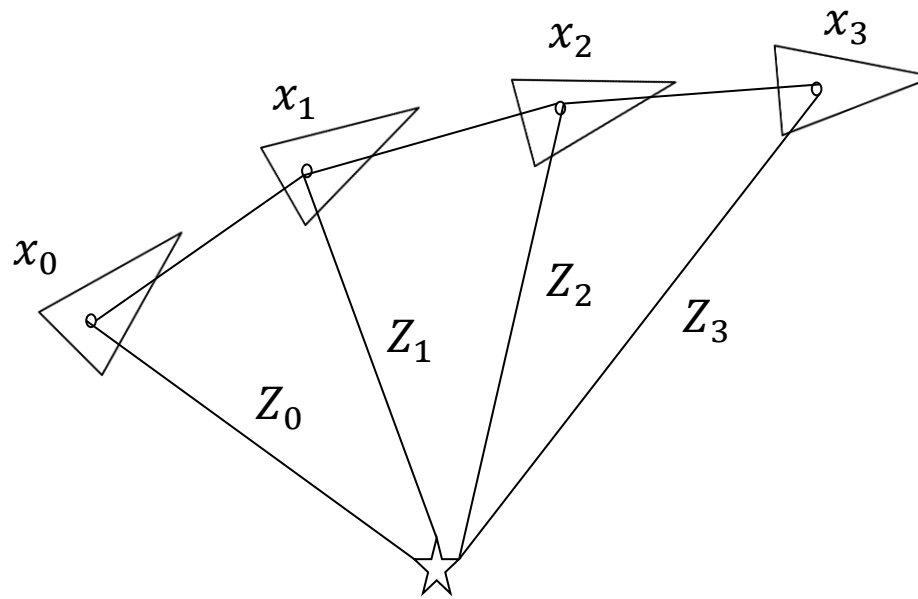


Mobile Robotics

**Robot Motion:
SLAM**

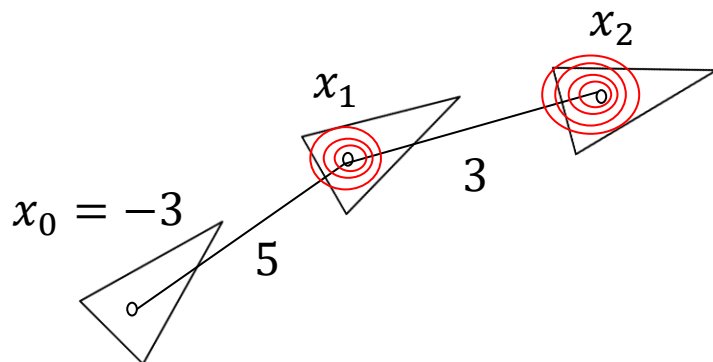
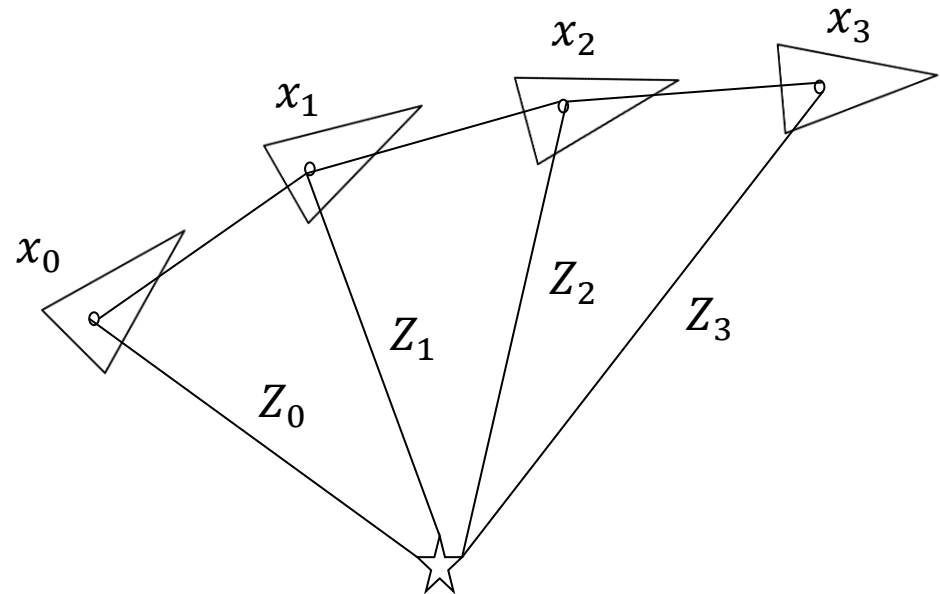
SLAM

- Simultaneously Localization And Mapping
- When mapping an environment with a mobile robot, uncertainty in robot motion forces us to also perform robot localization.
- Type of Maps: Landmark-based or Grid-based



Graph SLAM

- Construct local constraints
 - Initial Location Constraint
 - Relative Motion Constraints
 - Relative Measurement Constraints.
- Maximize the probabilities of each constraints



$$p(x_1) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1(x_1 - x_0 - 5)^2}{2\sigma^2}}$$

$$p(x_2) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1(x_2 - x_1 - 3)^2}{2\sigma^2}}$$

Implementing constraints

- Assume robot moving along one-dimensional space in which there are some landmarks.
- Assume $x_0 \rightarrow x_1 \rightarrow x_2$ and $x_1 = x_0 + 5$ and $x_2 = x_1 - 4$

	x_0	x_1	x_2	L_0	L_1					
x_0	1	-1							-5	
x_1	-1	1							5	
x_2										
L_0										
L_1										

+

	x_0	x_1	x_2	L_0	L_1					
x_0										
x_1		1	-1						4	
x_2		-1	1						-4	
L_0										
L_1										

→

	x_0	x_1	x_2	L_0	L_1					
x_0	1	-1							-5	
x_1	-1	2	-1						9	
x_2		-1	1						-4	
L_0										
L_1										

$$x_0 - x_1 = -5$$

$$-x_0 + x_1 = 5$$

$$x_1 - x_2 = 4$$

$$-x_1 + x_2 = -4$$

Adding Landmarks

- Assume robot moving along one-dimensional space in which there are some landmarks.
- Assume $x_0 \rightarrow x_1 \rightarrow x_2$ and $x_1 = x_0 + 5$ and $x_2 = x_1 - 4$
- x_1 to L_0 : Distance is 9

	x_0	x_1	x_2	L_0	L_1	
x_0	1	-1				-5
x_1	-1	2	-1			9
x_2		-1	1			-4
L_0						
L_1						



	x_0	x_1	x_2	L_0	L_1	
		1		-1		-9
		-1		1		9



	x_0	x_1	x_2	L_0	L_1	
	1	-1				-5
	-1	3	-2	-1		0
		-1	1			-4
		-1		1		9

$$x_1 - L_0 = -9$$

$$-x_1 + L_0 = 9$$

Adding Landmarks

- Assume robot moving along one-dimensional space in which there are some landmarks.
- Assume $x_0 \rightarrow x_1 \rightarrow x_2$ and $x_1 = x_0 + 5$ and $x_2 = x_1 - 4$
- x_1 to L_1 : Distance is 12

	x_0	x_1	x_2	L_0	L_1	
x_0	1	-1				-5
x_1	-1	2	-1			9
x_2		-1	1			-4
L_0						
L_1						

+

	x_0	x_1	x_2	L_0	L_1	
x_0						
x_1		1			-1	-12
x_2						
L_0						12
L_1		-1			1	

→

	x_0	x_1	x_2	L_0	L_1	
x_0	1	-1				-5
x_1	-1	3	-2	-1		0
x_2		-1	1			-4
L_0		-1		1		9
L_1						

