University of Michigan, NA/EECS 568, ROB 530

Mobile Robotics: Methods & Algorithms, Winter 2025

Homework 5 — SLAM

- **See the course Canvas for syllabus, due dates, and homework and grading policies.**
- This course utilizes an autograder to evaluate homework. For each of the five problems, carefully read the submission instructions and complete the TODOs in the corresponding Python script. Once you have finished coding, upload all scripts to GradeScope for automatic assessment and grading. Please note, the autograder retains only the latest score, not the highest.
- You are encouraged to talk at the conceptual level with other students, but you must complete all work individually and may not share any non-trivial code or solution steps. See the syllabus for the full collaboration policy.
- For each problem, the autograder will check the **return value** of the function you implement. Additionally, the variables are printed in this notebook for you to review.

Overview

In this homework, you're going to solve the pose graph SLAM problem using the GTSAM library. If you are not familiar with GTSAM, a detailed tutorial is on their website: https://gtsam.org/tutorials/intro.html. While GTSAM is developed using C++, it also provides MATLAB and Python wrapper. In this assignment, we are going to use the Python wrapper.

After you successfully install GTSAM, write a function to read G2O files and solve the graph optimization problem for both 2D and 3D cases using GTSAM. In this assignment, we use datasets provided at https://lucacarlone.mit.edu/datasets/.

GTSAM Installation Guide

Below we provide an guide for installing the Python wrapper of GTSAM library.

1. Method 1 (preferred): Using `conda` :

```
conda create -n na568 python==3.9 numpy==1.26.4 conda-forge::gtsam==4.2.0 conda-forge::matplotlib==3.8.3 conda-forge::jupyterlab scipy
```

Run this to activate the environment:

```
conda activate na568
```

2. Method 2: Using `pip`. According to pypi only Linux and MacOS is supported.

```
pip install gtsam==4.2.0
```

3. Method 3: Build from source. Follow the instructions here to install. Below are some guides on how to install the Python wrapper.

   - After you successfully clone the repository and create the build folder, you'll have to first go into the cython folder and install the required dependencies. `pip install -r <gtsam_folder>/python/requirements.txt`
   - Then you'll have to do cmake differently by specifying the the Python version you want to use and enable Python wrapper: `cmake .. -DGTSAM_BUILD_PYTHON=1 -DGTSAM_PYTHON_VERSION=<your_python_version>`
   - Compile the files in build (-j means using multi-thread. 10 is the number of threads you want to use) `make -j10`
   - Install it to your machine `sudo make python-install`

You may refer to some python gtsam examples here.

Read the Following FAQ before Getting Started!

1. Q: Which version of GTSAM should I use?

   A: This homework is built with GTSAM 4.2.0 and the autograder will use the same version to test your code. We noticed that GTSAM has changed its Python interface multiple times before. It is recommended to use this version in order to avoid error.

2. Q: The logic of my code is correct but I can't get the expected result.

   A: We noticed some students use the code shown below experienced imperfect plot caused by precision issue. `gtsam.Pose2([x,y,theta])`.

   Instead, the correct construction of the `Pose2` is `gtsam.Pose2(x,y,theta)`.

   You should follow the same pattern when constructing `Pose3`.

3. Q: How can I resolve the issues when installing the libraries?

A: Google your error information first, and try to find the answer on the GitHub issues page and piazza. If it still exists, please send a new piazza post with your system information, the version of your coding language, and your error information.

4. Q: I'm a Python user, but GTSAM only has C++ Doxygen documentation. How do I know how to implement the algorithms?

   A: Great question! Looking at GTSAM python examples from Github would be sufficient for the Homework! Also, if you wish to look into detailed function explanation and usage, unfortunately, you have to refer to C++ documentation.

5. Q: Since GTSAM is available in C++/Python/MATLAB, which language should I use for other GTSAM projects?

   A: Generating plots is easier in Python/MATLAB, while C++ has better documentation of GTSAM. Mixing these is also acceptable, you can save your optimization result from C++ and write a script to visualize it in Python/MATLAB. Also, check this nice library for plotting in C++ https://github.com/lava/matplotlib-cpp.

   In practice, when the computational time matters in the application, which is mostly true for robotics projects if we want to deploy the algorithms on the robot eventually, C++ is preferred among the three languages. Writing GTSAM in C++ is a more common practice for real applications.

