

16-833: Robot Localization and Mapping, Spring 2021  
**Homework 3 - SLAM Solvers**

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## 1 2D Linear SLAM

### Q1.1 Measurement function

Given robot poses at time  $t$  and  $t+1$ , write out the measurement function and its Jacobian. Similarly, given the robot pose at time  $t$  and the  $k$ -th landmark  $\mathbf{l}^k = [l_x^k, l_y^k]^\top$ , find the Jacobian and measurement function.

Measurement

Odometry Function:  $h_o = r_{t+1} - r_t$

$$\Rightarrow h_o = \begin{bmatrix} r_{t+1x} - r_{tx} \\ r_{t+1y} - r_{ty} \end{bmatrix}$$

To compute Jacobian  $H_o$ ,  $X_o = \begin{bmatrix} r_{tx} \\ r_{ty} \\ r_{t+1x} \\ r_{t+1y} \end{bmatrix}$

$$H_o = \frac{\partial h_o}{\partial X_o} = \begin{bmatrix} \frac{\partial h_{o1}}{\partial X_{o1}} & \frac{\partial h_{o1}}{\partial X_{o2}} & \frac{\partial h_{o1}}{\partial X_{o3}} & \frac{\partial h_{o1}}{\partial X_{o4}} \\ \frac{\partial h_{o2}}{\partial X_{o1}} & \frac{\partial h_{o2}}{\partial X_{o2}} & \frac{\partial h_{o2}}{\partial X_{o3}} & \frac{\partial h_{o2}}{\partial X_{o4}} \end{bmatrix}$$

$$H_o = \begin{bmatrix} -1 & 0 & 1 & 0 \\ 0 & -1 & 0 & 1 \end{bmatrix}$$

Measurement Function :

$$h_e = l_e - x_e$$

$$h_e = \begin{bmatrix} l_{tx} - x_{tx} \\ l_{ty} - x_{ty} \end{bmatrix}$$

To compute Jacobian,  $X_e = \begin{bmatrix} x_{tx} \\ x_{ty} \\ l_{tx} \\ l_{ty} \end{bmatrix}$

$$H_e = \frac{\partial h_e}{\partial X_e} = \begin{bmatrix} \frac{\partial h_e}{\partial x_{tx}} & \frac{\partial h_e}{\partial x_{ty}} & \frac{\partial h_e}{\partial l_{tx}} & \frac{\partial h_e}{\partial l_{ty}} \\ \frac{\partial h_e}{\partial x_{tx}} & \frac{\partial h_e}{\partial x_{ty}} & \frac{\partial h_e}{\partial l_{tx}} & \frac{\partial h_e}{\partial l_{ty}} \end{bmatrix}$$

$$= \begin{bmatrix} -1 & 0 & 1 & 0 \\ 0 & -1 & 0 & 1 \end{bmatrix}$$

#### Q1.4.4 Comparison of Linear Solvers

Running the `2dlinear.npz` program shows that *LU* is the fastest solver in the system followed by *LCOLAMD*, *QR<sub>COLAMD</sub>*, *QR*, and *P<sub>INV</sub>*. The sparsity of each method appears to present a relation between the decrements in solving time and sparsity of the matrix. The *LU* solver is clearly much faster than the *QR* solver, which is interesting as the *LU* solver is specifically used for square matrices and it is optimized to find the fastest solution, however, system impact includes issues in mathematical stability. Additionally, it is also observed that the *QR* solver is marginally faster than *QR<sub>COLAMD</sub>* solver due to the implementation column tracking optimization in the latter. The results of these runs are shown in the following pages and the times for each solver are as below:

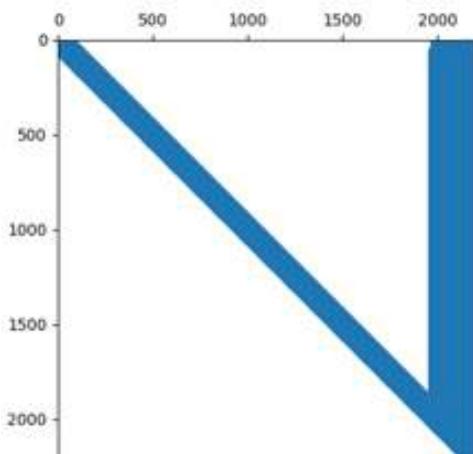
```

adi@adi-XPS-15-9570:~/SLAM/3/code$ python3 linear.py
Applying pinv
pinv takes 3.3977463245391846s on average
Applying qr
/home/adi/.local/lib/python3.8/site-packages/scipy/sp
  warn('CSR matrix format is required. Converting to'
qr takes 0.8322124481201172s on average
Applying lu
lu takes 0.04329371452331543s on average
Applying qr_colamd
/home/adi/.local/lib/python3.8/site-packages/scipy/sp
  warn('CSR matrix format is required. Converting to'
qr_colamd takes 0.7072768211364746s on average
Applying lu_colamd
lu_colamd takes 0.14575886726379395s on average

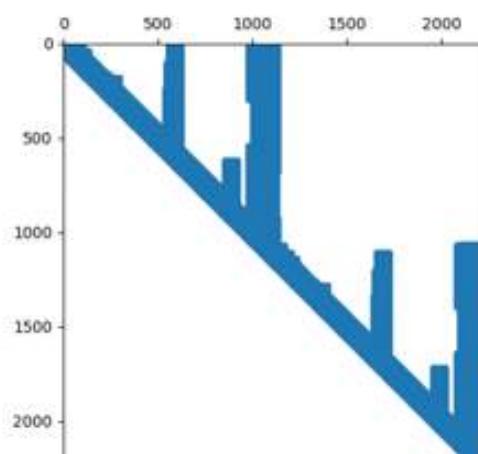
```

LU solver :	0.0433 s
LU_COLAMD solver :	0.145 s
QR_COLAMD solver :	0.707 s
QR solver :	0.832 s
PINV solver :	3.397 s

