Spring 2023 ECE 50024 / STAT 59800

Machine Learning I: Syllabus

Course Information

Instructor: Prof. Qi Guo
TA: Ruqi Bai, Wei Chen
Time: TuTh 1:30 pm-2:45 pm Eastern Time
Location: Wetherill Lab of Chemistry 172
Course Credit Hours: 3.00

Course Website: https://ml1.qiguo.org

For Spring 2023, the class is offered both in-person and asynchronously online. For online students, you can find recordings of the lectures on BrightSpace.

Contact and Office Hours

For any course-related issue, please use the course email below. Please do not email our teaching staff using their personal or Purdue email addresses. Emails sent to the teaching staff's Purdue emails are highly likely to be missed.

Email: ml1.ece.purdue@gmail.com

You may specify the person in your email. We will do our best to have him/her reply to your email as soon as possible.

Office Hours: To be posted on Piazza.

Course Description

This is a graduate-level machine learning course at Purdue ECE. Compared to the various machine learning classes offered on the Internet, this one will focus on the mathematics behind some traditional and fundamental topics in machine learning. The goal of this class is to help students gain a deeper understanding of the mathematical intuition and connection behind a variety of machine learning methods rather than programming per se.

The four clusters of topics that will be covered in this course are listed below.

Mathematical Preliminaries. Matrices, vectors, Lp norm, geometry of the norms, symmetry, positive definiteness, eigen-decomposition. Unconstrained optimization, graident descent, convex functions, Lagrange multipliers, linear least squares. Probability space, random variables, joint distributions, multi-dimensional Gaussians.

Linear Classifiers. Linear discriminant analysis, separating hyperplane, multi-class classification, Bayesian decision rule, geometry of Bayesian decision rule, linear regression, logistic regression, perceptron algorithms, support vector machines, nonlinear transformations.

Learning Theory. Bias and variance, training and testing, generalization, PAC framework, Hoeffding inequality, VC dimension.

Robustness. Adversarial attack, targeted and untargeted attack, minimum distance attack, maximum loss attack, regularization-based attack. Perturbation through noises. Robustness of SVM.

These topics could help you understand the principles and limitations of machine learning methods, which can be generalized to various popular tools nowaday not covered in this class. If you are taking this course as your *first* class in machine learning, it could lay a solid mathematical foundation for you as you journey on in this field. If you already have machine learning backgrounds, the class could possibly provide you addtional understanding of machine learning from a mathematical perspective.

Past Offerings

This course was initially developed by Prof. Stanley Chan. As it is evolving every year, please use the materials, e.g., homework, handouts, etc., published on https://ml1.qiguo.org for Spring 2023.

Pre-requisites

Linear Algebra: MIT 18.06 (textbook) / Stanford ENGR 108 (textbook) / Purdue MA 511
Optimization: MIT 6.079 / Stanford EE 364A (textbook) / Purdue ECE 647
Probability: MIT 6.012 (textbook) / Purdue ECE 302 (textbook)

To help you determine if you have adequate pre-requisites, we encourage you to try homework 0:

Homework 0: (PDF.)

Grades

All students will be graded by the rubrics listed below. Everyone (PhD, MS, undergrad, online) will be graded on the same curve. If you choose Pass-No Pass, you still need to do everything. If you are above the cut off, you will pass.

Homework (10%). There are six homeworks. I will drop the worst one. Each homework will have 2 points: If you complete the homework, you get 2. If you are partially done with the homework, you get 1. If you do not submit, you get 0. I do not accept late homework.

Quiz (40%). There will be six quizzes, and the worst one will be dropped. Each quiz is 60 minutes long. Each quiz will carry 8%. The quizzes are conducted after the due date of the homework. You will be given about 48-hour window to complete the 60-min quiz, completely online. During the quiz, I will ask you lecture questions. I will also ask you homework questions. For example, if in the homework I ask you to plot a figure, I may ask you to change a parameter and re-plot the figure. Quizzes will be open-book, open-note, open-computer. However, with only 60 minutes, you probably will not have time to read anything besides answering the questions. So, please do the homework.

Final Project (50%). Due Apr 29. You will need to re-implement from scratch the method from a paper I assign you, and write a final report. In the final report, you will need to introduce the methematical derivation of the method, and show experiments you performed using your re-implementation. See the project page for the list of papers. We will send out a survey at the beginning of the class to ask your preference on the papers and then make the assignment. Please refer to the project page for more details of the final project.

Textbook and References

There is no official textbook for this course. Please refer to the lecture note section of the website for our lecture materials.

A few good reference books for this course are:

Introduction to Probability for Data Science, by Stanley Chan, draft. 1st edition. 2020.

Pattern Classification, by Duda, Hart and Stork, Wiley-Interscience; 2 edition, 2000.

Learning from Data, by Abu-Mostafa, Magdon-Ismail and Lin, AMLBook, 2012.

Elements of Statistical Learning, by Hastie, Tibshirani and Friedman, Springer, 2 edition, 2009.

Pattern Recognition and Machine Learning, by Bishop, Springer, 2006.

Programming

We will be primarily using Python. As such, I expect you to have elementary programming skills, e.g., writing a hello world program. More information and resources on how to use Python can be found in the resource section of this website.

Besides Python, we use optimization packages to solve optimization problems. Of particular importance is CVX.

FAQ

- **Am I ready to take the course?**

  There is no official pre-requisite of the course (e.g., taking a prior course), although we expect students to have good background in linear algebra, optimization and probability.

  Historically, undergraduate students and non-ECE PhD students have found this course difficult.

  Pleaes check out the information about pre-requisite to see if you are ready for the course.

- **What is the difference between ECE 595 and other machine learning courses on campus?**

  We focus on general principles of learning.

  Our goal is to provide an in-depth discussion of the subject, rather than superficially glancing through different topics.

  We put significant emphasis on understanding the mathematics behind the algorithms.

  We have plenty of hands-on programming exercises.

- **What will I learn after taking ECE 595?**

  You will know what a linear model is, such as Bayesian decision rule, perceptron algorithm, logistic regressoin, support vector machine, etc.

  You will know how to understand a linear classifier from a geometric perspective.

  You will know how to attack a classifier.

  You will know the how much a machine learning algorithm can do, and what a machine learning algorithm cannot do.

  You will know how to implement machine learning algorithms using Python and CVX.

- **Can I audit the class?**

  Unfortunately, sorry.

- **Where can I get help for programming problems?**

  Please reach out to our teaching assistants.

Tentative Schedule

The actual is subject to change.

Week 1

- Jan 11, 2022. Lecture 0.
  - Topics: Course overview and mathematics review.
- Jan 13, 2022. Lecture 1.
  - Topics: Linear regression.

Week 2

- Jan 18, 2022. Lecture 2.
  - Topics: Outliers in linear regression
- Jan 20, 2022. Lecture 3.
  - Topics: Ridge and LASSO Regression

Week 3

- Jan 25, 2022. Lecture 4.
    - Topics: Optimization I
- Jan 27, 2022. Lecture 5.
    - Topics: Optimization II

Week 4

- Feb 1, 2022. Lecture 6.
    - Topics: Linear Separability
- Feb 3, 2022. Lecture 7.
    - Topics: Bayesian Classifier I

Week 5

- Feb 8, 2022. Lecture 8.
    - Topics: Bayesian Classifier II
- Feb 10, 2022. Lecture 9.
    - Topics: Classification Error and ROC curves

Week 6

- Feb 15, 2022. Lecture 10.
    - Topics: Parameter Estimation
- Feb 17, 2022. Lecture 11.
    - Topics: Logistic Regression I

Week 7

- Feb 22, 2022. Lecture 12.
    - Topics: Logistic Regression II
- Feb 24, 2022. Lecture 13.
    - Topics: Kernel Trick

Week 8

- Mar 1, 2022. Lecture 14.
    - Topics: Kernel Trick
- Mar 3, 2022. Lecture 15.

    - Topics: Probability Inequality

Week 9

- Mar 8, 2022. Lecture 16.
    - Topics: Is Learning Feasible?
- Mar 10, 2022. Lecture 17.
    - Topics: Probably-Approximately Correct

Week 10

- Spring Vacation

Week 11

- Mar 22, 2022. Lecture 18.
    - Topics: Generalization Bound
- Mar 24, 2022. Lecture 19.
    - Topics: Growth Function

Week 12

- Mar 29, 2022. Lecture 20.
    - Topics: Growth Function Example
- Mar 31, 2022. Lecture 21.
    - Topics: VC Dimension

Week 13

- Apr 5, 2022. Lecture 22.
    - Topics: Bias and Variance
- Apr 7, 2022. Lecture 23.
    - Topics: Overfitting

Week 14

- Apr 12, 2022. Lecture 24.
    - Topics: Intro to Neural Networks
- Apr 14, 2022. Lecture 25.
    - Topics: Convolutional Structures and Back Propagation

Week 15

- Apr 19, 2022. Lecture 26.
  - Topics: Recurrent Networks and Transformers
- Apr 21, 2022. Lecture 27.
  - Topics: Generative Adversarial Networks

Week 16

- Apr 26, 2022. