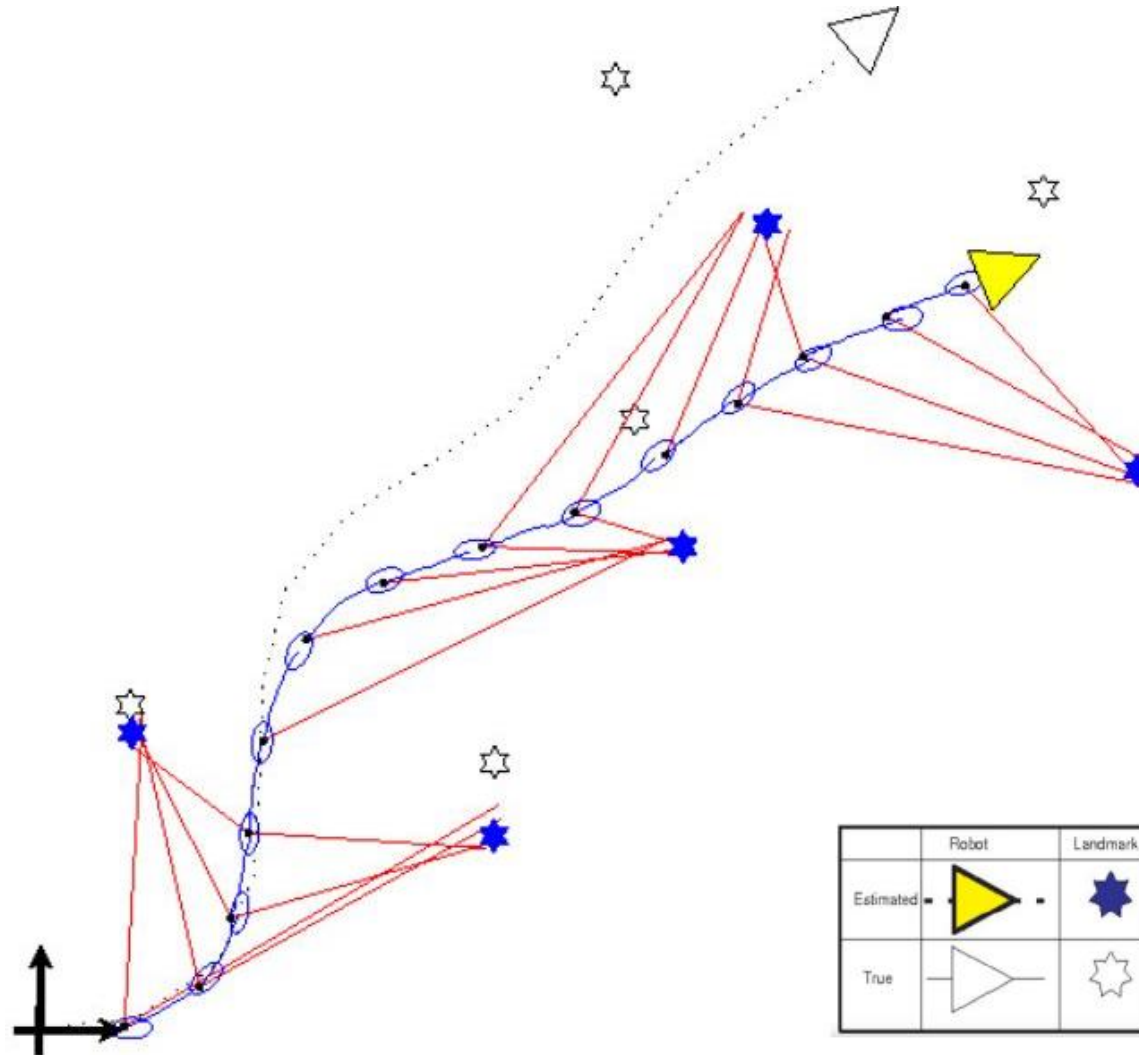


# Bundle Adjustment

- Maximum likelihood for normally distributed measurements
- Sensitive to outliers
  - The Gaussian has extremely small tail compared to most real measurement error distribution
- Non-linear least squares problem
- Solved using an iterative process
- General problem is non-convex,  
can settle in a local minima
- Requires a reasonable starting point