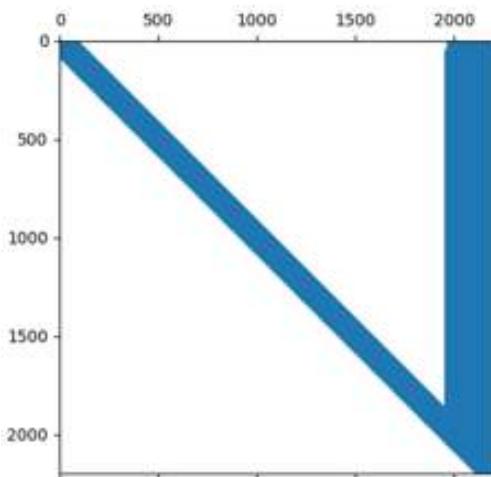
Figure 1: Timestamps for Solvers



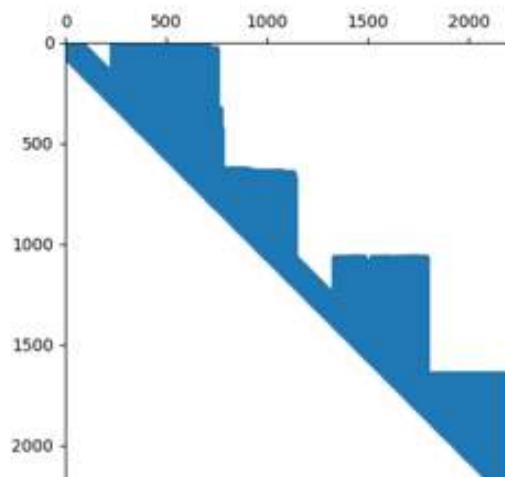
QR solver 2D\_linear.npz



QR\_COLAMD solver 2D\_linear.npz

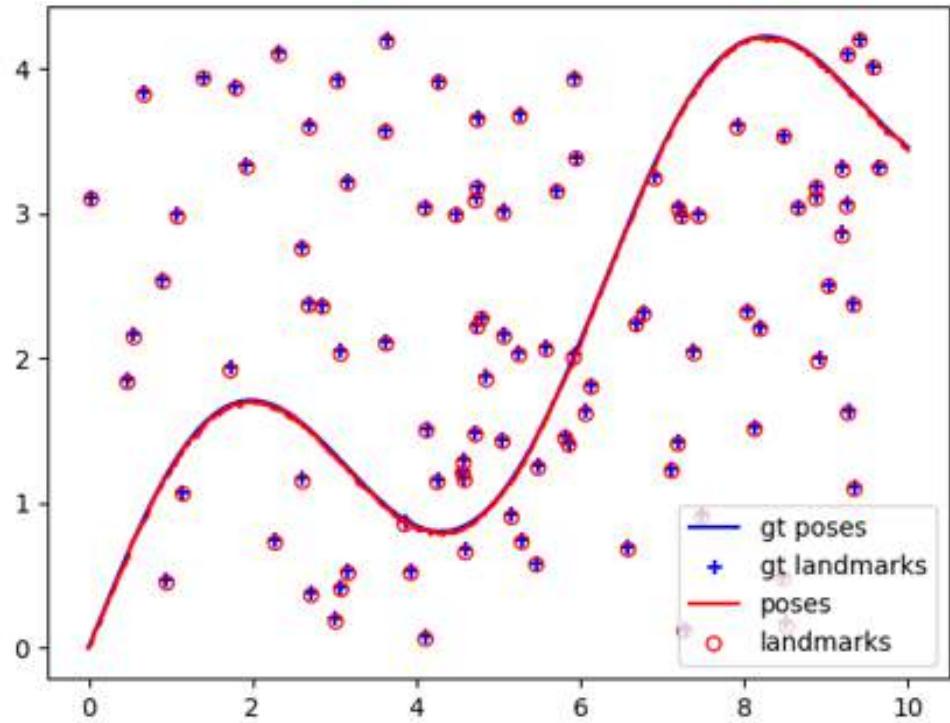


LU solver 2D\_linear.npz

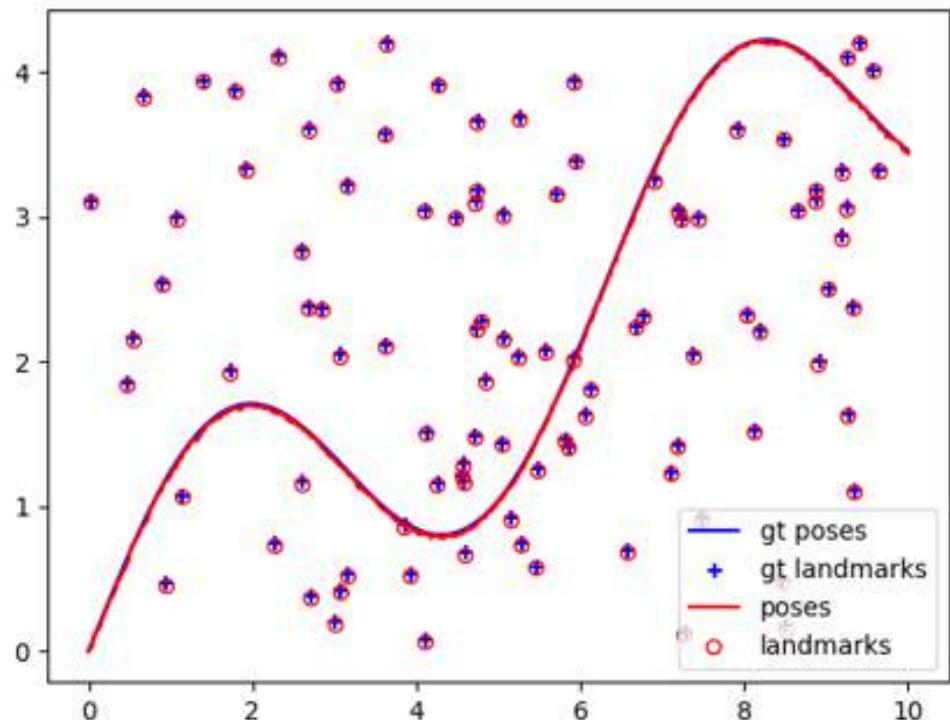


LU\_COLAMD solver 2D\_linear.npz

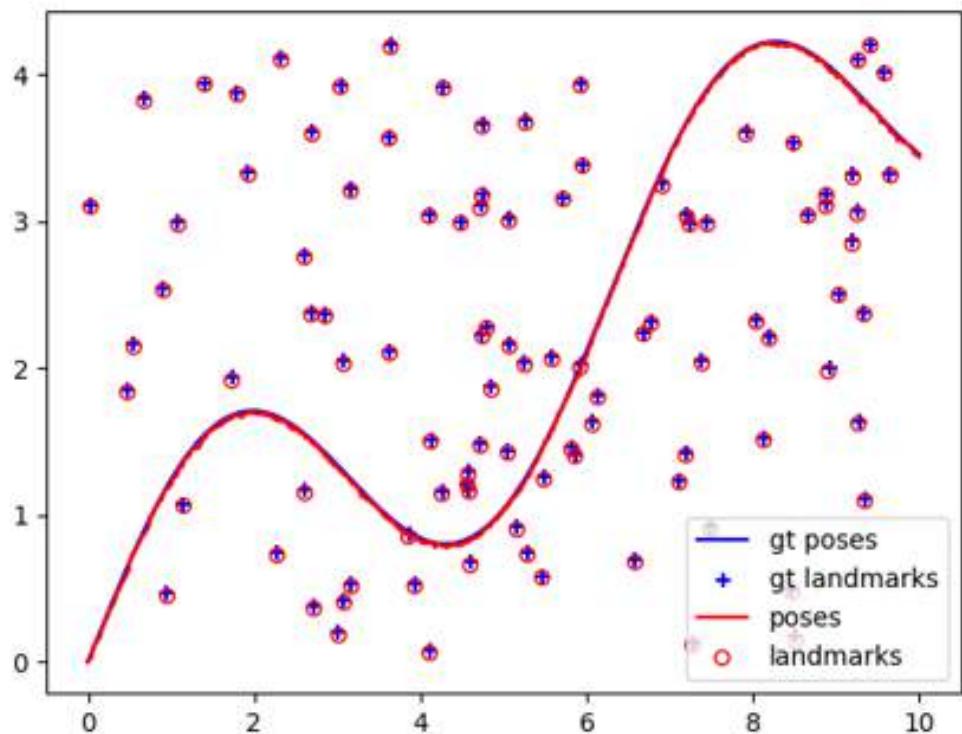
Figure 2: Sparsity Map of Solvers



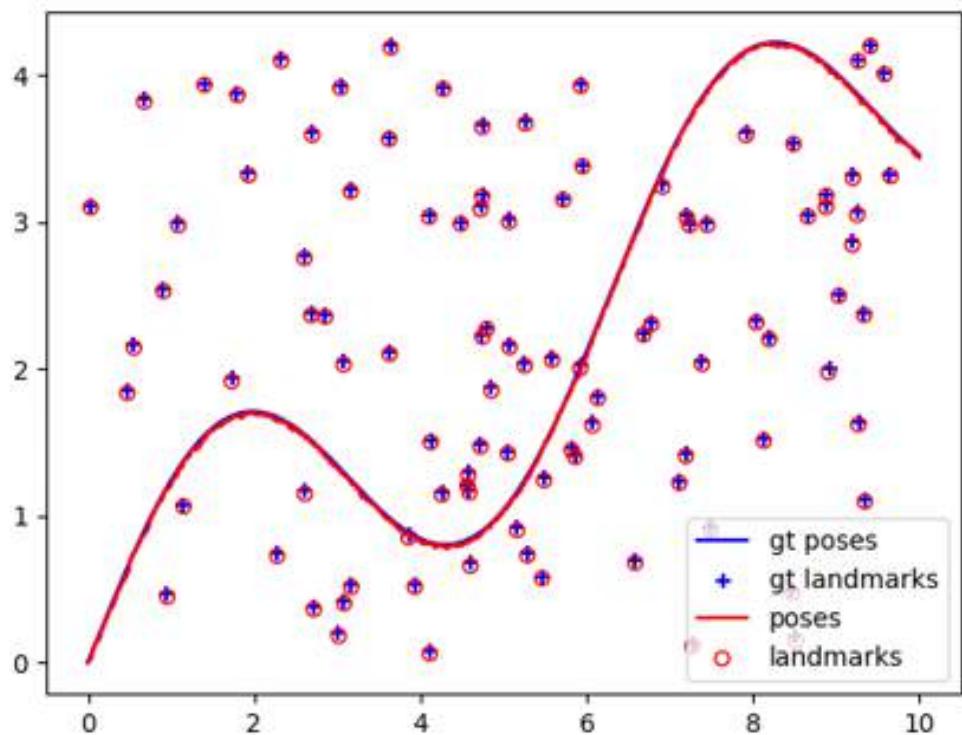
LU solver 2D\_linear.npz



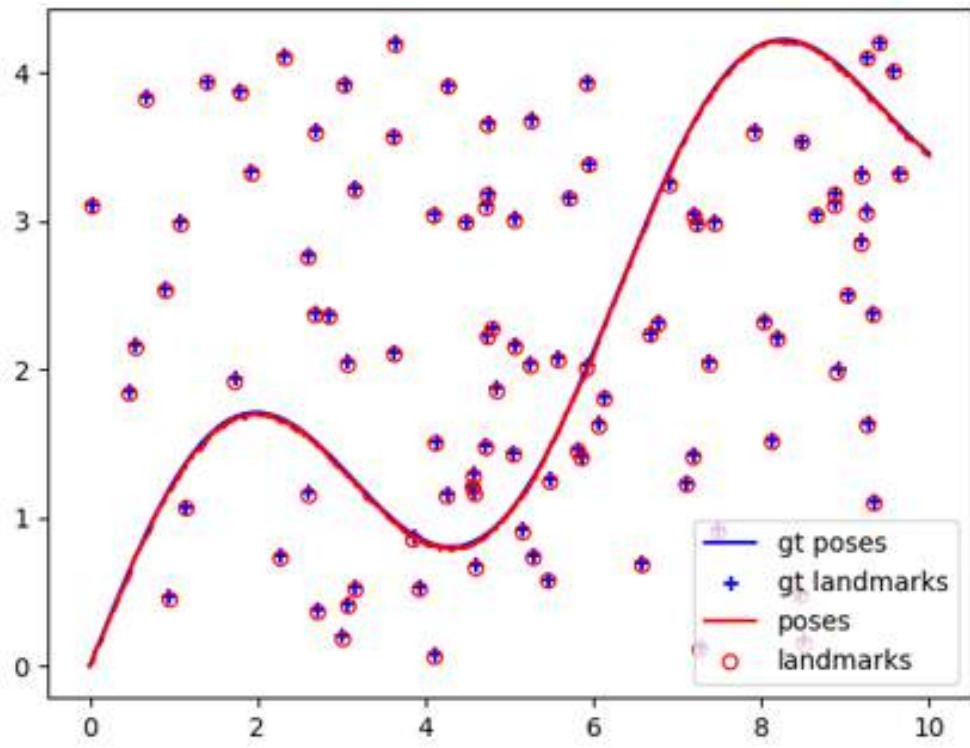
