

# Honours Logbook

Semester 1 2024 - Semester 1 2025

N.B.: This logbook contains notes and updates on my progress and findings throughout my Honours year.

Maintainer:

Jeffrey Liang (u7013004), ANU School of Computing

Contributors:

Jeffrey Liang (u7013004), ANU School of Computing

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# 1 Overview

## Welcome to my progress logbook!

 $\operatorname{Hello}.$  Topic. Challenges. Research interest.

### 2 Progress Logbook

#### 2.1 Progress

#### Sun 12/05/2024:

Reading MeshSDF paper.

#### Sat 18/05/2024:

Reading MeshSDF, the Learning Implicit Fields papers, and Structure from Motion. Need to look up what the following mean:

• differentiable rendering, surface reconstruction

#### Sun 19/05/2024:

Reading more from Structure-from-Motion Revisited. Didn't really understand much of SfM last night.

#### Thu 27/06/2024:

Attempting 3D version of the ellipse problem.

Question: Why do we invert the  $u_i$ s? Answer: you bring the 1 over and multiply by some expression on both sides.

#### Fri 5/07/2024:

Having been making headway on the non-axis-aligned ellipsoid. I've been able to fit an ellipse to one but I haven't been able to do the bi-level optimisation. I'm going to try a couple approaches:

- ullet reparametrise everything to radians and a,b,c rather than squared inverses of semi-axes
- try original objective function rather than focusing on optimising rotation
- last resort is to figure out what the SqrtBackward error is

#### Sun 7/07/2024:

Was able to switch implementation to radians and a, b, c rather than squared inverses  $1/a^2, ..., 1/c^2$ . It's still temperamental though and will hopefully be finetuned when meeting with Chamin who hopefully has a few tricks. Going to read some papers today about DRWR and the DDN and take notes to try and fully understand derivations etc.

#### Sat 20/07/2024:

Reading additional papers and waiting for Steve's meeting. Reading "Small Steps and Level Sets" by Chamin and will document.

#### Mon 29/07/2024:

Trying to do experiments to ensure I know the cause of my errors and that it's not some implementation error. Will do:

- small volume initialisations
- close to ground truth initialisations
- tightening the constraint slowly
- PCA?

Ideal semi-axes lengths is: 0.28209 Trials:

- $1. \ \, initialisation: \ \, 0.2, \ \, 0.4, \ \, 0.3, \ \, 30^{\circ}, \ \, 25^{\circ}, \ \, -120^{\circ}. \ \, final: \ \, 0.271, \ \, 0.296, 0.28, \ \, 29.98^{\circ}, \ \, 24.99^{\circ}, \ \, 60.0^{\circ}$
- 2. initialisation: 0.1, 0.2, 0.3, 30°, 25°, -120°. final: 0.479, 0.29,0.0913, 83.83°, 128.2°, 47.02° (no improvement). the issue here is that the fitted ellipse is too far away from a sphere for it to approach a sphere?
- 3. initialisation: close to ideal. result: optimised fine and as expected.

Perhaps farthest point sampling would prevent the ellipse from over concentrating at the poles.

Issue! For Trial 2, a close reinitialisation of 0.1, 0.3, 0.5 and angles  $30^{\circ}$ ,  $25^{\circ}$ ,  $-120^{\circ}$  worked well. In fact, an exact reinitialisation worked?! But then when reverting back so that the fitted ellipse had those params, the gradients calculated were zero.

Steps to reproduce error:

- 1. Initialise with 0.1, 0.2, 0.3 and 30°, 25°, -120°. Run the first cell and then second cell, and we should see no deformation of the fitted ellipsoid to a sphere the parameters remain as 0.479, 0.29,0.0913, 83.83°, 128.2°, 47.02°. The gradients are very close to 0.
- 2. Initialise with the parameters 0.479, 0.29,0.0913 and 83.83°, 128.2°, 47.02°. We see that the gradients are non-zero and we optimise to a sphere.

a, b, c = 0.4786546028, 0.2901328092, 0.09132074619 yaw, pitch, roll = 83.82856741, 128.3492915, 47.0228292

#### Thu 15/08/2024:

Steve told me that I needed to update the DDN package and it worked!