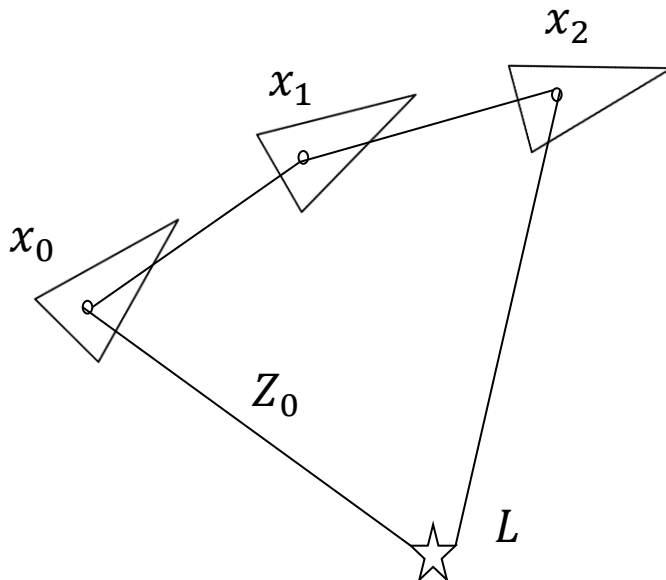
$$x_1 - L_1 = 12$$

$$-x_1 + L_1 = 12$$

Graph SLAM Questions

- True or False?
 - Graph SLAM is all about local constraints
 - They require multiplications
 - They require additions
- How to represent initial constraint $x_0 = 0$?
- Which matrix cells need to be modified? If we have

	x_0	x_1	x_2	L
x_0				
x_1				
x_2				
L				



	x_0	x_1	x_2	L
x_0				
x_1				
x_2				
L				

Omega, Xi, and Mu

- Let Ω be the matrix and ξ be the vector, then $\mu = \Omega^{-1}\xi$ gives the robot and landmark locations
- Example 1: compute x_0 x_1 x_2

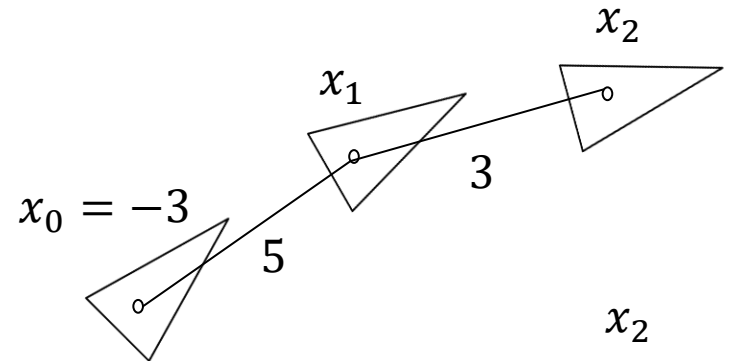
$$x_0 = -3$$

$$x_1 = x_0 + 5$$

$$x_2 = x_1 + 3$$

	x_0	x_1	x_2
x_0			
x_1		Ω	
x_2			

ξ



- Example 2: compute L

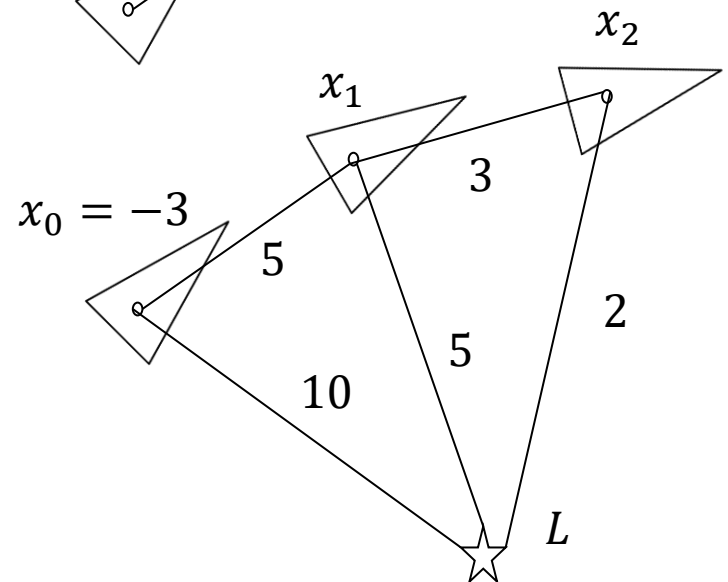
$$L = x_0 + 10$$

$$L = x_1 + 5$$

$$L = x_2 + 2$$

	x_0	x_1	x_2	L
x_0				
x_1		Ω		
x_2				
L				

ξ



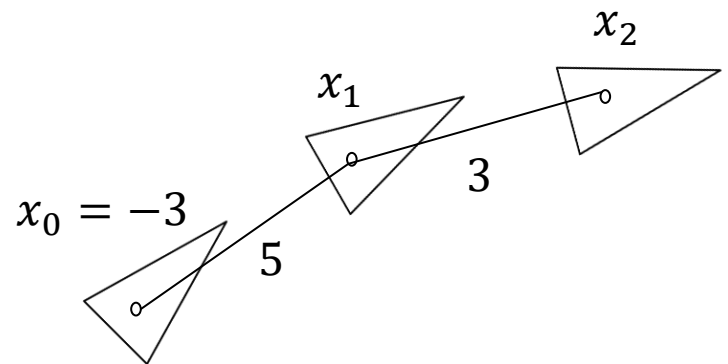
PA6A: Compute $\mu = \Omega^{-1}\xi$

- Write a function, `doit`, that takes as its input an initial robot position, `move1`, and `move2`.
 - It should compute the Omega and Xi matrices, and
 - It should return the mu vector
-
- Example 1: compute x_0 x_1 x_2

$$\begin{aligned}x_0 &= -3 \\x_1 &= x_0 + 5 \\x_2 &= x_1 + 3\end{aligned}$$

	x_0	x_1	x_2
x_0			
x_1		Ω	
x_2			

ξ



PA6A: Compute $\mu = \Omega^{-1}\xi$

- Example 1: compute $x_0 \ x_1 \ x_2$

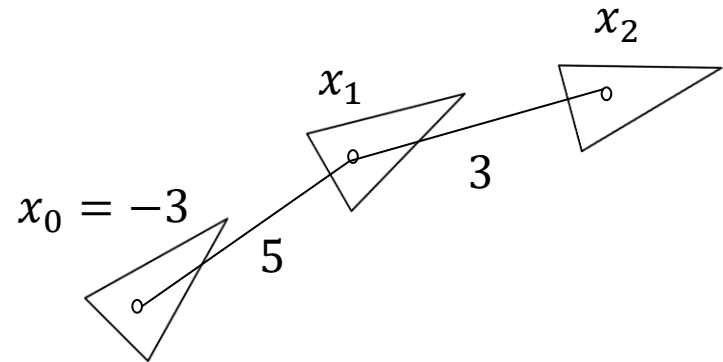
$$x_0 = -3$$

$$x_1 = x_0 + 5$$

$$x_2 = x_1 + 3$$

	x_0	x_1	x_2
x_0			
x_1		Ω	
x_2			

ξ



$$\Omega = \begin{array}{c} x_0 \ x_1 \ x_2 \\ \begin{array}{|c|c|c|} \hline 1 & & \\ \hline & & \\ \hline & & \\ \hline \end{array} \end{array} + \begin{array}{c} x_0 \ x_1 \ x_2 \\ \begin{array}{|c|c|c|} \hline 1 & -1 & \\ \hline -1 & 1 & \\ \hline & & \\ \hline \end{array} \end{array} + \begin{array}{c} x_0 \ x_1 \ x_2 \\ \begin{array}{|c|c|c|} \hline & & \\ \hline & 1 & -1 \\ \hline & -1 & 1 \\ \hline \end{array} \end{array}$$

$$\xi = \begin{array}{|c|} \hline -3 \\ \hline \\ \hline \end{array} + \begin{array}{|c|} \hline -5 \\ \hline 5 \\ \hline \end{array} + \begin{array}{|c|} \hline \\ \hline -3 \\ \hline 3 \\ \hline \end{array}$$