LU\_COLAMD solver 2D\_linear.npz



QR solver 2D\_linear.npz



QR\_COLAMD solver 2D\_linear.npz

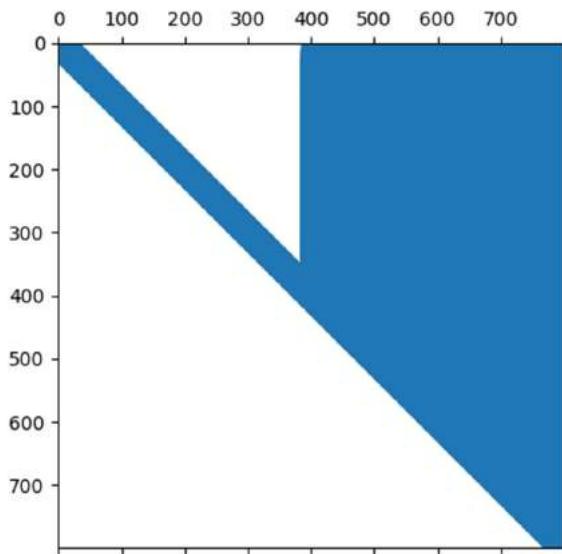


PINV solver 2D\_linear.npz

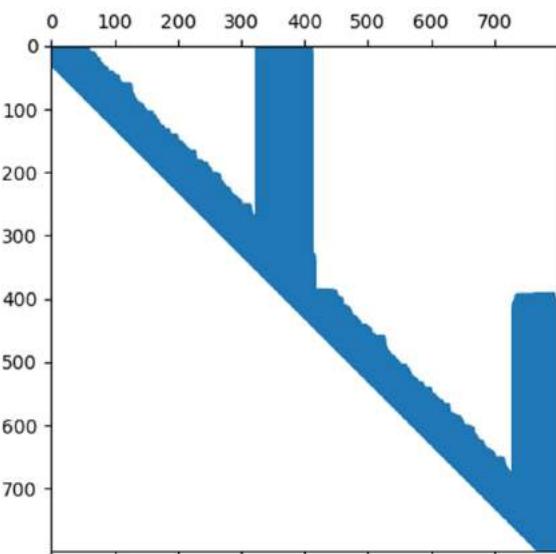
#### Q1.4.5 Comparison of Linear Loop Solvers

Running the *2dlinearloop.npz* program shows a more or less similar performance to the *2dlinear* case, i.e. the *LU* solver is faster compared to the *QR* solver. Interestingly, the pseudo-inverse *PINV* solver appeared