In [1]:
```
# run this block to enable autoreload of modules
%load_ext autoreload
%autoreload 2

import matplotlib.pyplot as plt
from mpl_toolkits import mplot3d
from pose_graph_slam import *
```

2D Graph SLAM (50 points)

Submission

Please fill the **TODO**s in the function contained in **pose_graph_slam.py** and submit the file to gradescope.

Instructions

1. Implement `read_g2o_2d` function (10 points)
2. Implement `gn_2d` function (20 points)
3. Implement `isam_2d` function (20 points)

Your code is evaluated at each step using test input independently. Specifically, during steps 2 and 3, the autograder will use the correct `read_g2o_2d` function to test your code. For example, even if the `read_g2o_2d` function from step 1 is incorrect, implementing `gn_2d` correctly in step 2 can still earn you full credits.

Task 1A. Reading 2D G2O (10 pts)

Write a function to read 2D Intel dataset from G2O format and output poses and edges. The file used in task 1 is `data/input_INTEL_g2o.g2o`. These poses and edges are used in later problems.

For 2D data, the pose in G2O format is `[VERTEX_SE2 i x y theta]` and the edge in G2O format is `[EDGE_SE2 i j x y theta info(x, y, theta)]`, where `info(x, y, theta)` is a 1×6 vector $[q_{11}\ q_{12}\ q_{13}\ q_{22}\ q_{23}\ q_{33}]$ where the elements are the upper-triangle matrix of the 3×3 information matrix $\Omega = \begin{bmatrix} q_{11} & q_{12} & q_{13} \\ q_{12} & q_{22} & q_{23} \\ q_{13} & q_{23} & q_{33} \end{bmatrix}$. By inverting this information matrix, you can obtain the covariance matrix for the noise model.

You may look into detail in the g2o repository.

In [ ]:
```
data = read_g2o_2d('data/input_INTEL_g2o.g2o')

p = data['poses']
e = data['edges']


print('First 3 pose in the dataset:')
for i in range(3):
    print(f'pose {i}: {p[i]}')

print('\nFirst 3 edges in the dataset:')
for i in range(3):
    print(f'edge {i}: {e[i]}')
```

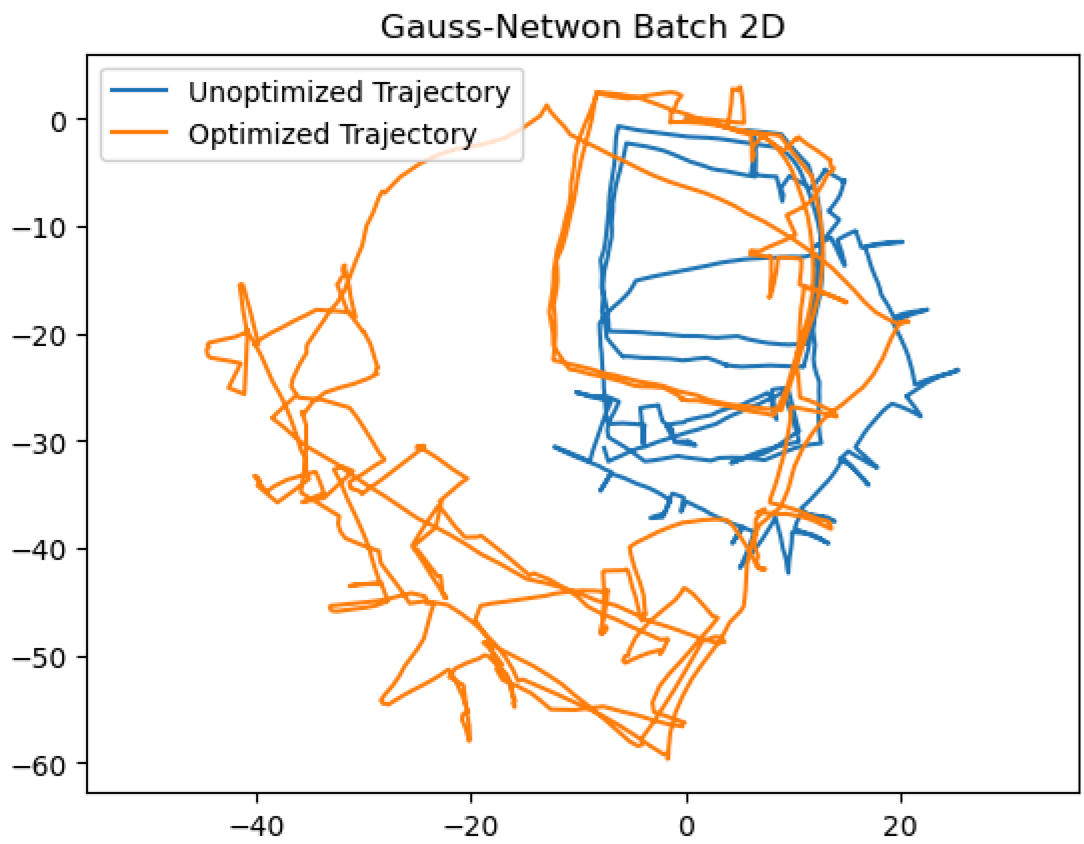
Task 1B. Batch Solution (20 pts)