PA6B: Expand

- Modify your doit function to incorporate 3 distance measurements to a landmark (z_0, z_1, z_2).
- You should use the provided expand function to allow your Omega and Xi matrices to accommodate the new information.
- Each landmark measurement should modify 4 values in your Omega matrix and 2 in your Xi vector.
- Example 2: compute L

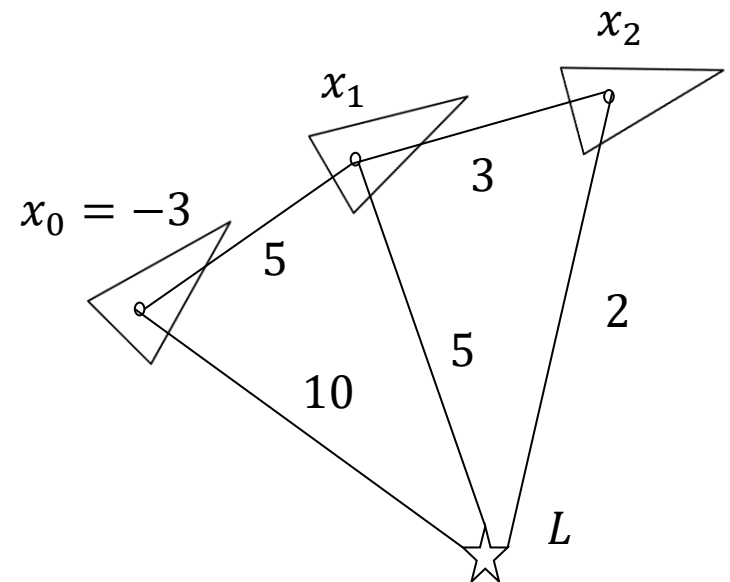
$$L = x_0 + 10$$

$$L = x_1 + 5$$

$$L = x_2 + 2$$

	x_0	x_1	x_2	L
x_0				
x_1		Ω		
x_2				
L				

ξ



PA6B: Expand

- Example 2: compute L

$$L = x_0 + 10$$

$$L = x_1 + 5$$

$$L = x_2 + 2$$

	x_0	x_1	x_2	L
x_0				
x_1		Ω		ξ
x_2				
L				

$$\Omega =$$

x_0	x_1	x_2	L
2	-1	0	
-1	2	-1	
0	-1	1	

$$+$$

x_0	x_1	x_2	L
1			-1
-1			1

$$+$$

x_0	x_1	x_2	L
	1		-1
	-1		1

$$+$$

x_0	x_1	x_2	L
		1	-1
		-1	1

$$\xi =$$

-8
2
3

$$+$$

-10
10

$$+$$

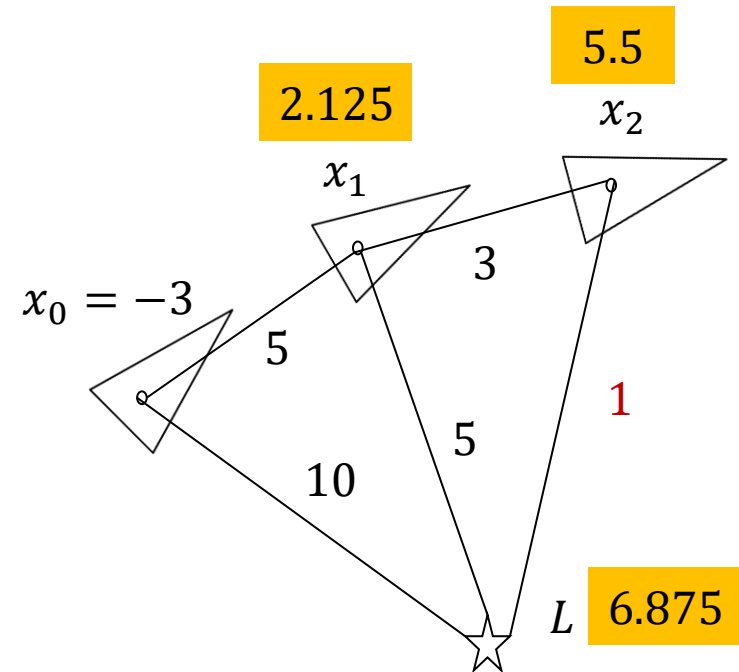
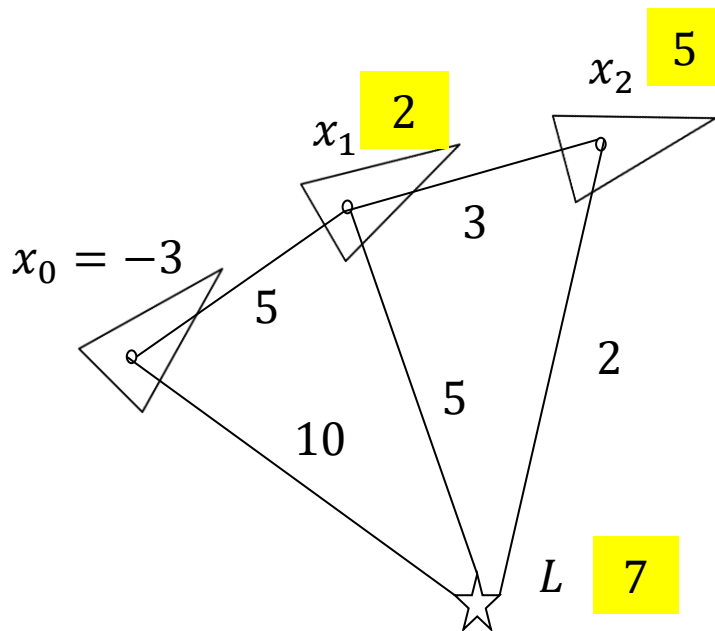
-5
5

$$+$$

-2
2

Introducing Noise

- If the last measurement (from x_2 to L) down to 1, what will happen?
 - x_0 has no change
 - x_1 becomes larger
 - x_2 becomes larger
 - L becomes smaller