to be computationally faster than the *QR* solver even on repeated trials. This can be attributed to the matrix density of *QR* which is computationally expensive. The *LU* solver is the optimal choice when selecting a faster solver due to its prior factorisation. The estimation results for all 4 solver models can be seen below.

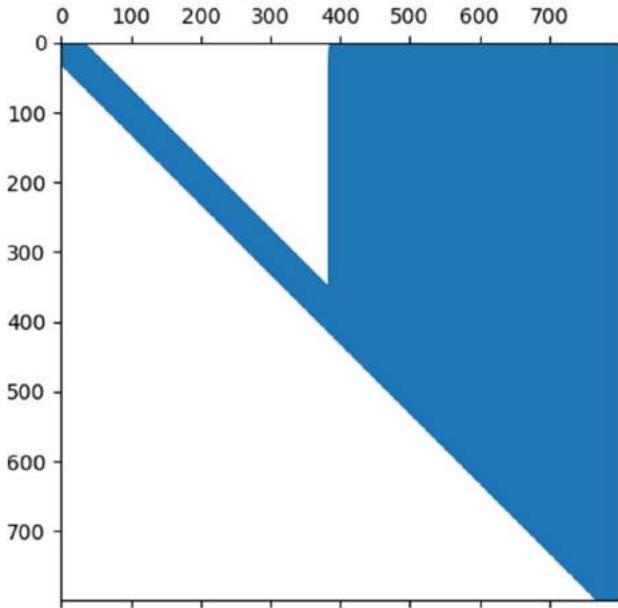
LU_COLAMD solver:	0.00575 s
LU solver:	0.0389 s
QR_COLAMD solver:	0.05 s
PINV solver:	0.3266 s
QR solver:	0.429 s