A batch solution means when we construct the entire graph and solve it at the end altogether. Construct a 2D nonlinear factor graph using GTSAM. Use the Gauss-Newton solver. Visualize and compare the optimized trajectory against the initial trajectory. The key is to understand the graph construction process and its parameters.

For this problem, Gauss Newton solver will fall into a local minimum if we don't give any perturbation. It is okay to get a plot that doesn't work as expected.

Hint: You may use `NonlinearFactorGraph` as your graph, use `GaussNewtonOptimizer` as you optimizer, use `Values` for your initial estimation, `noiseModel.Gaussian.Covariance()` for your noise model, `graph.add()` and `initial.insert()` functions as you see fit. However, function names might be different for different versions of gtsam.

Expected result for task 1B:



In [ ]:
```
data = read_g2o_2d('data/input_INTEL_g2o.g2o')
init_poses = np.array([[p.x, p.y, p.theta] for p in data['poses']])
opt_poses = gn_2d(data)

plt.plot(init_poses[:,0], init_poses[:,1])
plt.plot(opt_poses[:,0], opt_poses[:,1])
plt.title('Gauss-Netwon Batch 2D')
plt.legend(['Unoptimized Trajectory', 'Optimized Trajectory'])
plt.axis('equal')
plt.show()
```

Task 1C. Incremental Solution (20 pts)

Use ISAM2 solver to optimize the trajectory incrementally (as you build the graph gradually). A detailed algorithms is described below. Visualize and compare the optimized trajectory against the initial trajectory.

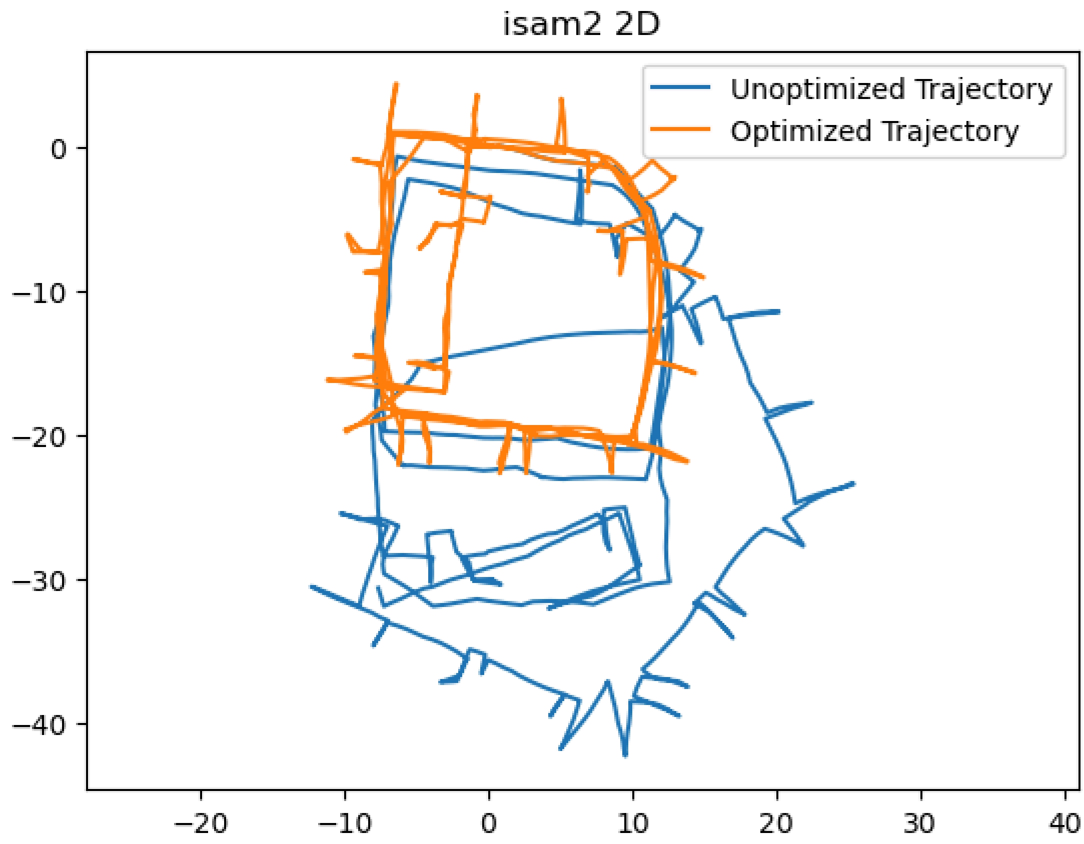
Algorithm 1 `incremental_solution_2d`(poses, edges)

