	Solution
	Process:
	Definition:
	Example:
2	Problem 2: Prescribe a strategy to optimize the NN.
	Process:
	Definition:
	Example:
3	Problem 3: Explain step by step inference for basic algorithms (MLP, CNN, GNN, attention mechanism) in terms of numpy or basic tensor operations.
	Process:
	Definition:
	Example:
4	Problem 4: Be able to explain why such a solution might work or fail.
	Process:
	Definition:
	Example:

Problem 1: Description of the Problem, Subscribe a ML/NN Based

5 Neural Network Engineering

5.1 Data

Summary:

- 5.2 Evaluation
- 5.3 Optimization/Training
- 5.4 Regularization & Modelling
- 5.5 Experiments
- 6 Loss Functions

Summary:

7 Algorithms

Summary: Algorithm Inputs Outputs **Equations** RNN x_t, h_{t-1} $h_t = \tanh(\operatorname{Linear}(h_{t-1}) + \operatorname{Linear}(x_t))$ y_t, h_t $y_t = MLP(h_t)$ • x_t : Input, h_t : Hidden state, y_t : Output GRU x_t, h_{t-1} y_t, h_t $z_t = \operatorname{sigmoid}(\operatorname{Linear}(x_t) + \operatorname{Linear}(h_{t-1}))$ $r_t = \operatorname{sigmoid}(\operatorname{Linear}(x_t) + \operatorname{Linear}(h_{t-1}))$ $h(t) = \tanh(\operatorname{Linear}(x_t) + \operatorname{Linear}(r_t \odot h_{t-1}))$ $h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$ • z_t : Update gate, r_t : Reset gate • h_t : Hidden state LSTM $f_t = \operatorname{sigmoid}(\operatorname{Linear}(x_t) + \operatorname{Linear}(h_{t-1}))$ x_t, h_{t-1} h_t, c_t $i_t = \operatorname{sigmoid}(\operatorname{Linear}(x_t) + \operatorname{Linear}(h_{t-1}))$ $o_t = \operatorname{sigmoid}(\operatorname{Linear}(x_t) + \operatorname{Linear}(h_{t-1}))$ $\tilde{c}_t = \tanh(\operatorname{Linear}(x_t) + \operatorname{Linear}(h_{t-1}))$ $c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$ $h_t = o_t \odot \tanh(c_t)$ • f_t : Forget gate, i_t : Input/Update gate, o_t : Output gate • h_t : Hidden state, c_t : Cell state

7.1 Geometric DL Blueprint for NNs

Summary: Unify various networks around symmetry. ADD IMAGE

8 Code to Paper

8.1 Ideas

Summary:

Exercise

Write research ideas. Get a mentor to rate them

Ask other researchers about their taste

Read about history of research ("The Structure of Scientific Revolutions")

De-risk your ideas: Proactive idea evaluation mitigates research risks (kill fast, learn fast)

- 1. Identify potential bottlenecks
- 2. Prioritize and commit X amt. of time to exploring them
- 3. Decide if you should continue or pivot
- Research Taste

Warning:

- Getting attached to one direction.
- Lack of research knowledge / intimacy.
- Environment is not supportive of your interests.

8.2 Code / Experiments

Summary:

Tools Links

Artifacts to create/track w/ experiments

• Data, code (scripts / modules), models (weights, configurations), results, predictions, plots, meeting notes, papers, documentation, etc.

Git (Version Control): Enables effective tracking and collaborative changes

Git Guide

- Tracking changes, collaboration, backup, revert.
- Add, commit -m "message", push, pull, merge, diff, revert, branch, checkout, log, status, etc.
- .gitignore: Ignore files, directories, or patterns

GitHub (Collaborative Code Hosting): Facilitates sharing and collaboration on code GitHub

• Collaboration, sharing, open science, project hosting.

Cookiecutter (Project Template): Standardizes project structure

Cookiecutter Repo

- Logical, flexible, and reasonably standardized project structure for doing and sharing data science work.
- File Structure
 - data/:
 - * external/: Data from third party sources.
 - * interim/: Intermediate data that has been transformed.
 - * processed/: The final, canonical data sets for modeling.
 - $\ast\,$ raw/: The original, immutable data dump.
 - src/: Source code for use in this project.
 - * ___init___.py: Makes src a Python module.
 - * config.py: Configuration settings.
 - * dataset.py: Code to load data.
 - * features.py: Code to build features.
 - * modeling/: Code to train models.
 - · init .py: Makes modeling a Python module.
 - · predict.py: Code to make predictions.
 - · train.py: Code to train models.
 - * plots.py: Code to create plots.
 - docs/: Documentation for this project.
 - models/: Trained and serialized models, model predictions, or model summaries.
 - notebooks/: Jupyter notebooks.
 - references/: Data dictionaries, manuals, and all other explanatory materials.
 - reports/: Generated analysis as HTML, PDF, LaTeX, etc.
 - * figures/: Generated graphics and figures to be used in reporting.
 - pyproject.toml: Project information and dependencies.
 - requirements.txt: The requirements file for reproducing the analysis environment.
 - setup.cfg: Configuration file for setting up the project.
 - LICENSE:
 - Makefile:
 - README.md:

Summary:

