



# **Internship Project Report**

Matthew Ward

August 4, 2025

- BYU Applied and Computational Math (DS & ML, April 2026)
- Biophysics Simulation Group—computer vision and competition dataset curation
- Music
- Handball
- Data engineer intern with you until August 16<sup>th</sup>!

Acadia-related work, no hardware yet.

Primarily point cloud registration and processing performance report, plenty more though.

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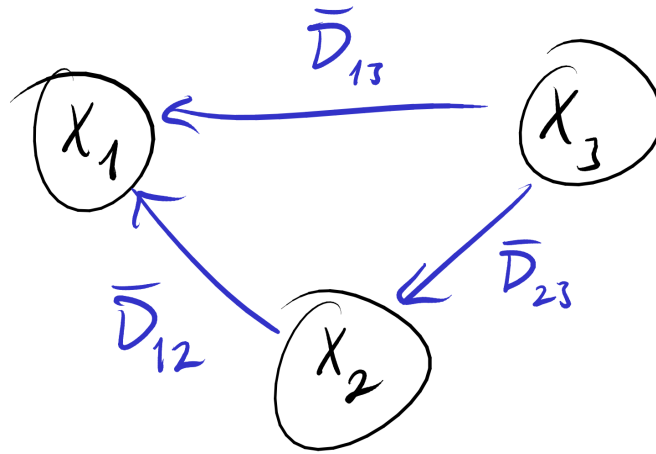
## **A few goals to discuss.**

1. Infer global registrations from pairwise registrations
2. Model laser spot illumination as a Gaussian from sensor data
3. Generate a processing performance report



# Global registration from pairwise registration

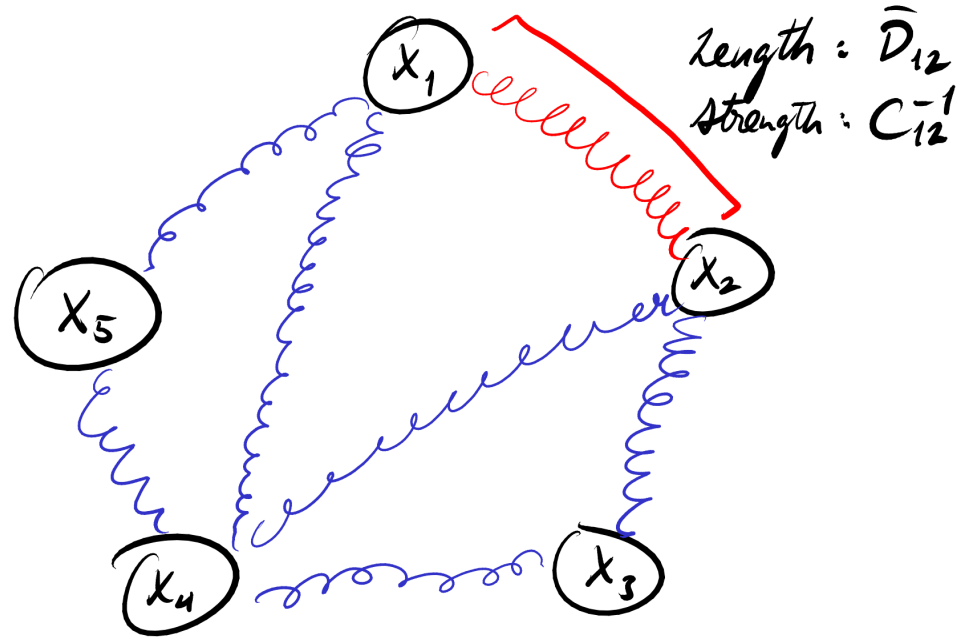
Straightforward to move one scan to align with another, less so to move  $n$  scans to align with each other.



Unfortunately,  $\bar{D}_{13} \neq \bar{D}_{12}\bar{D}_{23}$ .

# Global registration from pairwise registration

Pose graph optimization.

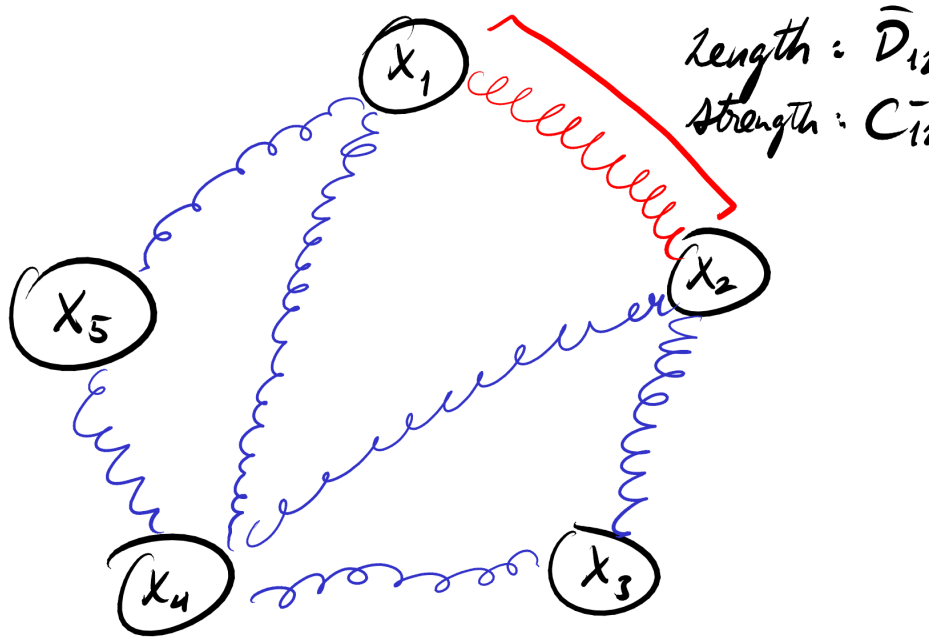


$$\underset{\{X_1, \dots, X_n\}}{\text{minimize}} \quad \sum_{i,j} \left( \bar{D}_{ij} - (X_i - X_j) \right)^T C_{ij}^{-1} \left( \bar{D}_{ij} - (X_i - X_j) \right)$$



# Global registration from pairwise registration

Pose graph optimization.

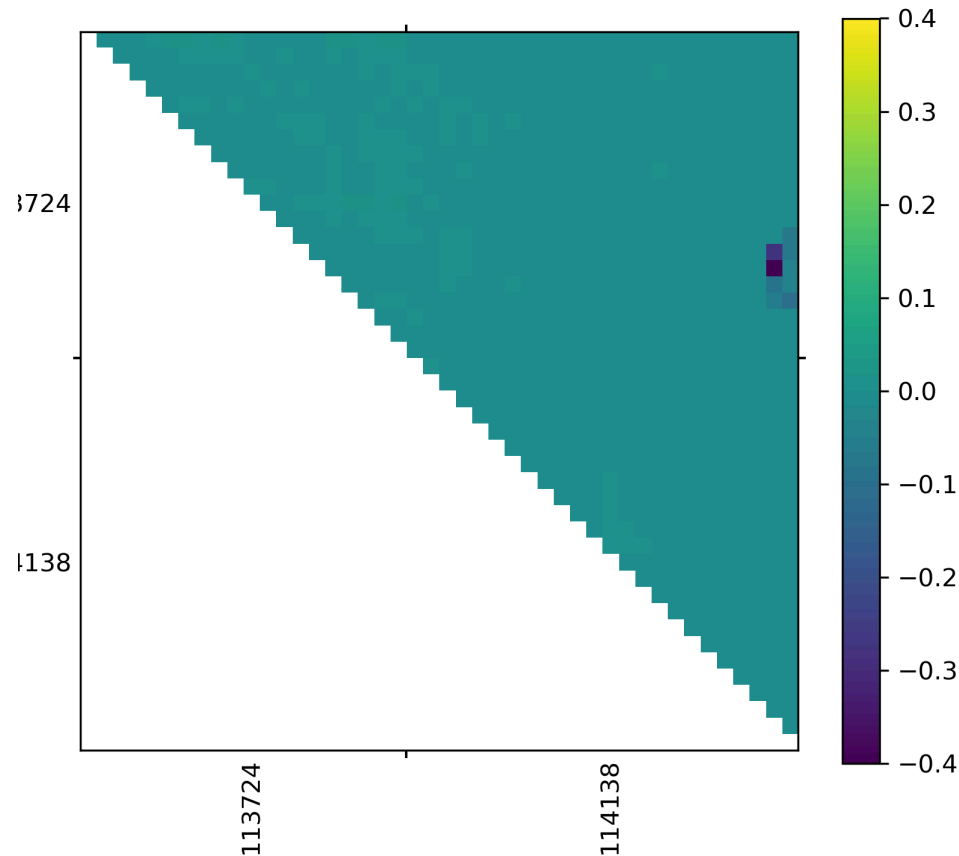


- Constant stretchiness
- Model stretchiness manually.  
 $(i, j) \rightarrow C_{ij}^{-1}$
- Model stretchiness with machine learning (Optuna)

$$\underset{\{X_1, \dots, X_n\}}{\text{minimize}} \quad \sum_{i,j} \left( \bar{D}_{ij} - (X_i - X_j) \right)^T \bar{C}_{ij}^{-1} \left( \bar{D}_{ij} - (X_i - X_j) \right)$$

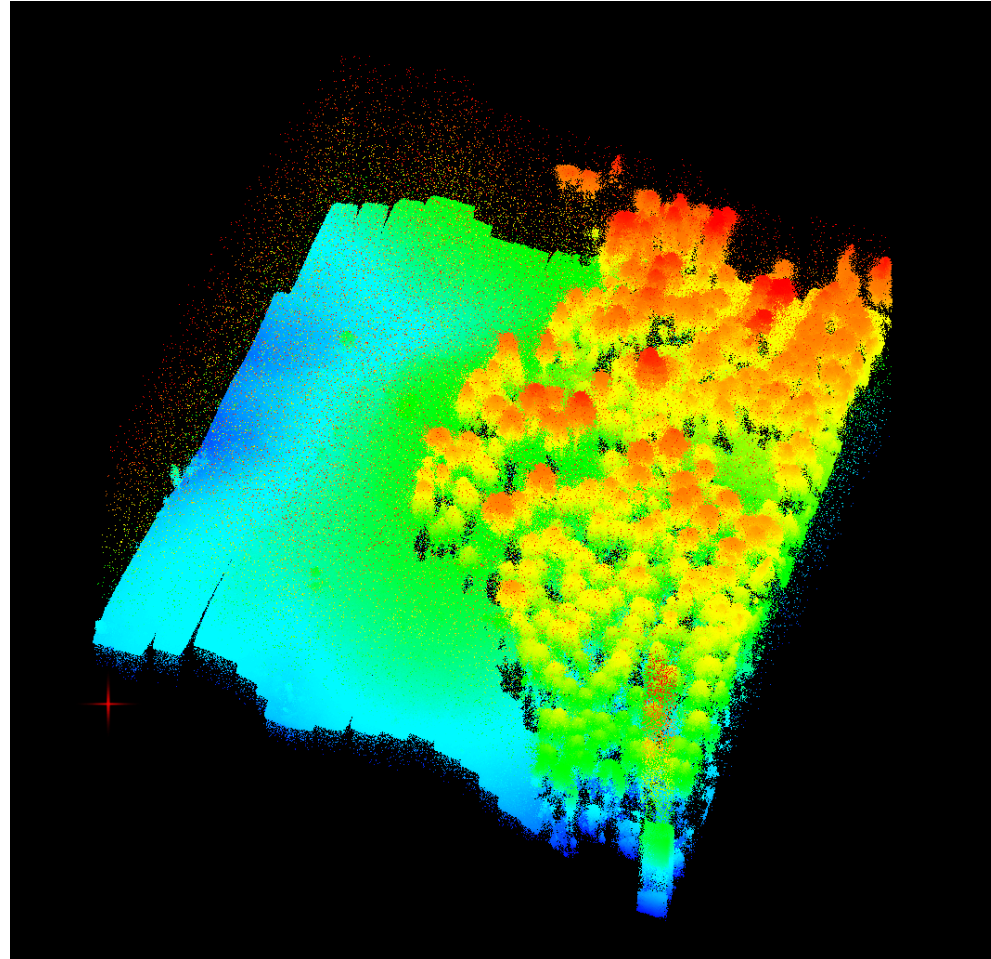
# Global registration from pairwise registration

Pruning and weighting.