Require: poses: a N × 4 array that each row is $pose = (id_p, x, y, \theta)$; edges: a M × 11 array that each row is $edge = (id_{e1}, id_{e2}, dx, dy, d\theta, info)$

$isam \leftarrow$ gtsam.ISAM2() ▷ Initialize isam solver
for every pose in poses **do**
  $graph \leftarrow$ NonlinearFactorGraph ▷ Initialize the factor graph
  $initialEstimate \leftarrow$ Values ▷ Initialize the initial estimation
  $(id_p, x, y, \theta) \leftarrow pose$ ▷ Extract information from the current pose
  if $id_p == 0$ **then** ▷ The first pose
    $priorNoise \leftarrow$ some noiseModel ▷ Use a predefined noise model
    $graph$.add(PriorFactorPose2(0, Pose2(x, y, θ), $priorNoise$))
    $initialEstimate$.insert(id_p, Pose2(x, y, θ))
  else ▷ Not the first pose
    $prevPose \leftarrow result$.at($id_p - 1$) ▷ Use last optimized pose
    $initialEstimate$.insert(id_p, $prevPose$)
    for every edge in edges **do**
      $(id_{e1}, id_{e2}, dx, dy, d\theta, info) \leftarrow edge$ ▷ Extract information from the current edge
      if $id_{e2} == id_p$ **then**
        $cov = construct\_covariance(info)$ ▷ Construct a covariance matrix from the information vector.
        $Model \leftarrow$ noiseModel.Gaussian.Covariance(cov)
        $graph$.add(BetweenFactorPose2(id_{e1}, id_{e2}, Pose2($dx, dy, d\theta$), $Model$))
      end if
    end for
  end if
  $isam$.update($graph$, $initialEstimate$)
  $result = isam$.calculateEstimate()
end for

Hint: You may use `NonlinearFactorGraph` as your graph, use `gtsam.ISAM2()` as your update algorithm, use `Values` for your initial estimation, and use `graph.add()`, `initial.insert()`, `isam.update()`, and `isam.calculateEstimate()` functions as you see fit. However, function names might be different for different versions of gtsam.

Expected result for task 1C:



In [ ]:
```
data = read_g2o_2d('data/input_INTEL_g2o.g2o')
init_poses = np.array([[p.x, p.y, p.theta] for p in data['poses']])
opt_poses = isam_2d(data)

plt.plot(init_poses[:,0], init_poses[:,1])
plt.plot(opt_poses[:,0], opt_poses[:,1])
plt.title('isam2 2D')
plt.legend(['Unoptimized Trajectory', 'Optimized Trajectory'])
plt.axis('equal')
plt.show()
```

3D Graph SLAM (50 points)

Submission

Please fill the **TODO**s in the function contained in **pose_graph_slam.py** and submit the file to gradescope.