I spent the past week a bit confused on how to do projection but Steve gave me some clear instructions. I've switched the volume and surface area constraints, but the optimisation is being worse.

#### Sun 18/08/2024:

Going to work on optimising the volume to be a certain target now and read a paper. Then, I'll write some things in the template. Efficiency!

#### Wed 4/09/2024:

For the past few days, I've been trying to mathematically formulate the projection. Just tested it in code today and it seems that I am minimising the area of the cross-section with the x-y plane instead. So, just need to take Schur complement instead of projection with matrix P.

One strange observation is that the gradients seem to increase in magnitude as time goes on; not decreasing.

#### Sun 15/09/2024:

Finally writing about the point-sampling approach. Have been busy with side project website.

#### Fri 20/09/2024:

Trying to add a regulariser between iterations for lower problem.

#### Sun 22/09/2024:

Going to fully do the regulariser and report results. Will also provide warm-starting with previous solution.

#### Mon 23/09/2024:

Tried switching to float64 and it's not working. Going to try add more views. For

#### Sun 29/09/2024:

Worked on Chamfer distance and it worked! Forgot to take inverse of square root matrix but figured it all out after reading my projection notes.

Going to write my ellipsoid stuff in this logbook until I have to copy it over into my thesis.

**2024-09-29**, : Figure out Blender stuff, proposal, and whether to use other nearest-neighbour method.

#### Sun 6/10/2024:

Wrote up some stuff for ellipsoid. Still unsure how to tackle boundary?

#### Mon 21/10/2024:

Basically spent 2 weeks without doing work. Time to do more! Going to attempt the alpha shapes approach. Hopefully converting back and forth from tensor to numpy won't do weird things.

#### Thu 23/01/2025:

Not sure how the mesh will be able to handle concavities if only the boundary points are detected in the upper-level loss, these will only be able to handle convex parts. I guess that the lower-level loss will handle that by moving in those concave sections in more.

### 3 Ellipsoid Formulation

An ellipsoid is a 3-dimensional surface obtained by deforming a sphere under an affine transformation. As ellipsoid surfaces can be represented as the zero set of a quadratic polynomial in three variables, it is considered a quadric surface.

There are multiple mathematical representations of ellipsoids. Ellipsoids have three pairwise perpendicular axes of symmetry known as principal axes which intersect at the centre of the ellipsoid. The most general ellipsoid is a triaxial ellipsoid, where each of these three principal axes are of different lengths. The line segments along these axes from the origin to the surface boundary are named the principal semi-axes as they are half the length of the principal axes. An ellipsoid centred at the origin and with its axes aligned to the standard basis of  $\mathbb{R}^3$  is commonly represented in Cartesian coordinates as the points  $(x, y, z) \in \mathbb{R}^3$  which satisfy

$$\frac{x^2}{a^2} + \frac{y^2}{b^2} + \frac{z^2}{c^2} = 1, (3.1)$$

where a, b, and c are the lengths of the semi-axes. If we let  $\mathbf{x} = [x, y, z]^{\top} \in \mathbb{R}^3$ , then we can represent this expression becomes

$$\mathbf{x}^{\top} \mathbf{A} \mathbf{x} = 1, \tag{3.2}$$

where

$$\mathbf{A} = \begin{bmatrix} 1/a^2 & 0 & 0\\ 0 & 1/b^2 & 0\\ 0 & 0 & 1/c^2 \end{bmatrix}.$$

However, ellipsoids need not be axis-aligned with respect to the standard basis. Rather than having  $\mathbf{A}$  be a diagonal matrix with the inverse squared semi-axes lengths, we can generalise ellipsoids to be non-axis-aligned by letting  $\mathbf{A}$  be any symmetric positive-definite matrix – that is, having  $\mathbf{A} \in \mathbb{S}^3_{++}$  such that  $\mathbf{A} = \mathbf{A}^\top \succ 0$ . This represents an ellipsoid  $\mathcal{E}$  as the convex set

$$\mathcal{E} = \left\{ \mathbf{x} \in \mathbb{R}^3 \mid \mathbf{x}^\top \mathbf{A} \mathbf{x} = 1, \mathbf{A} \in \mathbb{S}_{++}^3 \right\}. \tag{3.3}$$