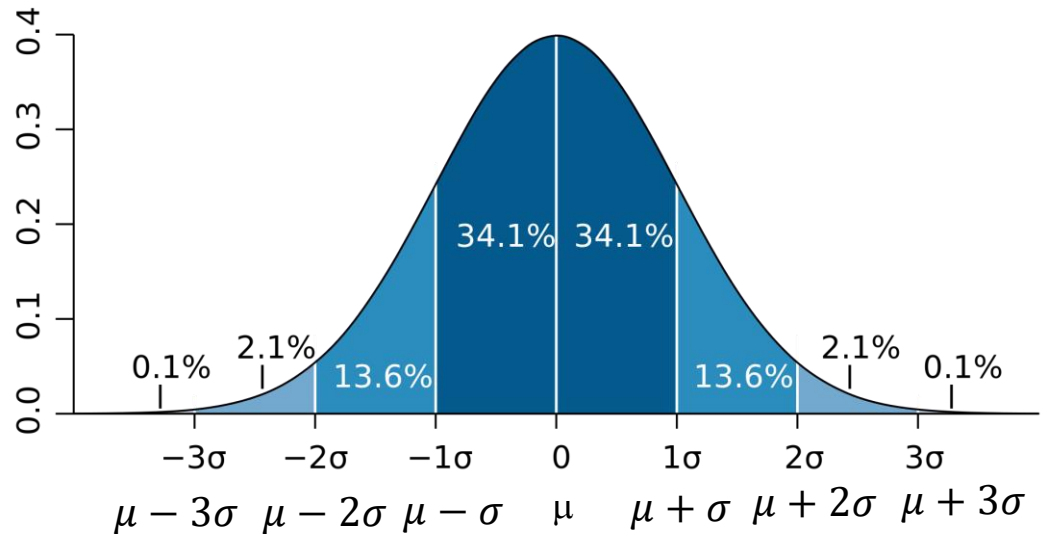


Recall: Gaussian (Normal) Distribution: Univariate

Univariate

$$X \sim N(\mu, \sigma^2):$$

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1(x-\mu)^2}{2\sigma^2}}$$

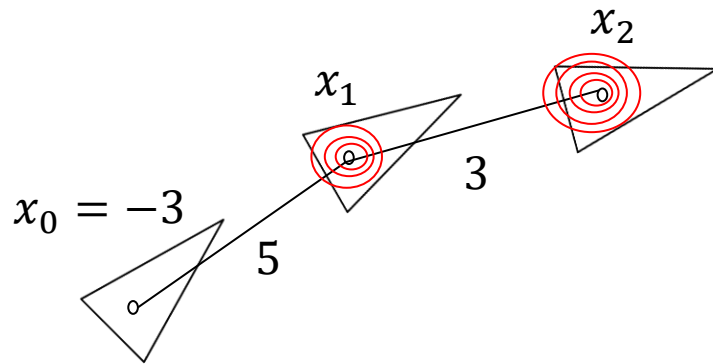


- μ : Mean
- σ^2 : Variance
- σ : Standard Deviation

$$\mu = E(X)$$

$$\sigma^2 = E((X - \mu)^2)$$

Confident Measurements



$$p(x_1) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1(x_1 - x_0 - 5)^2}{2\sigma^2}}$$

$$p(x_2) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1(x_2 - x_1 - 3)^2}{2\sigma^2}}$$

- We want to maximize $p(x_1)p(x_2)$
- This is equivalent to minimize $\frac{(x_1 - x_0 - 5)^2}{\sigma^2} + \frac{(x_2 - x_1 - 3)^2}{\sigma^2}$
- So, we want

$$\frac{1}{\sigma}x_1 - \frac{1}{\sigma}x_0 = \frac{1}{\sigma}5$$

$$\frac{1}{\sigma}x_2 - \frac{1}{\sigma}x_1 = \frac{1}{\sigma}3$$

- Note that the smaller σ is, the more confident you are!

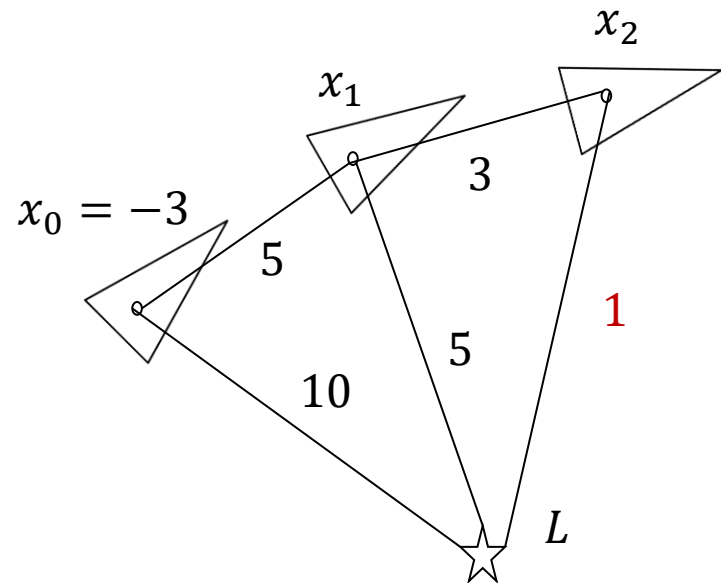
PA6C: Confident Measurements

- Modify the previous code to adjust for a highly confident last measurement.
- Do this by adding a factor of 5 ($\sigma = 0.2$) into your Omega and Xi matrices as shown below.

$$5x_2 - 5L = -5 \times 1$$

$$-5x_2 + 5L = 5 \times 1$$

	x_0	x_1	x_2	L
x_0				
x_1				
x_2			5	-5
L			-5	5



PP6A: 2D Graph SLAM (1)

- In this project you will implement SLAM in a 2-dimensional world.
Please define a function, slam, which takes three parameters as input and returns the vector mu.

- Suppose there are N robot poses and M landmarks

- Omega Matrix will have dimension

$$2(N + M) \times 2(N + M)$$

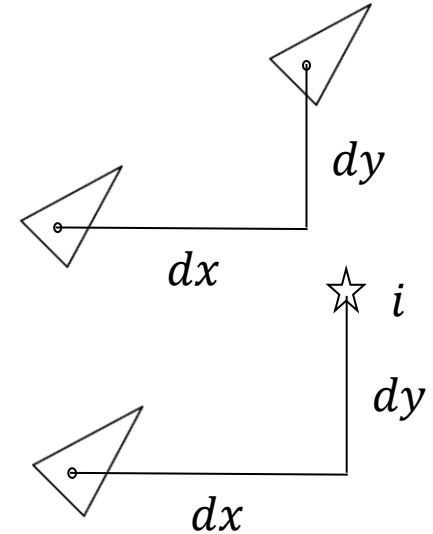
- Xi Matrix will have dimension

$$2(N + M) \times 1$$

	S_0	S_1	S_2		L_0	L_1	...
	$x y$	$x y$	$x y$		$x y x$	y	...
S_0							
S_1							
S_2							
...							
...							
L_0							
L_1							
...							

PP6A: 2D Graph SLAM (2)

- Robot moving in 2D:
 - Move along x-axis and along y-axis (dx, dy).
- Measurement in 2D
 - Distance to x-axis and to y-axis (dx, dy)
- Initial position of robot is at the center of 2D world
- The three inputs to SLAM function
 - data: a list of $[Z, [dx, dy]]$, where Z is measurements, $[dx, dy]$ is next move
 - Z is a list of $[i, dx, dy]$, where dx, dy is the measure to the i 's landmark
 - N : number of robot poses. Note robot moves $N-1$ times.
 - Num_landmarks



- Update Omega and Xi.
 - Initial constraint

$$\begin{array}{ccccccccccc} S_0 & | & S_1 & | & S_2 & | & \dots & | & L_0 & | & L_1 & \dots \\ x|y & | & x|y & | & x|y & | & \dots & | & x|y|x & | & y & \dots \end{array}$$

[illegible]

S_0	x	50
	y	50
S_1	x	
	y	
S_2	x	
	y	
...		
...		
L_0		
L_1		
...		