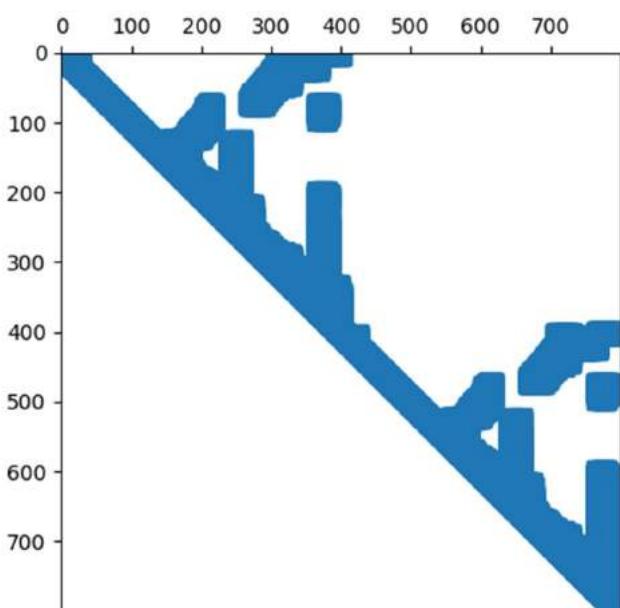
LU solver 2D\_linear\_loop.npz



LU\_COLAMD solver 2D\_linear\_loop.npz

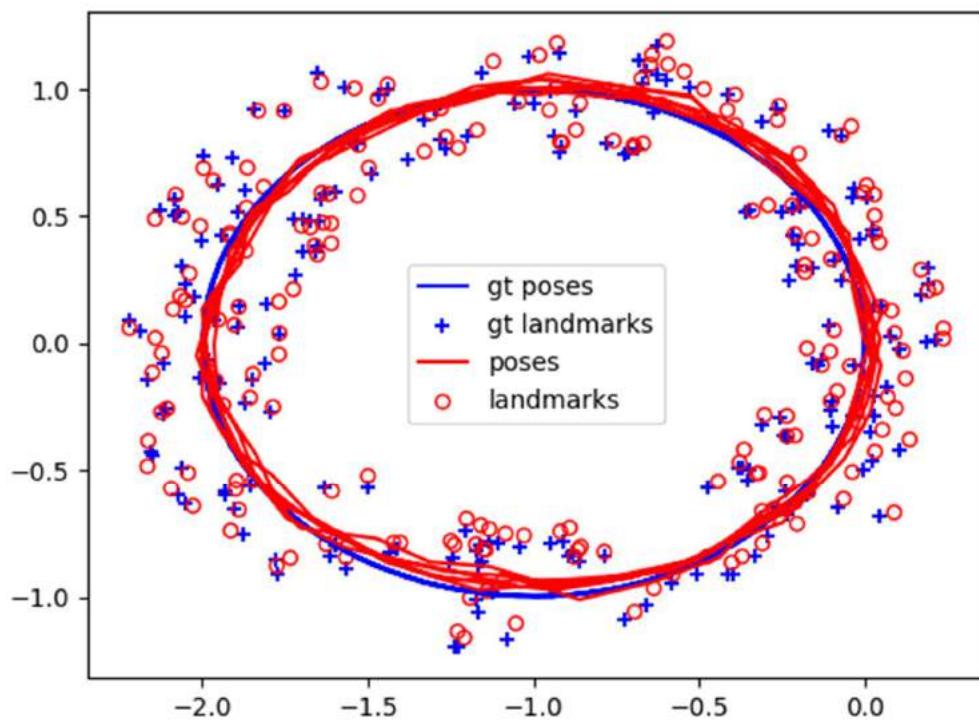


QR solver 2D\_linear\_loop.npz

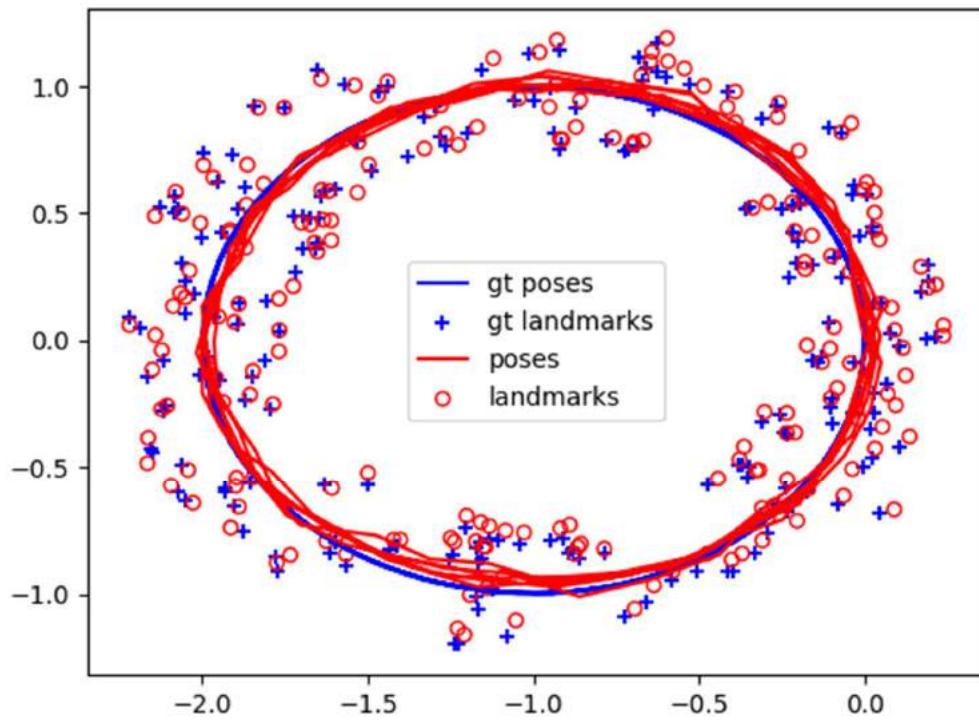


QR\_COLAMD solver 2D\_linear\_loop.npz

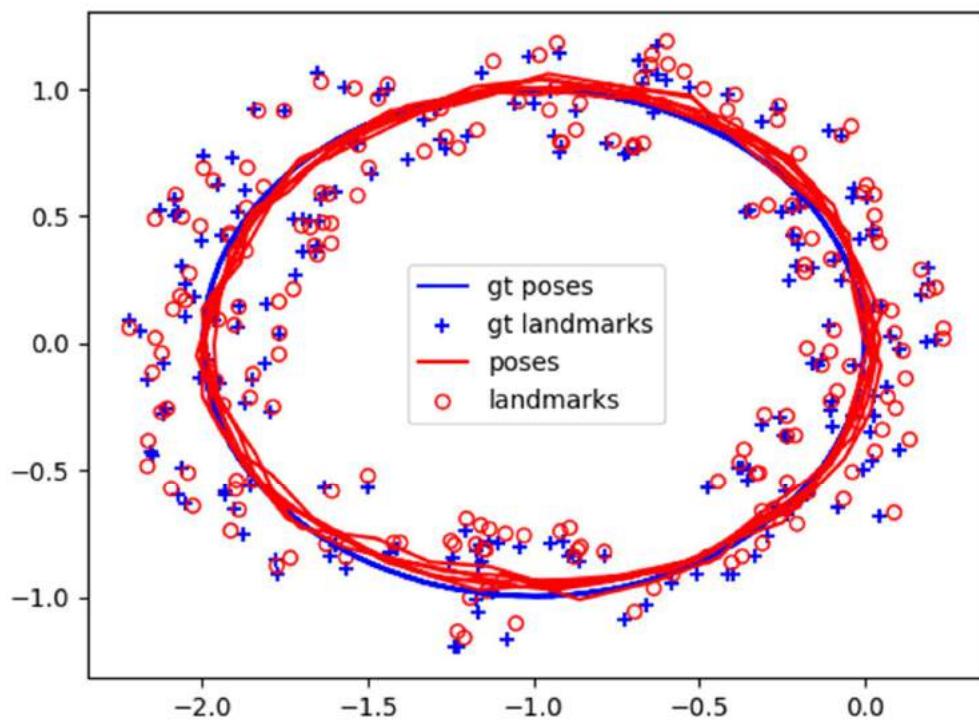
```
dearadice takes 0.100755207007000087s on average
adi@adi-XPS-15-9570:~/SLAM/3/code$ python3 linear.py /home/adi/SLAM/3/
Applying pinv
pinv takes 0.32667112350463867s on average
Applying qr
/home/adi/.local/lib/python3.8/site-packages/scipy/sparse/linalg/_dsol
    warn('CSR matrix format is required. Converting to CSR matrix.', 
qr takes 0.42997050285339355s on average
Applying lu
lu takes 0.03891444206237793s on average
Applying qr_colamd
/home/adi/.local/lib/python3.8/site-packages/scipy/sparse/linalg/_dsol
    warn('CSR matrix format is required. Converting to CSR matrix.', 
qr_colamd takes 0.0500640869140625s on average
Applying lu_colamd
lu_colamd takes 0.005754232406616211s on average
```