Instructions

1. Implement `read_g2o_3d` function (10 points)
2. Implement `gn_3d` function (20 points)
3. Implement `isam_3d` function (20 points)

Your code is evaluated at each step using test input independently. Specifically, during steps 2 and 3, the autograder will use the correct `read_g2o_3d` function to test your code. For example, even if the `read_g2o_3d` function from step 1 is incorrect, implementing `gn_3d` correctly in step 2 can still earn you full credits.

Task 2A. Reading 3D G2O (10 pts)

Write a function to read 3D Garage G2O file from G2O format and output poses and edges. The file we use in task 2 is `data/parking-garage.g2o`.

For 3D data, the pose in G2O format is `[VERTEX_SE3:QUAT i x y z qx qy qz qw]` where (x, y, z) represents the translation and (qx, qy, qz, qw) the rotation as a quaternion. The edge in G2O format is `[EDGE_SE3:QUAT i j x y z qx qy qz qw info(x, y, z, qx, qy, qz)]`, where `info(x, y, z, qx, qy, qz)` is a 1×21 vector of the 6×6 information matrix. After similar process in task 1A, you can obtain the covariance matrix. You may look into detail in the g2o repository.

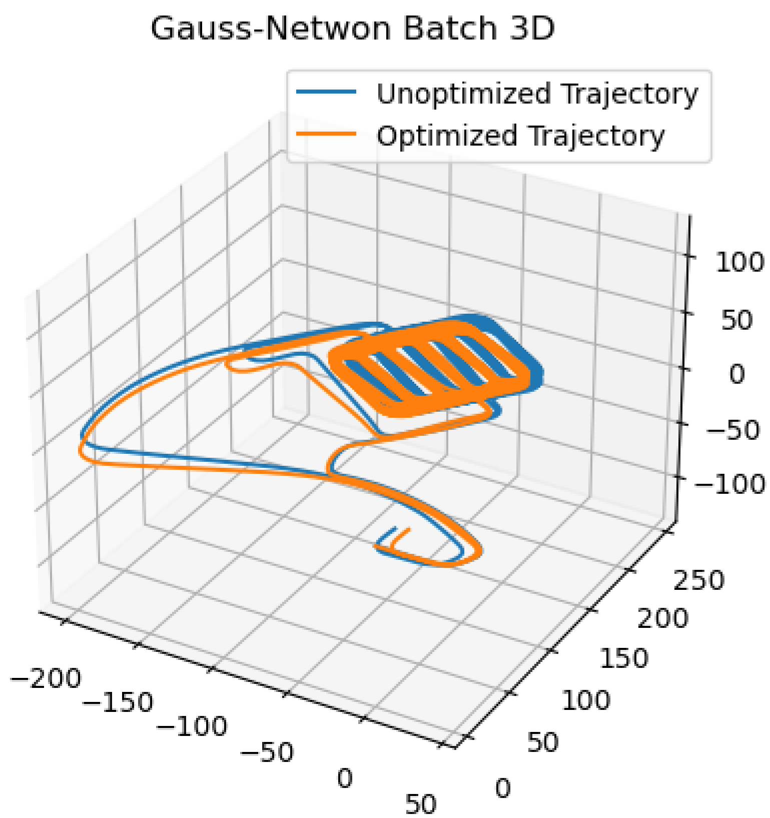
Please notice that the quaternion in GTSAM is in the order of `[qw qx qy qz]` and is different from the order in g2o files which is `[qx qy qz qw]`.

In [ ]:
```
data = read_g2o_3d('data/parking-garage.g2o')

p = data['poses']
e = data['edges']


print('First 3 pose in the dataset:')
for i in range(3):
    print(f'pose {i}: {p[i]}')

print('\nFirst 3 edges in the dataset:')
for i in range(3):
    print(f'edge {i}: {e[i]}')
```

Task 2B. Batch Solution (20 pts)

Construct a 3D nonlinear factor graph using GTSAM. Use the Gauss-Newton solver. Visualize and compare the optimized trajectory against the initial trajectory.