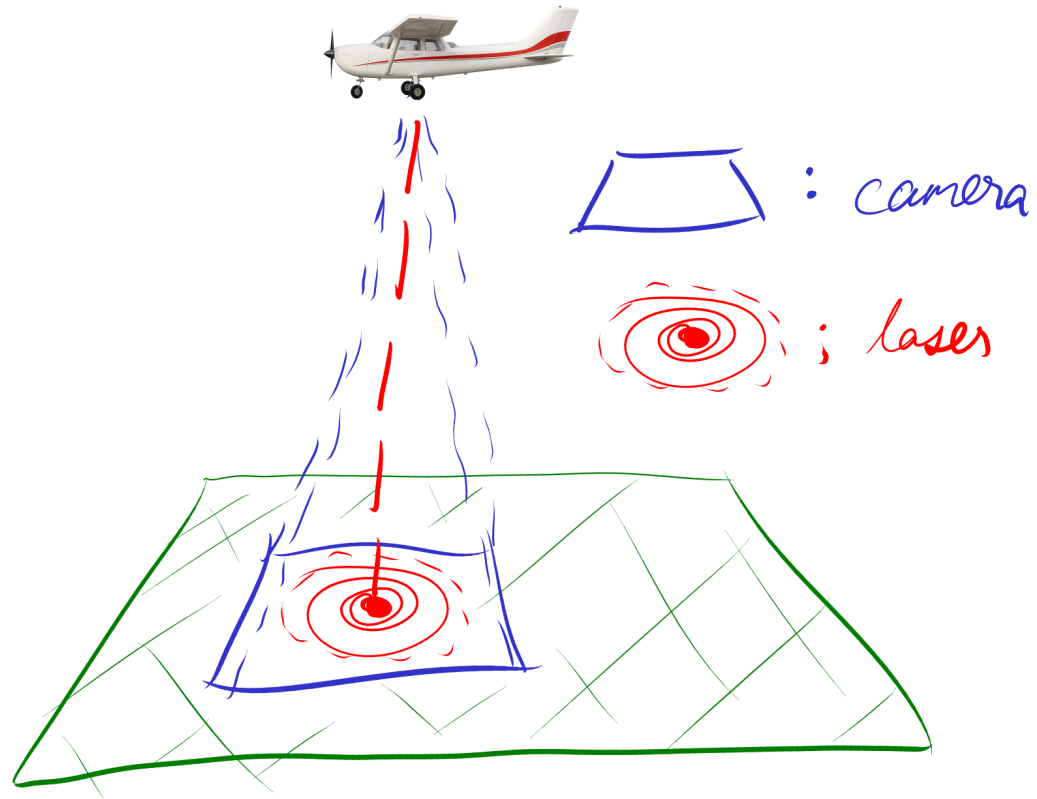


- After optimization, some springs (pairwise registrations) are stretched
- Lots of redundancy in the graph reveals poor pairwise registrations
- Weight those springs less or remove

