Syllabus Draft 7/25/2024

BIOM/ECE580C7 Machine Learning in Imaging and Spectroscopy

Fall 2024

Instructor: Jesse Wilson

Lectures (Sections 001): MWF 9:00-9:50AM, ENGR B105.

Lectures (Sections 801): live via Zoom or recorded via Echo360 (links will be posted to Canvas).

The first two lectures (8/19/2024 and 8/21/2024) will be delivered remotely, as I will be away at a conference. Zoom links will be posted to Canvas ahead of time.

Office Hours: MTW 3-4pm, Scott 324 or via MS Teams

Course Description: Advances in optical imaging and spectroscopy are relying more and more on machine learning tools such as principal component analysis, neural networks, and convolutional networks. Students will investigate and critique applications of current techniques such as convolutional networks to problems such as deconvolution, computed tomography, phase retrieval, hyperspectral unmixing, and learn how to apply these methods to datasets of their own. Throughout the course will be a special emphasis on biomedical imaging technologies and applications such as phase contrast microscopy, low-dose x-ray computed tomography, sparse fast magnetic resonance imaging, etc.

Prerequisites: ECE312 or ECE457, BIOM/ECE403 (co-requisite) or ECE441 (co-requisite) or ECE504, ECE303 or STAT303 or ECE431, CS152

Textbook: Deep Learning with Pytorch (Manning), 1st edition (2020).
https://www.manning.com/books/deep-learning-with-pytorch

Additional reading materials: a selection of 5-6 landmark papers in each of the application areas to be discussed.

Software: python/numpy/pyplot/pytorch hosted on ETS virtual computing lab and ETS linux GPU servers. See https://www.engr.colostate.edu/ets/computing-resources/. PowerPoint or other presentation software may be used if it can export to .ppt, .pptx, or .pdf formats.

Course Learning Objectives (CLOs): Upon successful completion, students will be able to:

1. Select a neural network architecture and training strategy to perform common tasks in optical imaging and spectroscopy, such as deconvolution, spectral unmixing, phase retrieval, etc.
2. Identify and mitigate overfitting and underfitting.
3. Identify successful applications of machine learning to optics.
4. Apply recent techniques in machine learning to an optics problem or dataset of their choosing.
5. Critique current published literature on machine learning in optics, identify potential limitations, and assess whether claims are fully substantiated by the experiments therein.
6. Explain the difference between supervised and unsupervised learning.

7. Extend a supervised learning approach by adding a physical model in the training loop.
8. Recognize common elementary operations (e.g. fully-connected artificial neurons, convolutional filters, pooling, activation function) and common network design patterns (e.g. VGG-like convolutional encoders and U-Net autoencoders).
9. Evaluate the physical limitations of optical measurements/experiments, and limitations of conventional algorithms that motivate machine learning for parameter estimation and model inversion.

Topics / Weekly Schedule

Week	Lecture Content	CLO Number
1	Introduction, pytorch/jupyter environment setup, Gradient descent, overfitting/underfitting and cross-validation, loss functions overview, adversarial training,	1,2,4,6,8,9
2	fully-connected network example classifier, convolutional network classifier example, Segmentation example	1,4,5,8
3	Review and exam.	1,2,4,5,6,8,9
4	Noise sources in optical measurements, conventional denoising approaches, limitations Student presentations: current machine learning methods for denoising and extreme low light	1,2,3,4,5,7,8, 9
5	Student presentations continued, review, project work day.	1,2,3,4,5,7,8
6	Diffraction limit and abberrations in optical imaging, conventional super-resolution and deconvolution methods. Student presentations: current machine learning methods for deconvolution and superresolution	1,2,3,4,5,7,8,9
7	Student presentations continued, review, exam	1,2,3,4,5,7,8
8	Holography, quantitative phase imaging and conventional phase retrieval algorithms. Student presentations: current machine learning methods for phase retrieval.	3,5,7,9
9	Student presentation continued, review, project work day.	1,2,3,4,5,7,8
10	Projection tomography, optical setup, applications, conventional reconstruction algorithms. Student presentations: current machine learning methods for tomographic reconstruction	1,2,3,4,5,7,8,9
11	Student presentations continued, review, exam	1,2,3,4,5,7,8
12	Hyperspectral imaging, endmember/unmixing approaches, principal component / independent component analysis, Harsanyi-Farrand-Chang estimation of endmember count Student presentations: current machine learning methods for bind endmember estimation and unmixing	1,2,3,4,5,7,8
13	Student presentations continued, review, exam	1,2,3,4,5,7,8
14	Laser-scanning microscopy, instrument-to-image domain mapping, conventional interpolation/gridding methods	3,5,7,8

15	Bonus topic(s): machine learning methods for instrument-to-image domain mapping (e.g. AUTOMAP), ultrafast pulse reconstruction, or virtual staining / modality transform. Project work day.	1,2,3,5,7,8
16	Project presentations	1-9

Assessment Components

Assessment components	**Percent of grade (total 100%)**
Midterm exams / quizzes	40%
Project	20%
Participation: each student will present and critique an assigned scientific journal article. Additional participation credit from evaluating peers' presentations and final projects.	20%
Homework / coding assignments	20%

Deadlines and extensions. In lieu of extensions and exceptions, in the homework assignments category, the lowest 2 scores will be dropped, and from the exam category, the lowest score will be dropped from the final grade. Accommodations beyond this will only be considered in the case of extreme circumstances with documentation from CSU Student Case Management.

Homework / coding assignments:

- HW01: install/load Jupiter and pytorch env, show versions and GPU (textbook ch1)
- HW02: hand calculations (receptive field, simple backprop, etc) -- see Stevens Ch13 for receptive field
- HW03: load and evaluate pre trained models (textbook ch 2)
- HW04: hyperparameter tuning / cross-validation
- HW05: denoising, supervised setup, MNIST or something simple
- HW06: deconvolution, supervised setup, show what happens if you change PSF after training
- HW07: phase retrieval, unsupervised. Set up FFT coherent diffractive imaging forward model, mix and match MNIST images for amplitude+phase.
- HW08: projection tomography. Set up forward model by rotations/projection. Sparse reconstruction.
- HW09: spectral imaging: set up basic unmixing network, on synthetic dataset

In-class presentations: each student will present and critique an assigned scientific journal article. 15min presentation + 5min Q&A. Online students (Sections 801) will need to either present during scheduled lecture via Zoom, or pre-record their presentations so we can play them back during scheduled lecture time, and will need to respond to questions via the online discussion board.

Projects: In lieu of a Final Exam, students will complete a project, and present on their approach and results to the class at the end of the semester. 15min presentation + 5min Q&A. Online students (Sections 801) will need to either present during scheduled lecture via Zoom, or pre-record their presentations so we can play them back during scheduled lecture time, and will need to respond to questions via the online discussion board. Project topic must involve optics, imaging, or spectroscopy **plus** the use of a forward model. For example: learning to deblur by training on a single blurry image, using reconstruction of the blurry image by convolution of the deblurred estimate with a point spread function. Examples of projects outside the scope of this class include LLMs, image classification, learning to denoise by matching the output to known clean images, etc.

AI Policy: AI tools such as large language models (e.g. ChatGPT) may be used in the same way that a tutor, textbook, or documentation may be consulted for assistance. All submitted assignments must be the student's own work, and the student must be able to explain to the instructor, if asked to do so, all their submitted work without AI assistance. AI usage must be disclosed (e.g. "I used ChatGPT to generate code for the U-net here, and made the following modifications…"). Examples of acceptable use include: asking for help with a syntax error, providing template/boilerplate code, or brainstorming project ideas. Examples of unacceptable use include: prompting the AI to complete the assignment, prompting the AI to evaluate your peers' work instead of evaluating it yourself. Failure to disclose AI usage or misuse of AI tools will be treated as academic misconduct.

CSU resources: The linked page provides policies relevant to your courses and resources to help with various challenges you may encounter. https://col.st/2FA2g