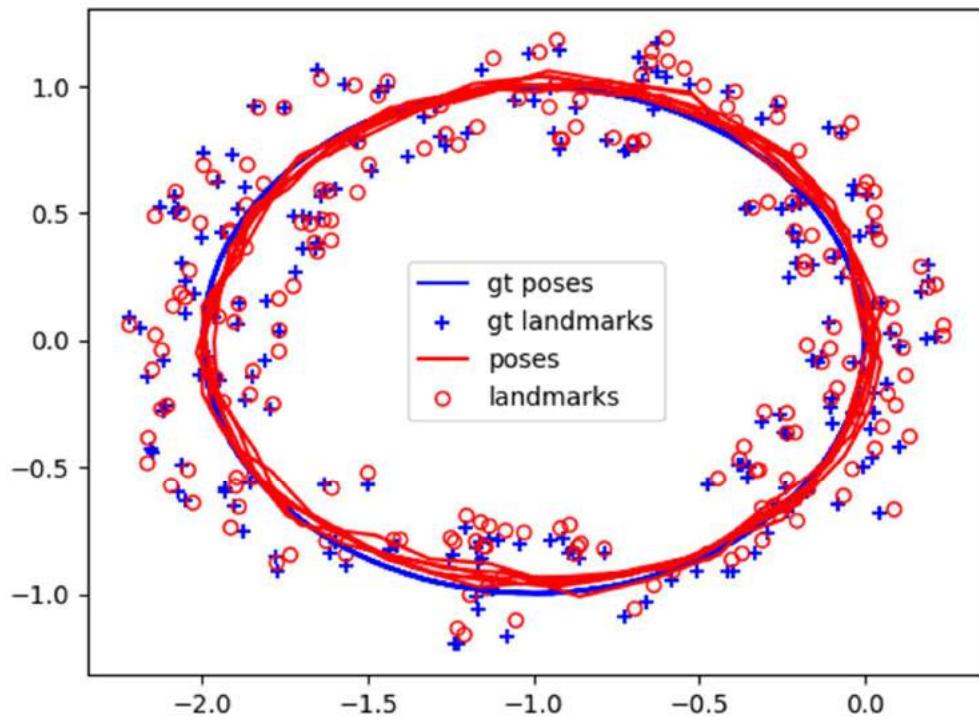
LU solver 2D\_linear\_loop.npz



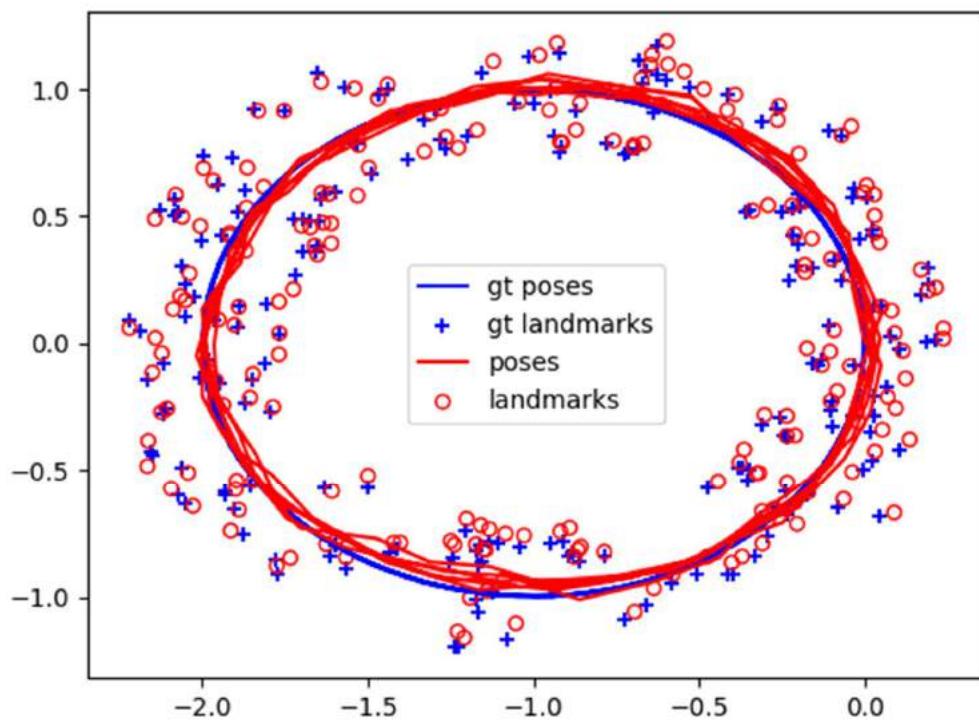
LU\_COLAMD solver 2D\_linear\_loop.npz



QR solver 2D\_linear\_loop.npz



QR\_COLAMD solver 2D\_linear\_loop.npz



PINV solver 2D\_linear\_loop.npz

### Q2.1 2D Non-Linear SLAM system Jacobian (measurement function)

Q2.1

$$\text{Non } X = \begin{bmatrix} r_{tx} \\ x_{ty} \\ l_{k_n} \\ l_{ey} \end{bmatrix}$$

$$H_e = \frac{\partial h_e}{\partial X} = \begin{bmatrix} \frac{dy}{(err)^2}, & -\frac{dx}{(err)}, & -\frac{dy}{(err)}, & \frac{dn}{(err)} \\ -\frac{dx}{err}, & -\frac{dy}{err}, & \frac{dx}{err}, & \frac{dy}{err} \end{bmatrix}$$

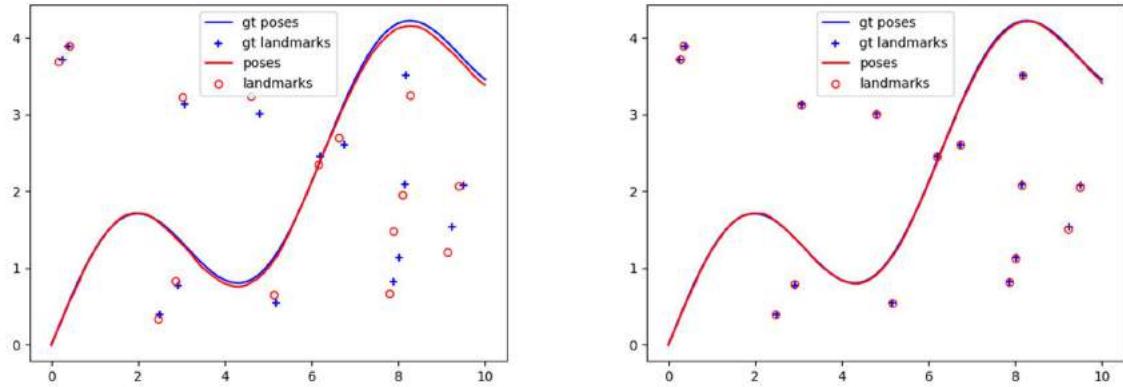
$$\therefore dx = (l_{k_n} - x_{tx})$$

$$\therefore dy = (l_{ey} - x_{ty})$$

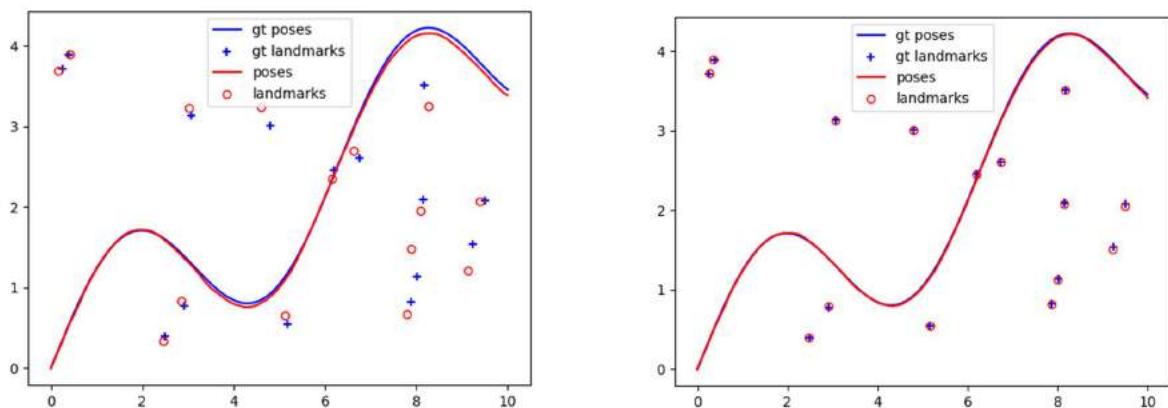
$$\therefore err = \sqrt{(dx)^2 + (dy)^2}$$