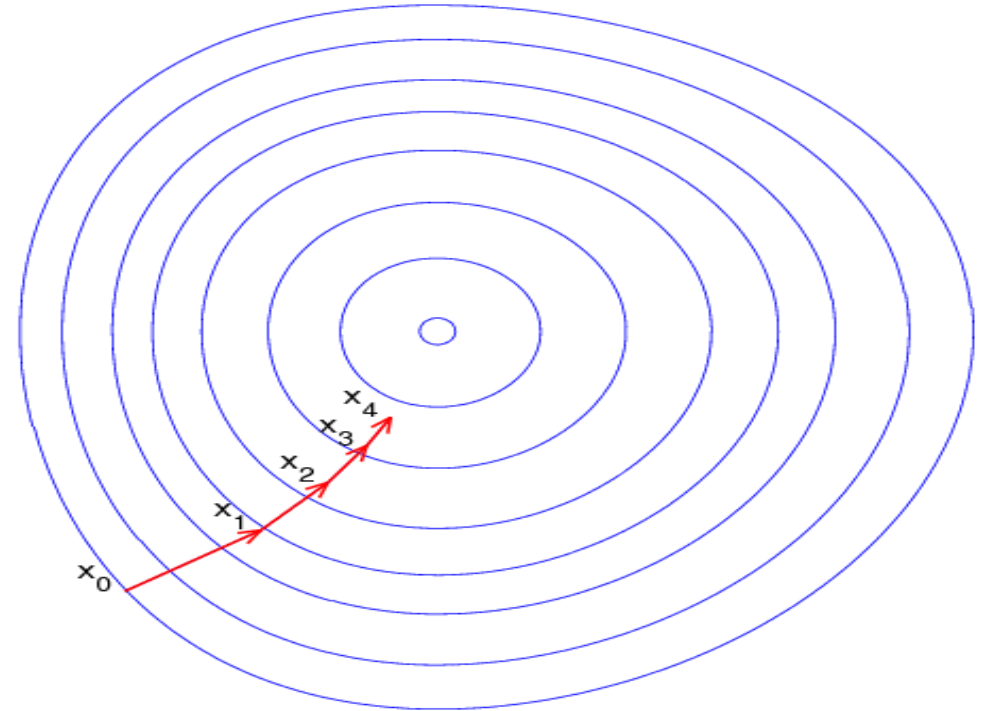
# Bundle Adjustment



Courtesy of Durrant-Whyte, Bailey; Slam: The essential algorithm

# Bundle Adjustment

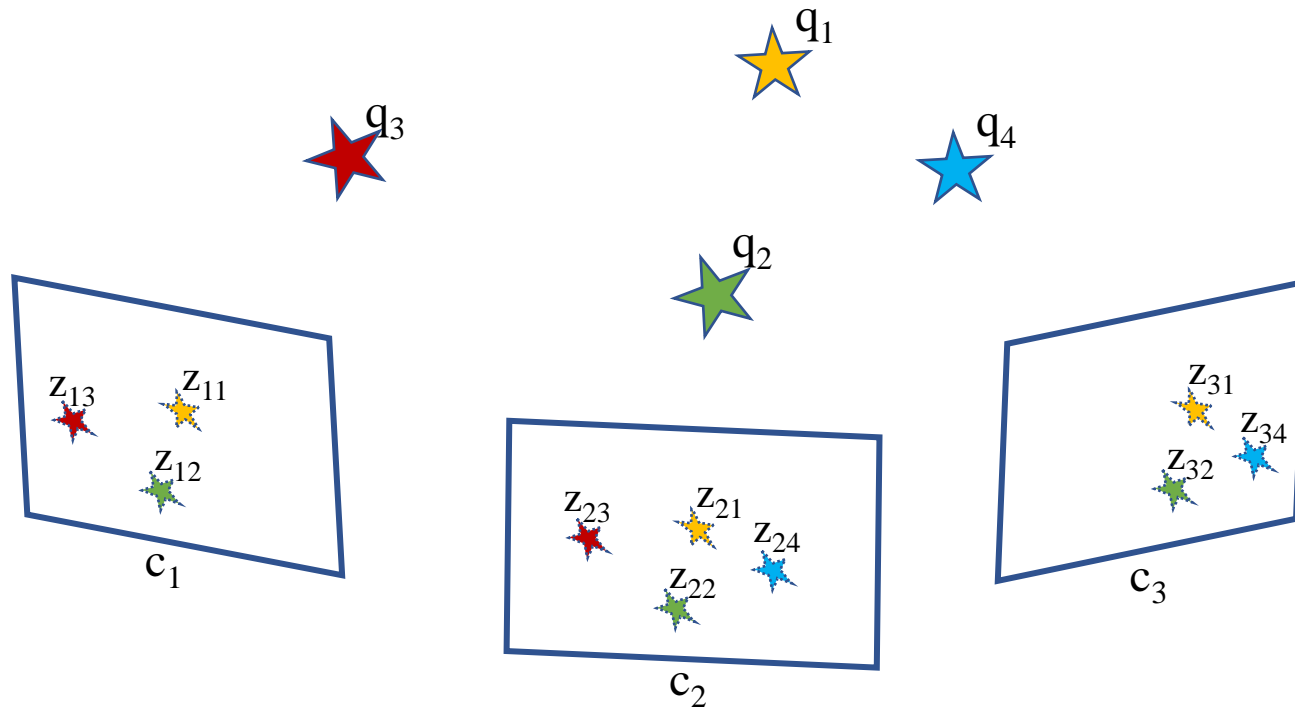
- Define a measurement function  $f$  that given the problem parameters calculates the expected measurements
- In optimal conditions  $f(x) = z$
- Minimize  $\|f(x) - z\|_{\Sigma}^2$
- Iterative solution