Expected result for task 2B:



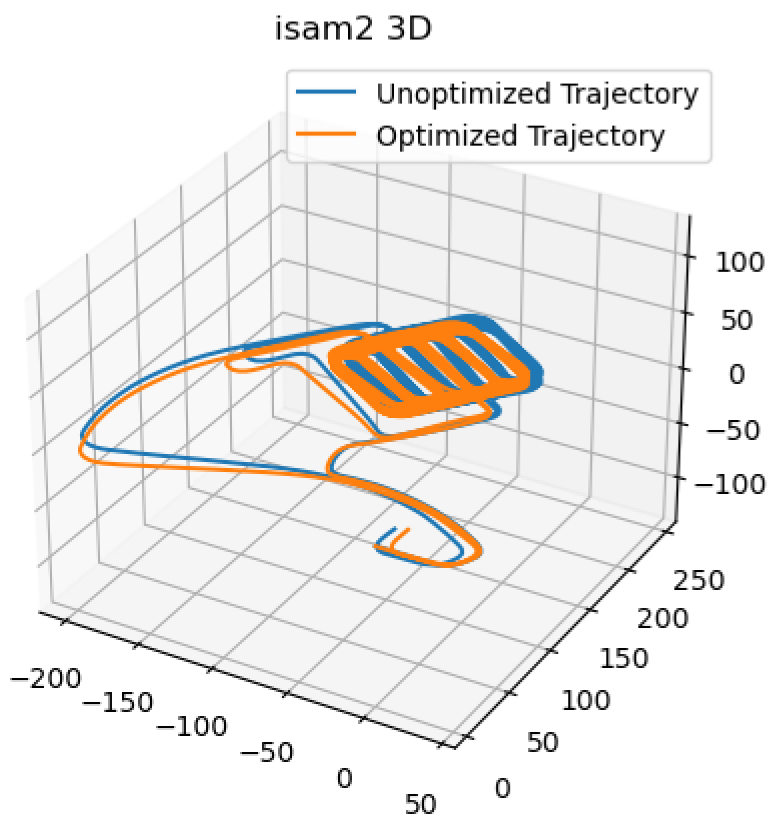
In [ ]:

```
data = read_g2o_3d('data/parking-garage.g2o')
init_poses = np.array([[p.x, p.y, p.z] for p in data['poses']])
opt_poses = gn_3d(data)

ax = plt.axes(projection='3d')
plt.plot(init_poses[:,0],init_poses[:,1],init_poses[:,2])
plt.plot(opt_poses[:,9],opt_poses[:,10],opt_poses[:,11])
plt.title('Gauss-Netwon Batch 3D')
plt.legend(['Unoptimized Trajectory', 'Optimized Trajectory'])

X = opt_poses[:,9]
Y = opt_poses[:,10]
Z = opt_poses[:,11]
max_range = np.array([X.max()-X.min(), Y.max()-Y.min(), Z.max()-Z.min()]).ma

mid_x = (X.max()+X.min()) * 0.5
mid_y = (Y.max()+Y.min()) * 0.5
mid_z = (Z.max()+Z.min()) * 0.5
ax.set_xlim(mid_x - max_range, mid_x + max_range)
ax.set_ylim(mid_y - max_range, mid_y + max_range)
ax.set_zlim(mid_z - max_range, mid_z + max_range)

plt.show()
```

Task 2C. Incremental Solution (20 pts)

Use ISAM2 solver to optimize the trajectory incrementally. Visualize and compare the optimized trajectory against the initial trajectory.

Expected result for task 2C:



In [ ]:
```
data = read_g2o_3d('data/parking-garage.g2o')
init_poses = np.array([[p.x, p.y, p.z] for p in data['poses']])
opt_poses = isam_3d(data)

ax = plt.axes(projection='3d')
plt.plot(init_poses[:,0],init_poses[:,1],init_poses[:,2])
plt.plot(opt_poses[:,9],opt_poses[:,10],opt_poses[:,11])
plt.title('isam2 3D')
plt.legend(['Unoptimized Trajectory', 'Optimized Trajectory'])

X = opt_poses[:,9]
Y = opt_poses[:,10]
Z = opt_poses[:,11]
max_range = np.array([X.max()-X.min(), Y.max()-Y.min(), Z.max()-Z.min()]).ma

mid_x = (X.max()+X.min()) * 0.5
mid_y = (Y.max()+Y.min()) * 0.5
mid_z = (Z.max()+Z.min()) * 0.5
ax.set_xlim(mid_x - max_range, mid_x + max_range)
ax.set_ylim(mid_y - max_range, mid_y + max_range)
ax.set_zlim(mid_z - max_range, mid_z + max_range)

plt.show()
```