- Update Omega and Xi.
 - Based on the robot motion

$$\begin{array}{ccccccc} S_0 & | & S_1 & | & S_2 & | \dots\dots\dots & | & L_0 & | & L_1 & \dots \\ x|y & | & x|y & | & x|y & | \dots\dots\dots & | & x|y|x & | & y & \dots \end{array}$$

S_0^x	1	-1							
y		1	-1						
S_1^x	-1	1							
y		-1	1						
S_2^x									
y									
...									
...									
L_0									
L_1									
...									

$$S_0 \longrightarrow S_1$$

```
dx = data[0][1][0]
```

```
dy = data[0][1][1]
```



S_0	x	-dx
	y	-dy
S_1	x	dx
	y	dy
S_2	x	
	y	
...		
...		
L_0		
L_1		
...		

- $S_1 \longrightarrow S_2$
- ```
dx = data[1][1][0]
dy = data[1][1][1]
```
- ↑

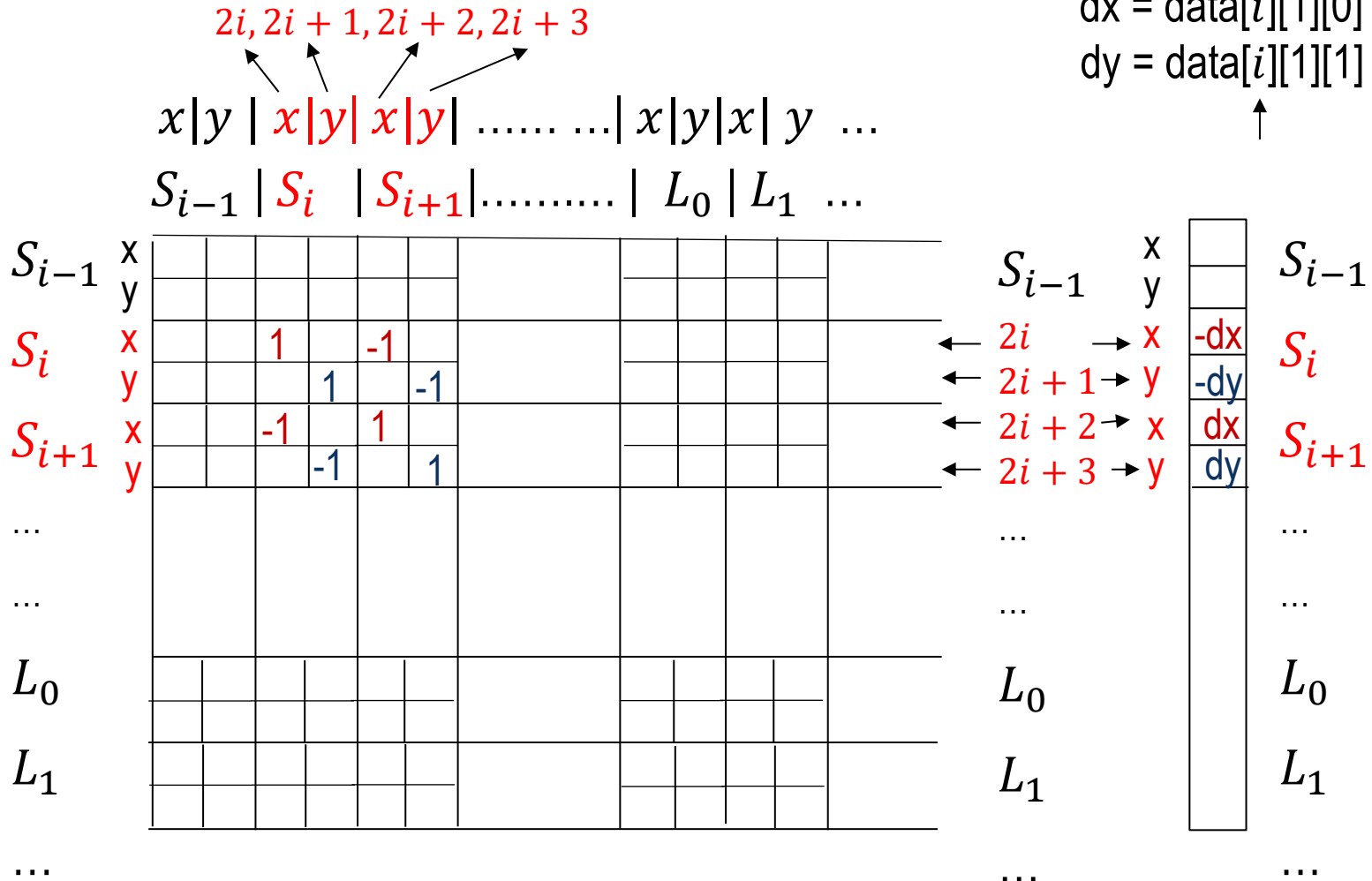
```
dx = data[1][1][0]
dy = data[1][1][1]
```

|       |   |     |
|-------|---|-----|
| $S_0$ | x |     |
|       | y |     |
| $S_1$ | x | -dx |
|       | y | -dy |
| $S_2$ | x | dx  |
|       | y | dy  |
| ...   |   |     |
| ...   |   |     |
| $L_0$ |   |     |
| $L_1$ |   |     |
| ...   |   |     |

\_\_\_\_\_

- $$S_i \longrightarrow S_{i+1}$$

```
dy = data[i][1][1]
```



\_\_\_\_\_

- suppose  $\text{id} = 1$

```

S0 → Z
for measure in data[0][0]
 id = measure[0]
 dx = measure[1]
 dy = measure[2]

```

|       |   |     |
|-------|---|-----|
| $S_0$ | x | -dx |
|       | y | -dy |
| $S_1$ | x |     |
|       | y |     |
| $S_2$ | x |     |
|       | y |     |
| ...   |   |     |
| ...   |   |     |
| $L_0$ |   |     |
| $L_1$ |   | dx  |
|       |   | dy  |
| ...   |   |     |