### Q 2.3 2D-Non-Linear Solvers

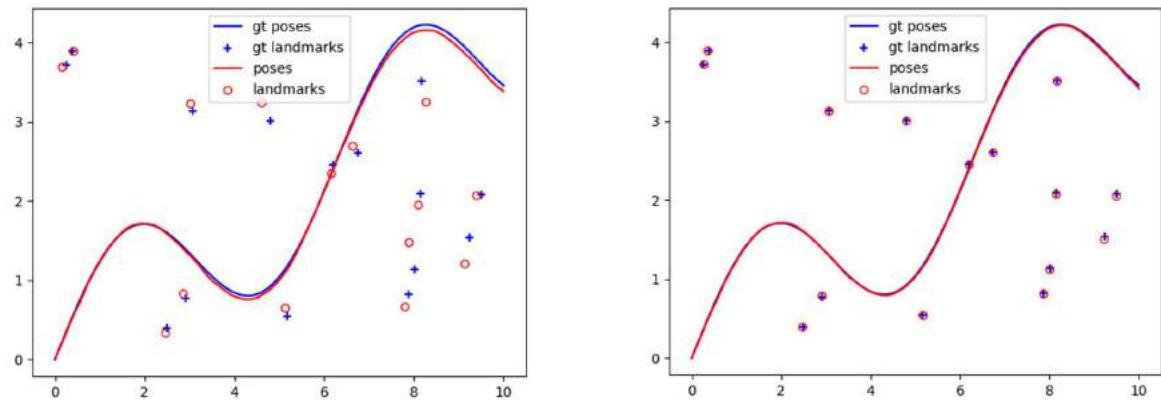
Running the `2d_nonlinear.npz` program outputs estimation plots for each of our solvers as shown in the following pages. The approach considered in this assignment involves computing the least-square error. This error must be minimized iteratively. The nonlinear system is first linearized as it is not possible to implement the decomposition otherwise. Below all 4 non-linear landmark and trajectories can be seen for the solvers are shown, both prior to, and after optimization.



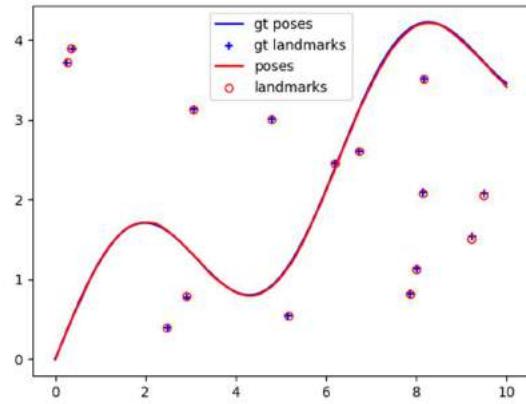
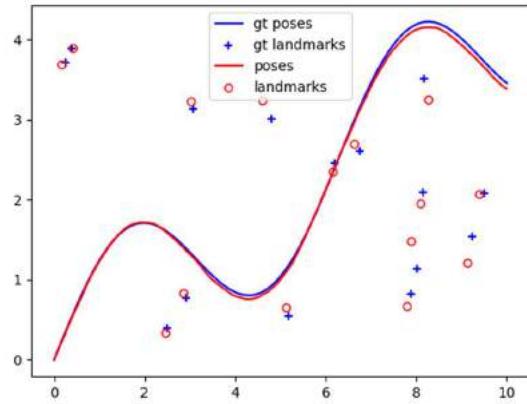
PINV 2D non-linear estimation before and after optimization



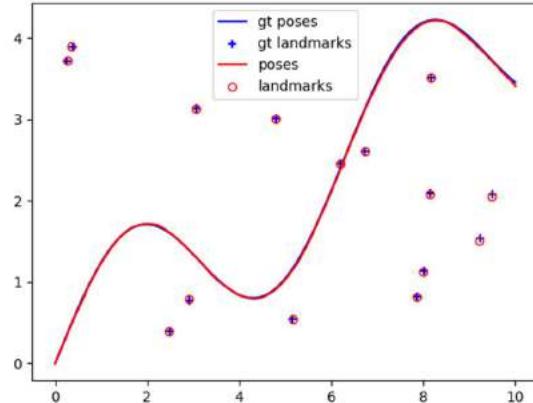
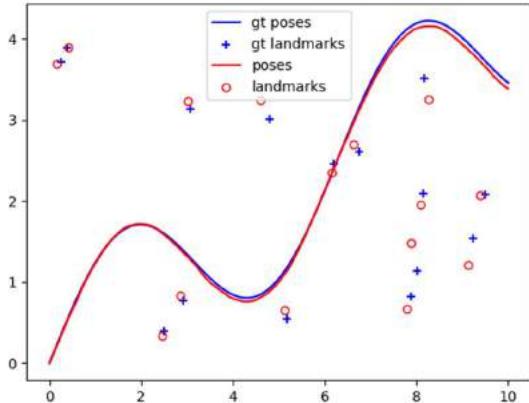
LU 2D non-linear estimation before and after optimization



LU\_COLAMD 2D non-linear estimation before and after optimization



QR 2D non-linear estimation before and after optimization



QR\_COLAMD 2D non-linear estimation before and after optimization