Analyzing 20230627\_095732\_cuchillo1\_scan00091.bpf

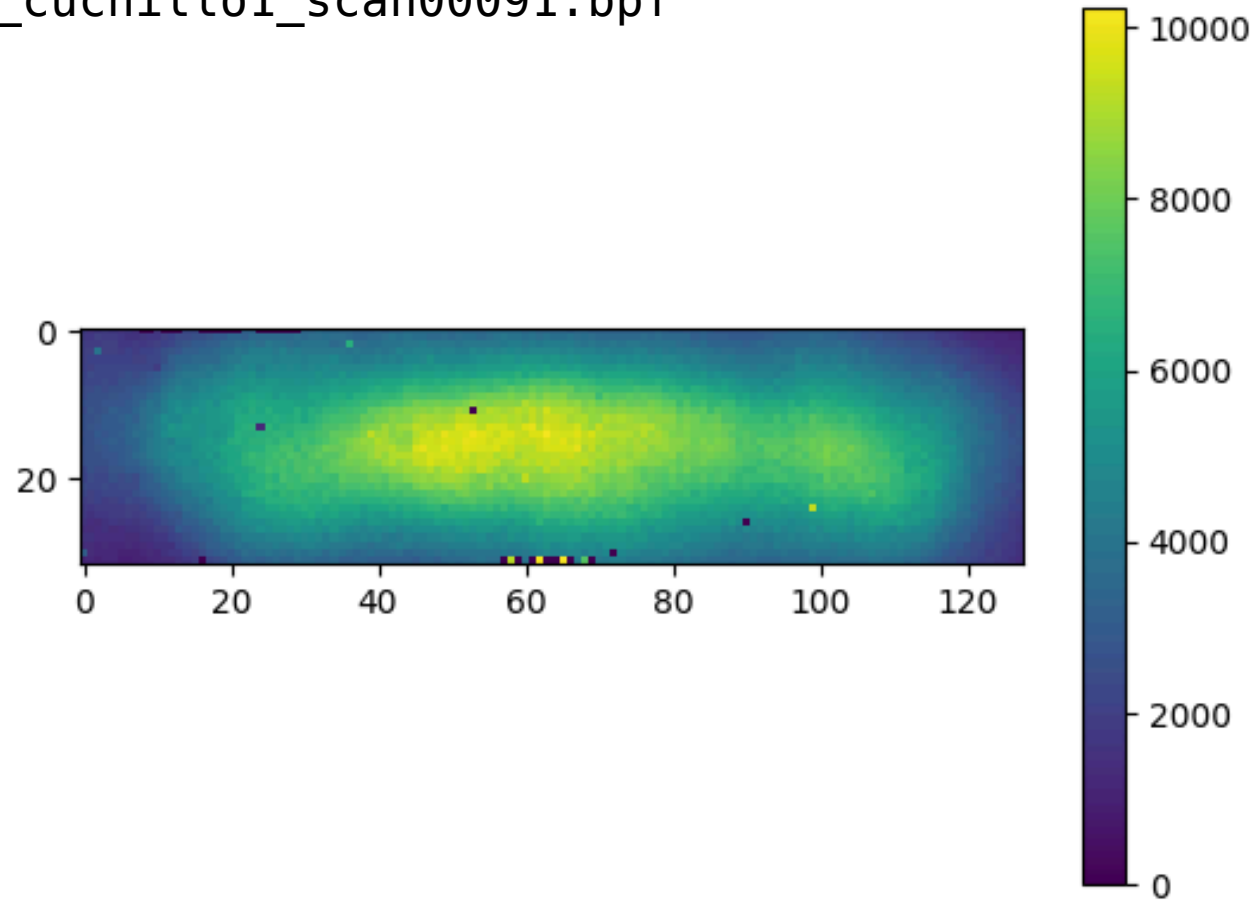


# Spot modeling



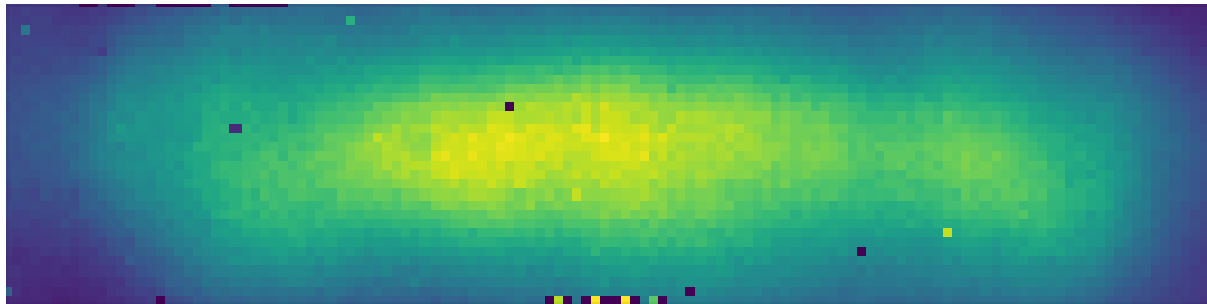
# Spot modeling

Total **photon detections per pixel** during  
20230627\_095732\_cuchillo1\_scan00091.bpf



Analyzing 20230627\_095732\_cuchillo1\_scan00091.bpf

- [30 frame moving average pixel hitmap](#)
  - [Model with Gaussian Mixture Model](#)
  - [Model with GMMis](#)
  - [Model with GMMis, keep only 1% of detections](#)
- 



## Truncated multivariate normal likelihood

■ Questions ■ v5 ■ modeling



Matthew\_Ward

2  May 22

Hello,

I am trying to fit the mean and covariance of a 2D normal distribution to some data with the complication that my data is truncated. I only have observations within a window, although the underlying distribution really is normal.

Some astronomers had this same problem (among others) while fitting GMMs and made an expectation maximization algorithm that I've successfully used to solve this problem ([Filling the gaps: Gaussian mixture models from noisy, truncated or incomplete samples](#) <sup>1</sup>), but I'd like to try Bayesian inference as well.

As far as I understand, PyMC only has a *univariate* truncated normal (`pymc.TruncatedNormal`), so I'm trying to define my own multivariate truncated normal with constant bounds of truncation. I'm really struggling to implement the normalization constant part. Here's an example, where the third and fourth-to-last lines don't actually work since they use `scipy` to show what I'm imagining.

```
import os
import pymc as pm
from scipy import stats
import numpy as np
rng = np.random.default_rng()

lower_bounds = np.zeros(2)
upper_bounds = np.array([128, 32])
```

# Processing performance report



Not to be confused with sensor performance report!

A consise, readable .pdf report summarizing key insights from processing.

[Single target report](#)

[Vulcan mapping run report](#)



Processing directory

say, albert:/shares/processed/cuchillo/flightData/FlatCreek



.json of filepaths and statistics

to be used in report



L<sup>A</sup>T<sub>E</sub>X report



.pdf report