# Bundle Adjustment Representation

$$z^T = [z_{11}^T \quad z_{12}^T \quad z_{13}^T \quad z_{21}^T \quad z_{22}^T \quad z_{23}^T \quad z_{24}^T \quad z_{31}^T \quad z_{32}^T \quad z_{34}^T]$$

$$x^T = [c_1^T \quad c_2^T \quad c_3^T \quad q_1^T \quad q_2^T \quad q_3^T \quad q_4^T]$$



$$f(x) \doteq \begin{bmatrix} \pi(c_1, q_1) \\ \pi(c_1, q_2) \\ \pi(c_1, q_3) \\ \pi(c_2, q_1) \\ \pi(c_2, q_2) \\ \pi(c_2, q_3) \\ \pi(c_2, q_4) \\ \pi(c_3, q_1) \\ \pi(c_3, q_2) \\ \pi(c_3, q_4) \end{bmatrix}$$

# Bundle Adjustment Representation

- Two system variables

- Camera  $c_i = [\psi \quad \theta \quad \phi \quad x \quad y \quad z]^T$ 
  - 3D position and Euler angles
  - Can produce camera matrix  $K[R_i|t_i]$
  - $R_i = R(\psi, \theta, \phi) = R_z(\psi)R_y(\theta)R_x(\phi)$
  - $t_i = [x \quad y \quad z]^T$
- Landmark  $q_i = [x \quad y \quad z]^T$ 
  - 3D position

- Projection:  $\lambda \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = K[R_i|t_i] \begin{bmatrix} q_j \\ 1 \end{bmatrix} \quad \longrightarrow \quad z_{ij} = \begin{bmatrix} u \\ v \end{bmatrix} = \pi(c_i, q_j)$

# Jacobian

- $f(x + \Delta x) \cong f(x) + J(x)\Delta x$

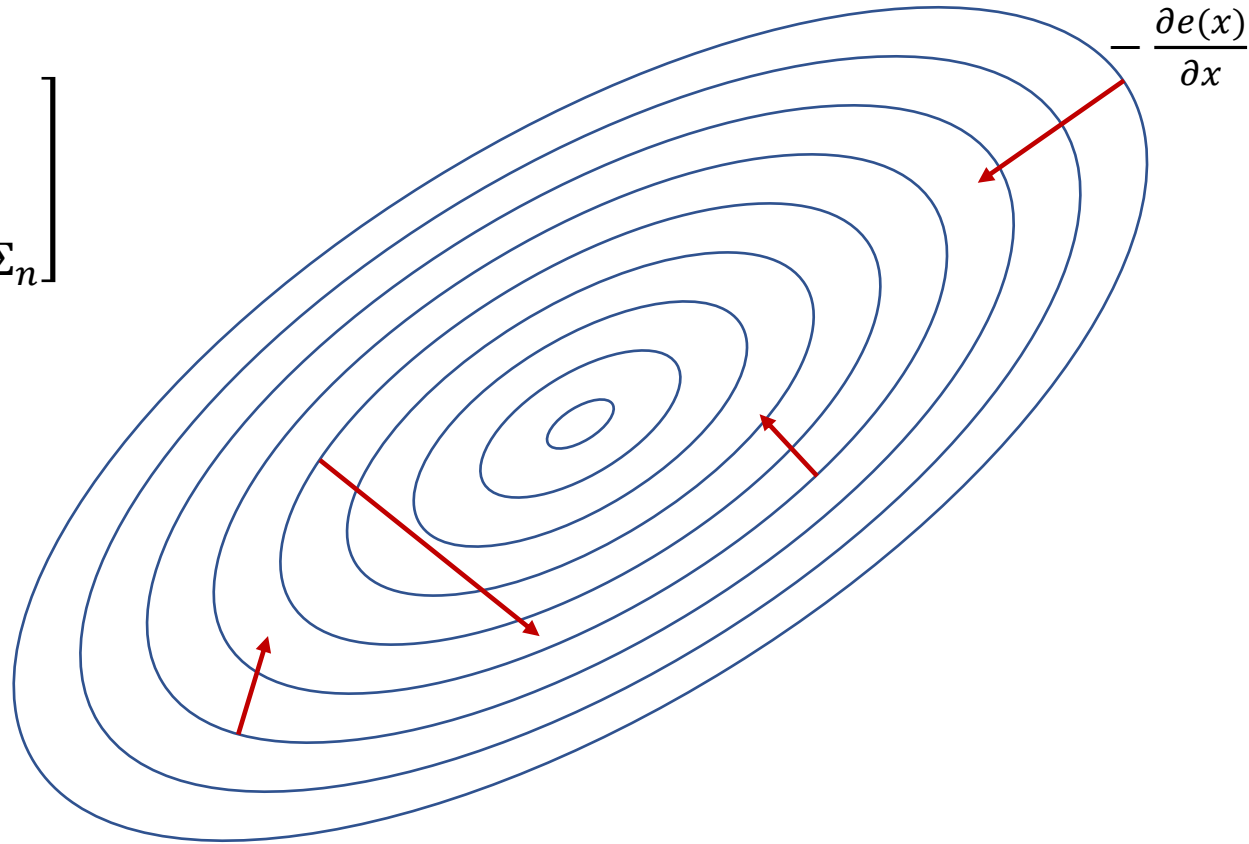
$$\begin{array}{ccc} \begin{bmatrix} f_1(x) \\ f_2(x) \\ \vdots \\ f_m(x) \end{bmatrix} & + & \begin{bmatrix} \frac{\partial f_1(x)}{\partial x_1} & \frac{\partial f_1(x)}{\partial x_2} & \cdots & \frac{\partial f_1(x)}{\partial x_p} \\ \frac{\partial f_2(x)}{\partial x_1} & \frac{\partial f_2(x)}{\partial x_2} & \cdots & \frac{\partial f_2(x)}{\partial x_p} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_m(x)}{\partial x_1} & \frac{\partial f_m(x)}{\partial x_2} & \cdots & \frac{\partial f_m(x)}{\partial x_p} \end{bmatrix} \begin{bmatrix} \Delta x_1 \\ \Delta x_2 \\ \vdots \\ \Delta x_p \end{bmatrix} \\ f(x) & & J_f(x) \quad \Delta x \end{array}$$

# Bundle Adjustment

## Gradient Decent

- Error function  $e(x) = \|f(x) - z\|_{\Sigma}^2$  :

$$\Sigma = \begin{bmatrix} \Sigma_1 & & \\ & \Sigma_2 & \\ & & \ddots \\ & & & \Sigma_n \end{bmatrix}$$



# Bundle Adjustment

## Linear Approximation

- $e(x) = \frac{1}{2} (f(x) - z)^T \Sigma^{-1} (f(x) - z)$
- $\left(\frac{\partial e(x)}{\partial x}\right)^T = J(x)^T \Sigma^{-1} (f(x) - z) = J(x)^T \Sigma^{-1} \Delta z$
- $e(x + \Delta x) \cong e(x) + \frac{\partial e(x)}{\partial x} \Delta x$
- $e(x + \Delta x) \cong e(x) - \frac{1}{\lambda} \left\| \frac{\partial e(x)}{\partial x} \right\|_2^2 < e(x)$
- $\Delta x = -\frac{1}{\lambda} J(x)^T \Sigma^{-1} \Delta z$

$$\Delta z \doteq f(x) - z$$

$$\Delta x = -\frac{1}{\lambda} \left( \frac{\partial e(x)}{\partial x} \right)^T$$

$$g \doteq J(x)^T \Sigma^{-1} \Delta z$$

$$\Delta x = -\frac{1}{\lambda} g$$



# Bundle Adjustment

## Gradient Decent