\_\_\_\_\_

- suppose  $\text{id} = 1$

```

S1 $\longrightarrow$ Z
for measure in data[1][0]
 id = measure[0]
 dx = measure[1]
 dy = measure[2]

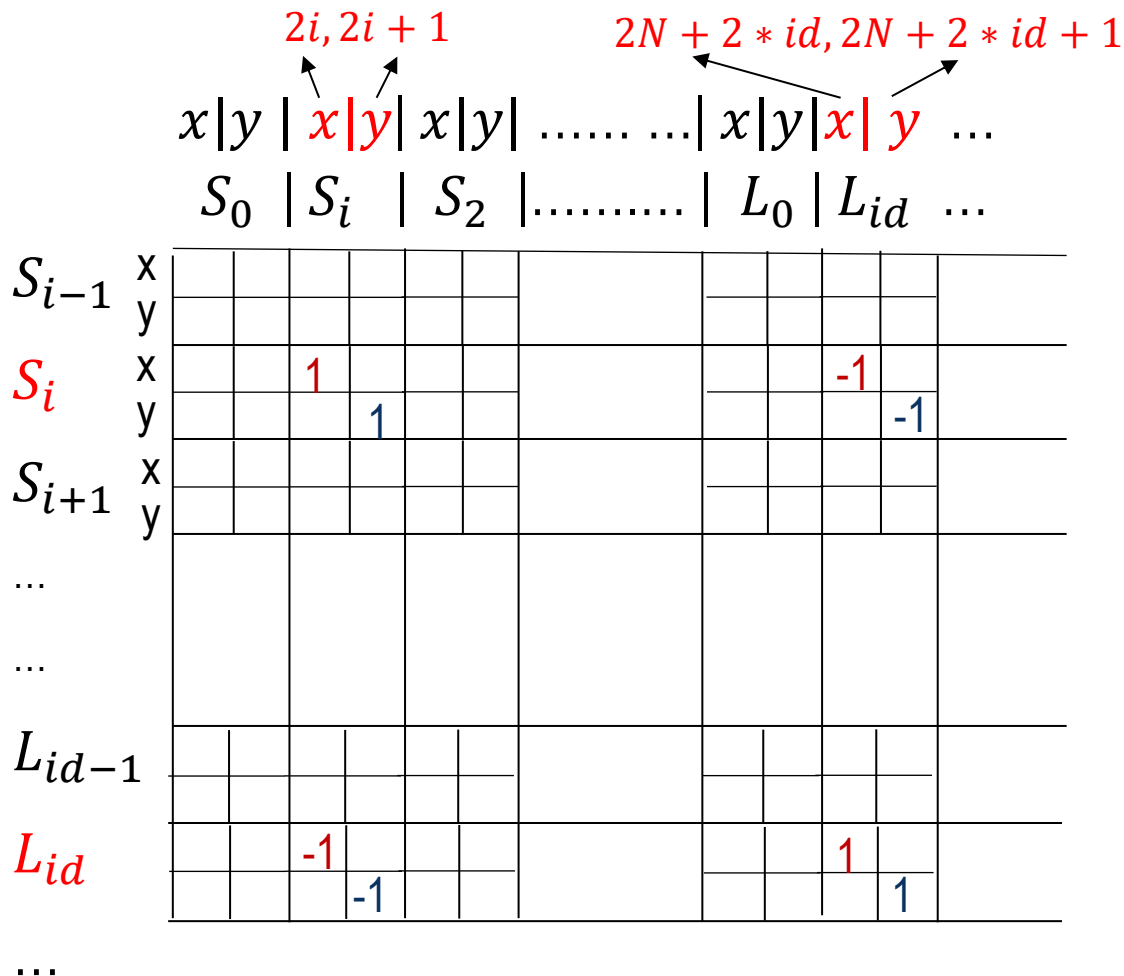
```

|       |     |       |
|-------|-----|-------|
| $S_0$ | $x$ |       |
|       | $y$ |       |
| $S_1$ | $x$ | $-dx$ |
|       | $y$ | $-dy$ |
| $S_2$ | $x$ |       |
|       | $y$ |       |
| ...   |     |       |
| ...   |     |       |
| $L_0$ |     |       |
| $L_1$ |     | $dx$  |
|       |     | $dy$  |
| ...   |     |       |

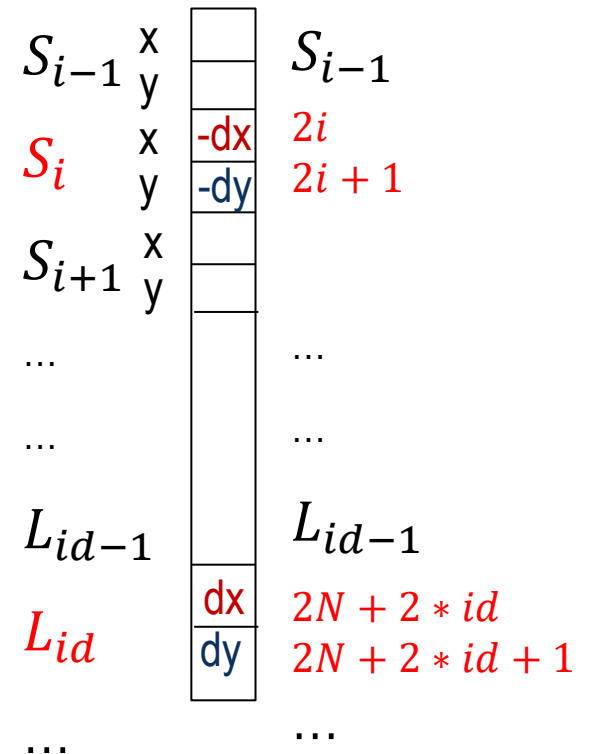


# PP6A: 2D Graph SLAM (9)

- Update Omega and Xi: Based on the measurement

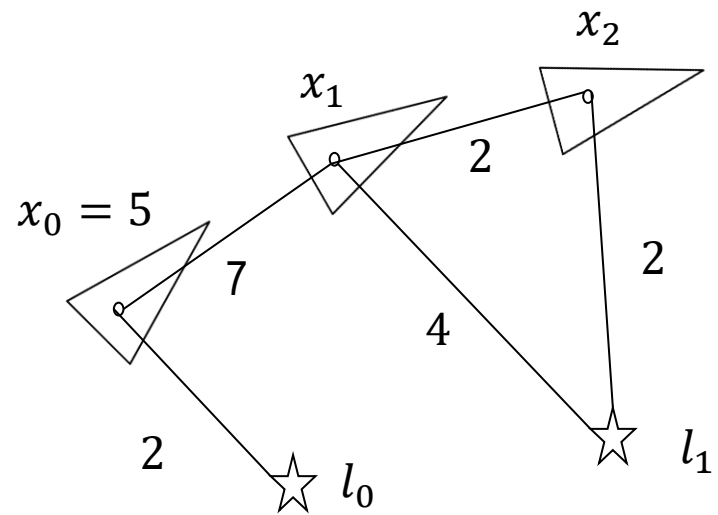
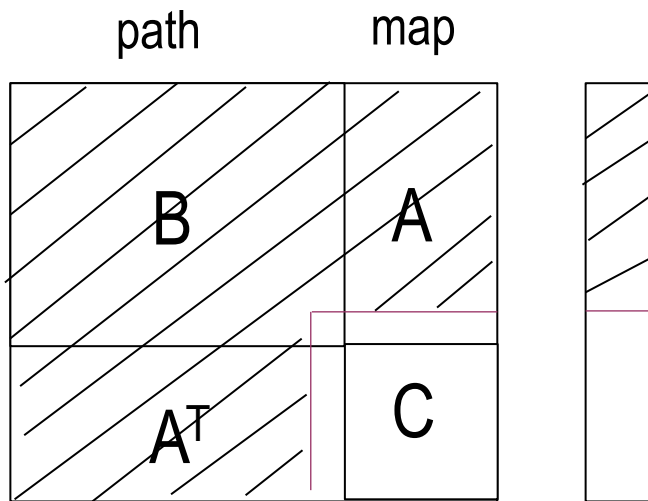


$S_i \longrightarrow Z$   
 for measure in data[i][0]  
 id = measure[0]  
 dx = measure[1]  
 dy = measure[2]