We can further perform an eigendecomposition on  $\mathbf{A}$  to express it in terms of an orthonormal rotation matrix  $\mathbf{R} \in SO(3)$  and a diagonal matrix  $\mathbf{\Lambda}$  containing the eigenvalues of  $\mathbf{A}$ , which are the inverse squares of the semi-axes lengths:

$$\mathbf{A} = \mathbf{Q}^{\top} \mathbf{\Lambda} \mathbf{Q},\tag{3.4}$$

where 
$$\mathbf{\Lambda}=\begin{bmatrix}1/a^2&0&0\\0&1/b^2&0\\0&0&1/c^2\end{bmatrix}$$
 and thus

$$\mathcal{E} = \left\{ \mathbf{x} \in \mathbb{R}^3 \mid \mathbf{x}^\top \mathbf{Q}^\top \mathbf{\Lambda} \mathbf{Q} \mathbf{x} = 1, \mathbf{Q} \in SO(3) \right\}. \tag{3.5}$$

### 4 Deep Declarative Nodes

Deep neural networks are themselves optimisation problems, where a loss function is minimised over the network weights. Backpropagation enables this optimisation to occur efficiently. However, incorporating constraints into a neural network complicates this procedure as constraints need to be respected in the optimisation process. Furthermore, constrained optimisation is often iterative and not naturally compatible with the differentiable nature of the current neural networks.

Deep declarative networks (DDNs) provide a new framework to achieve backpropagation through certain constrained optimisation problems. The conditions for these problems are that we need the optimal solution to the optimisation problem and twice-differentiable objective and constriant functions, and thus the method used to find the optimal solution can be non-differentiable, such as RANSAC.

### 5 Project Book Components

We can use sections organize the text into different parts such that specific topics are addressed in their own section.

#### **TODOs**

You will often have pending tasks that you need to track. This project logbook allows you to include both high and low priority todos that will be summarised in a list at the end of the file. Use the commands \hightodo{<date\_added>}{<author\_key>} and \lowtodo, including a date is recommended for tracking purposes.

Note: define your userId in the preamble

2016-05-23,: Try the code in the newest version of numpy compiled with optimized BLAS.

2016-05-27, u7013004: Perform convergence analysis with the latest version of the code.

#### 5.1 Algorithms

Sometimes the most straightforward way to explain a procedure is just to give it in a algorithmic format, it takes a little time but it will force you to go through the steps and you will most likely be able to reuse it on you paper. For the full documentation see here <a href="https://texdoc.org/serve/algorithmicx/0">https://texdoc.org/serve/algorithmicx/0</a>.

#### Algorithm 1 Euclid's algorithm

```
1: \operatorname{procedure} \operatorname{EUCLID}(a,b) \triangleright The g.c.d. of a and b

2: r \leftarrow a \bmod b

3: \operatorname{while} r \neq 0 \operatorname{do} \triangleright We have the answer if r is 0

4: a \leftarrow b

5: b \leftarrow r

6: r \leftarrow a \bmod b

7: \operatorname{return} b
```

#### **5.2** Code

If the algorithm is too vague and you feel like you need the source code you can also insert it. You can put LaTeX code inside by using <0 0> delimiters, highlight small pieces of the code with <| |> delimiters, and highlight full lines (see the source code). For now only Python colored syntax highlighting is available, but most languages are supported and the color scheme can be added. More information available here https://www.overleaf.com/learn/latex/Code\_listing.