Tools Links

Cookiecutter (Project Template): Standardizes project structure Opinions

• Design Philosophy: Prioritizes conventions and reasonable defaults to streamline project setup. Opinions:

- Data analysis is a DAG:
 - 1. Raw data
 - 2. Compute features
 - 3. Plot analysis on raw data
 - 4. Train model
 - 5. Compute statistics on features
- Raw data is immutable (i.e. never change raw data)
 - * Dos:
 - · Pipeline code: Process raw data \rightarrow final analysis.
 - · Cache outputs: Serialize or cache intermediate steps.
 - · Reproducible results: Enable full reproduction from code and raw data only.
 - * Don'ts:
 - · Never edit raw data: Avoid manual edits or format changes
 - · Never overwrite raw data: Do not replace raw data with processed data.
 - · Single raw data version: Maintain only one version of raw data.
- Data should (mostly) not be kept in source control
 - * GitHub warns for files over 50MB and rejects files over 100MB.
 - * Use s3, azcopy, gcloud, drive to store data (i.e. cloud services)
 - * Use cloudpathlib to access cloud data in the same way as pathlib to access local data.
- Notebooks are for exploration and communication, source files are for repetitions.
- Refactor the good parts into source code (Refactor Example).
 - * Don't write code to do the same task in multiple notebooks.
- Keep your modelling organized (PyTorch Example)
 - * Predictions (csv), training log (csv), stats (txt), model config / hyperparameters (json)
- Build from the environment up (Mamba)
 - * Use mamba rather than conda for faster environment management.
 - * Create a environment.yml file to manage dependencies.

8.3 Writing / Analyzing

Summary:

Exercise	Links
Writing Skeleton	Step-by-Step Guide to Undergraduate Writing How to write a first-class paper (Nature) Preparing Manuscript: Scientific Writing for Publication

- 1. Start w/ Figures (How would you want to tell the story?)
- 2. Write the structure (Introduction, Methods, Experiments and Results, Discussion)
- 3. 2-3 sentence pitch for your idea
- 4. Bullet points inside of each section (What are you expecting to cover?)
- 5. Fill in text, repeat.

Figures: Move quick, perfect later

- Figure #1: Tells problem in simple way (30s elevator pitch)
- Figure #2-3: Conceptual or data centric
 - How are you solving the problem?
 - What does the data look like?
- Figure #4-8: Quantitative evidence
- Recommendations:
 - Napkin/whiteboard figures first
 - Make good enough version w/ code (svg, png) using matplotlib, seaborn, etc.
 - Finetune w/ InkScape, Illustrator, GIMP, etc
- Anatomy of a Figure Examples (L8):
 - Slide 44: Task, Slide 45: Model + EDA
 - Slide 46-47: Quantitative evidence, Slide 48: Different ways of telling same story (e.g. tables or plots)

Pick good, consistent colors

ColorBrewer, Matplotlib Colormaps Seaborn Palettes, NeurIPS 18 Visualization for ML tutorial

• Be mindful of how colours can help tell a story, accessibility is also important.

Pair-writing (Como Pair-Coding)

Rubber Duck Debugging, Pair Programming Pair Writing, Pair Writing in Government

 \bullet Working together \to Help communicate thoughts adn put you in a diff. attitude.

Communar writing (Social pressure → account

Communal writing (Social pressure → accountable) Harvard Writing Center

- 1. Setup an objective, measurable goal.
- 2. Set a time for writing period, take breaks
- 3. Share progress at the end of each session, share writing stuggles if needed.
- 4. Reflect if there are some reasons why it is hard to write.

Writing: Focus on quick iterations

 $\bullet \ \ \text{Google docs and Paperpile (Copy DOI, paste, click, done)} \stackrel{\text{Export w/ bibtex}}{\Longrightarrow} \text{LaTex (Overleaf)}$

Interactive Apps	Streamlit, Gradio
	Hugging Face, Hugging Face Spaces
	Academic Project Page Template

9 Symmetries, Tabular Data, Sets

9.1 Symmetries in Data

Summary: Transformations that preserve data characteristics.

Transformation Type

Description

Invariance (f(g(x)) = f(x))

Invariant to a trans. if output is unchanged when the input does that trans.

- \bullet e.g. f = label, g = translation, scale, rotation. Regardless of transformation, label remains the same.
- Useful for classification tasks where transformations should not change the label.

Equivariance (f(g(x)) = g(f(x))) Equivariant to a trans. if output changes in the same way as input.

- e.g. f = position, g = translation. If f is applied first and then g, the output changes in the same way as applying g first and then f.
- Useful in tasks where spatial relationships need to be preserved, such as object localization.

Data Type Symmetry

Tabular Data Row permutation invariance

• Ordering of rows does not affect the output.

Sets Element permutation invariance

• Elements have no inherent order, so the output should not change if elements are swapped.

Images Translation, rotation, and scaling invariance

• Image recognition should not be affected by the translation, rotation, or scaling of the image.

Time-series Time shift invariance

• Patterns should be the same regardless of when they occur.

Graphs Node permutation invariance

• Nodes can be rearranged without changing the graph's structure since the edges remain the same.

Text Sentence structure and paraphrasing invariance

Rewording a sentence or changing its structure should not change its meaning.

- 9.2 Learning on Tabular Data
- 9.3 Learning on Sets