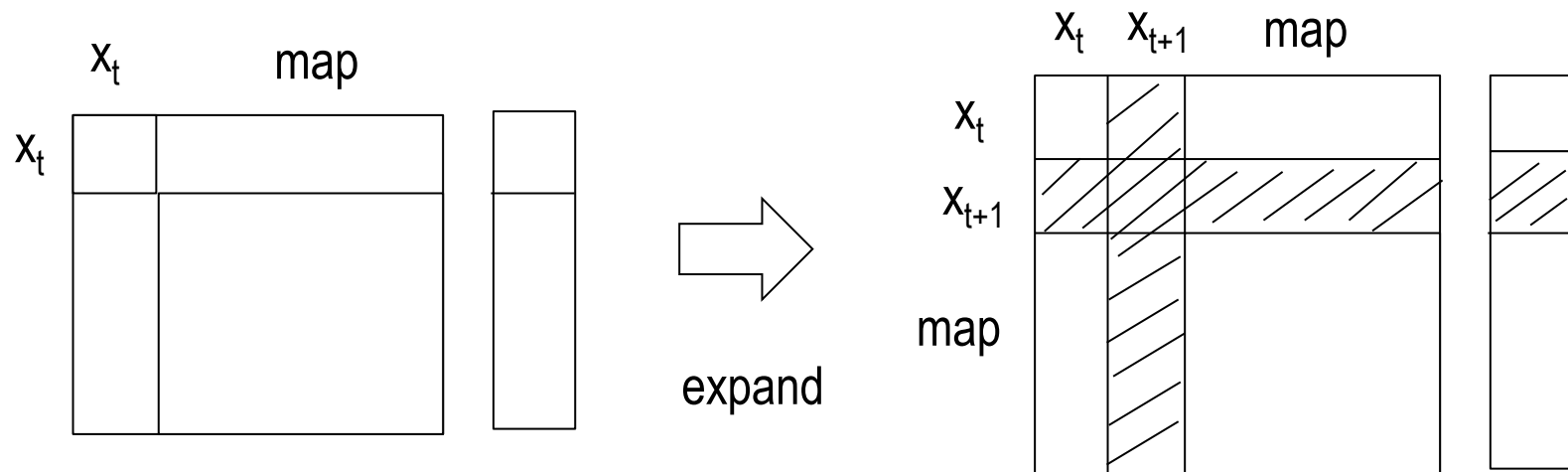
# Online SLAM

- Idea: Keep only the last robot pose in Omega matrix



# Online SLAM Algorithm (1)

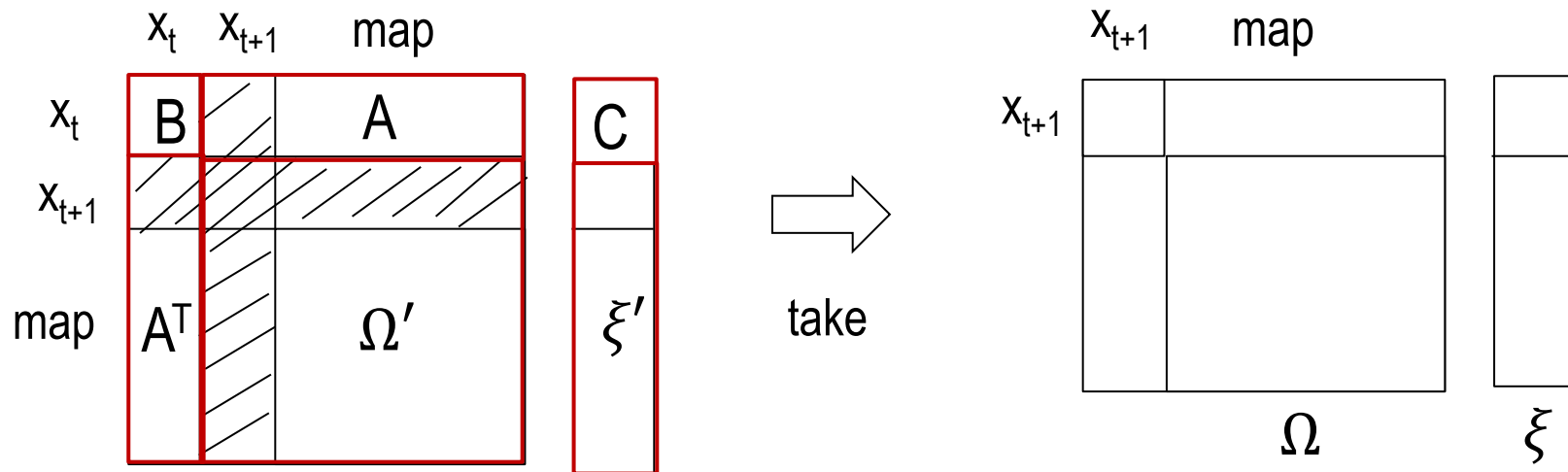
- When robot moves from  $x_t$  to  $x_{t+1}$ ,
  - Expand Omega and Xi and then update them.



```
expand
list1 = [0, 1]
for i in range(2,dim):
 list1.append(i+2)
OmegaU = expand(Omega, dim+2, dim+2, list1)
XiU = expand(Xi, dim+2, 1, list1, [0])
```

# Online SLAM Algorithm (2)

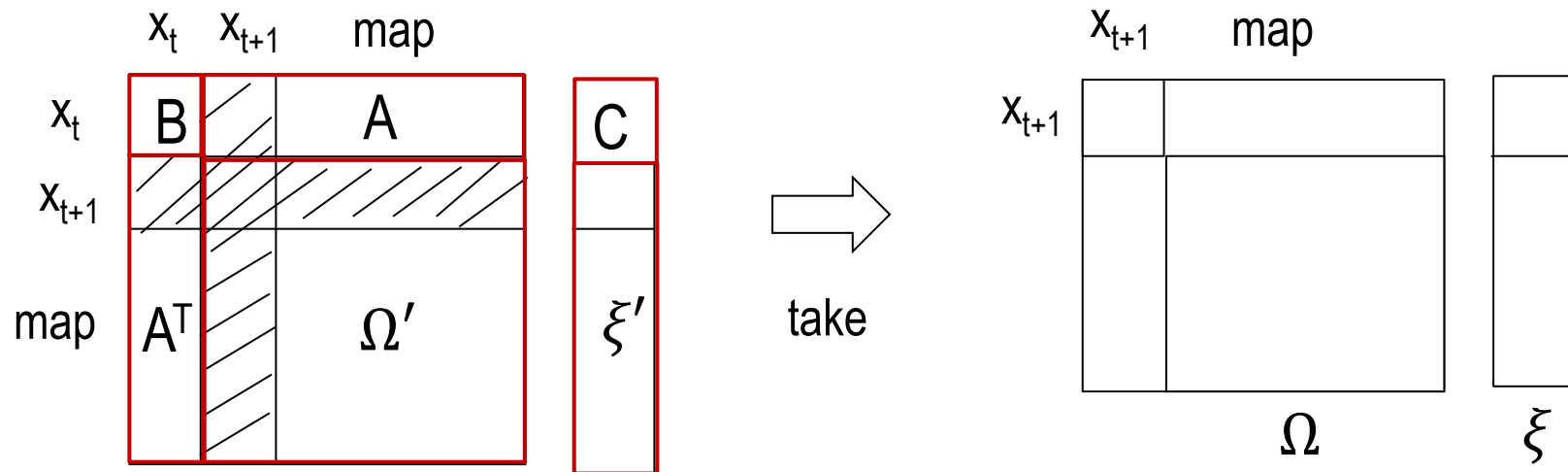
- When robot moves from  $x_t$  to  $x_{t+1}$ ,
  - Take from updated Omega and Xi and then calculate new Omega and Xi



```
take
list2 = []
for i in range(dim):
 list2.append(i+2)
OmegaN = take(OmegaU, list2)
A = take(OmegaU, [0, 1], list2)
B = take(OmegaU, [0, 1], [0, 1])
XiN = take(XiU, list2, [0])
C = take(XiU, [0, 1], [0])
```