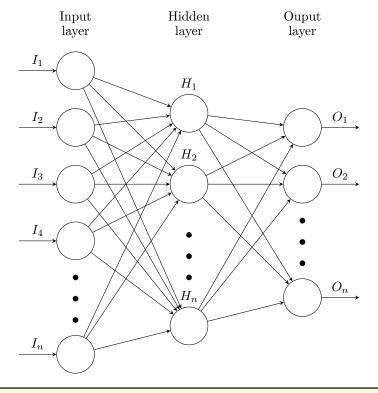
Note that these pieces of code in the LATEX document must start with no indent.

```
def DTW_distance(s1, s2):
1
       11 11 11
2
3
      Function to compute the Dynamic Time Warping in Python between two
      signals
4
5
      DTW = \{\}
6
7
       for i in range(len(s1)):
           DTW[(i, -1)] = float('inf') # By default \infty
8
9
       for i in range(len(s2)):
```

```
DTW[(-1, i)] = float('inf') # By default \infty
10
11
     DTW[(-1, -1)] = 0
12
13
     for i in range(len(s1)):
14
         for j in range(len(s2)):
            dist = (s1[i]-s2[j])**2
15
            16
17
18
     return sqrt(DTW[len(s1)-1, len(s2)-1])
19
```

#### 5.3 Diagrams

For simple diagrams I highly recommend learning TiKZ, you will be drawing the diagrams in pure LaTeXwhich has a steep learning curve but once you get used to it, it can be quite easy to display and do for loops to draw multiples line at once.



However, sometimes you will need more complicated diagrams (or maybe you do not like TiKZ, in that case I recommend a vector drawing tool such as Inkscape which allows LATEX embedding)

#### 5.4 Figures

In general the best way to visualize your results will be some figures, I recommend Python's matplotlib for generating them or any other tool you are familiar with.

#### 5.5 Tables

LATEX booktab environments are really good to showcase and track your results, however they can get fairly messy. My suggestion is to generate them via Python automatically and store the results in either a plain text file or a spreadsheet (there are packages to read spreadsheets with Python)

$\sigma \setminus \tau$	0	1	2	3	4	5	6	7	8
0.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
0.2	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
0.4	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
0.6	98.6	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
0.8	84.7	99.5	100.0	100.0	100.0	100.0	100.0	100.0	100.0
1.0	28.1	98.3	99.9	100.0	100.0	100.0	100.0	100.0	100.0
1.2	1.3	88.7	99.4	99.9	99.8	99.9	100.0	99.9	100.0
1.4	0.0	57.1	96.2	99.3	99.0	99.3	99.4	99.8	99.7
1.6	0.0	18.6	81.2	93.0	93.7	94.8	95.6	92.3	93.3
1.8	0.0	2.4	42.8	67.0	70.1	72.1	69.0	69.1	68.6
2.0	0.0	0.1	9.0	23.1	24.5	26.9	28.2	27.3	27.3
t(ms)	27.92	40.23	77.30	157.27	252.05	342.18	381.46	399.85	413.72

Table 5.1: Performance of the algorithm for 128-bit key and with multiple readings per key

# 6 Topic C to focus on

# A References

Do not forget to cite the papers that you are using in your research, this way your work will be infinitely easier to write down and to review when the time comes.

#### B Resources

It is a good idea to record sources that explain concepts or provide tools so the research is both better documented and if someone has to continue it there is enough supporting documentation.

- Quick read in DTW and Keogh Lower Bounding. http://alexminnaar.com/time-series-classification-and-clustering-with-python.html http://nbviewer.jupyter.org/github/alexminnaar/time-series-classification-and-clustering/blob/master/Time%20Series%20Classification%20and%20Clustering.ipynb
- Parallelizing DTW Good article on making a parallel version of DTW. Uses Keogh lower bound not as a linear approximation but as a pruning device. https://www.andrew.cmu.edu/user/mmohta/15418Project/finalreport.html
- Deep Learning
  - Intro to LSTM https://colah.github.io/posts/2015-08-Understanding-LSTMs
  - Intro to CNN https://colah.github.io/posts/2014-07-Conv-Nets-Modular/
  - Why are LSTMs are so useful, impressive result in character pattern and syntax learning https://karpathy.github.io/2015/05/21/rnn-effectiveness/

# C TODOS

Here you will have all your TODOs grouped with anchor links to the parts of the document where they are. Really handy if you do not know where to continue with your project.

# Todo list

<b>2024-09-29</b> , : Figure out Blender stuff, proposal, and whether to use other nearest-neighbour method.	6
2016-05-23, : Try the code in the newest version of numpy compiled with optimized BLAS	10
2016-05-27, u7013004: Perform convergence analysis with the latest version of the code	10