# Online SLAM Algorithm (3)

- When robot moves from  $x_t$  to  $x_{t+1}$ ,
  - Take from updated Omega and Xi and then calculate new Omega and Xi



$$\begin{pmatrix} B & A \\ A^T & \Omega' \end{pmatrix} \begin{pmatrix} x_t \\ X \end{pmatrix} = \begin{pmatrix} C \\ \xi' \end{pmatrix}$$

$$\Omega X = \xi$$

$$\begin{aligned} \Omega &= \Omega' - A^T B^{-1} A \\ \xi &= \xi' - A^T B^{-1} C \end{aligned}$$

# PP6B: Online 2D Graph SLAM (1)

---

- In this project you will implement a more manageable version of graph SLAM in 2-dimensional world.
- Please define a function, `online_slam`, that takes five inputs and return two matrices, `mu` and the final `Omega`
- The five inputs to `online_slam` function
  - **data**: a list of `[Z, [dx, dy]]`, where `Z` is measurements, `[dx, dy]` is next move
    - `Z` is a list of `[i, dx, dy]`, where `dx, dy` is the measure to the `i`'s landmark
  - **N**: number of robot poses. Note robot moves `N-1` times.
  - **Num\_landmarks**: number of landmarks
  - **motion\_noise**: The noise associated with motion. The update strength for motion should be `1.0 / motion_noise`
  - **measurement\_noise**: The noise associated with measurement. The update strength for measurement should be `1.0 / measurement_noise`.

# PP6B: Online 2D Graph SLAM (2)

## 1. Update Omega and Xi: Based on the measurement

$0, 1$   
 $\uparrow \quad \uparrow$   
 $x|y \mid x|y \mid x|y \mid \dots \dots \mid x|y \mid x|y \dots$   
 $\swarrow \quad \searrow$   
 $2 * id + 2, 2 * id + 3$

|            |   |       |       |       |       |          |            |     |
|------------|---|-------|-------|-------|-------|----------|------------|-----|
|            |   | $S_i$ | $L_0$ | $L_1$ | ..... | $L_{id}$ | $L_{id+1}$ | ... |
| $S_i$      | x | 1     |       |       |       |          | -1         |     |
|            | y |       | 1     |       |       |          | -1         |     |
| $L_0$      | x |       |       |       |       |          |            |     |
|            | y |       |       |       |       |          |            |     |
| $L_1$      | x |       |       |       |       |          |            |     |
|            | y |       |       |       |       |          |            |     |
| ...        |   |       |       |       |       |          |            |     |
| ...        |   |       |       |       |       |          |            |     |
| $L_{id}$   |   | -1    |       |       |       |          | 1          |     |
|            |   |       | -1    |       |       |          |            | 1   |
| $L_{id+1}$ |   |       |       |       |       |          |            |     |
|            |   |       |       |       |       |          |            |     |
| ...        |   |       |       |       |       |          |            |     |

$S_i \longrightarrow Z$   
 for measure in data[i][0]  
 id = measure[0]  
 dx = measure[1]  
 dy = measure[2]

|            |   |     |              |
|------------|---|-----|--------------|
| $S_i$      | x | -dx | 0            |
|            | y | -dy | 1            |
| $L_0$      | x |     |              |
|            | y |     |              |
| $L_1$      | x |     |              |
|            | y |     |              |
| ...        |   |     | ...          |
| ...        |   |     | ...          |
| $L_{id}$   |   | dx  | $2 * id + 2$ |
|            |   | dy  | $2 * id + 3$ |
| $L_{id+1}$ |   |     |              |
| ...        |   |     |              |

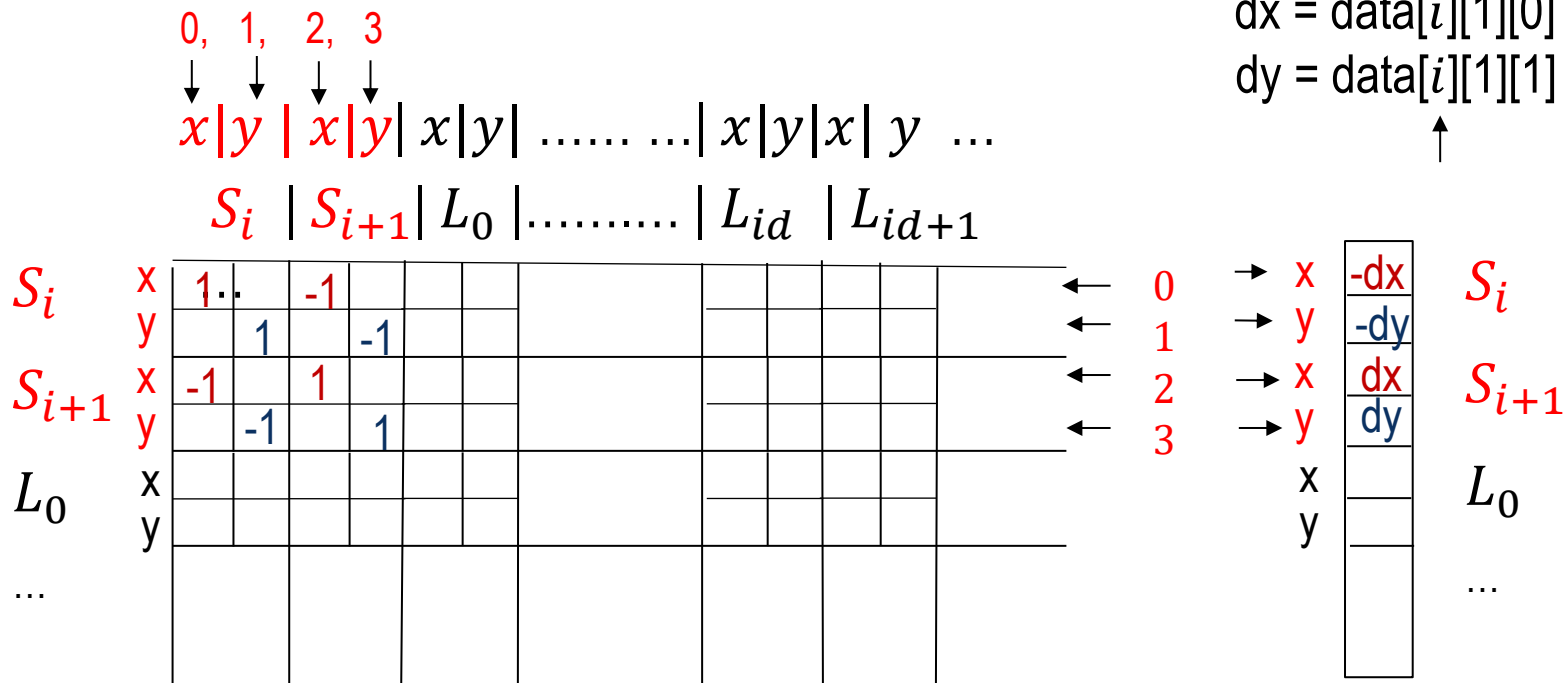
\_\_\_\_\_

2. Expand Omega and Xi and then update them based on the robot motion

$$S_i \longrightarrow S_{i+1}$$

```
dx = data[i][1][0]
```

```
dy = data[i][1][1]
```



3. Take from updated Omega and Xi and then calculate new Omega and Xi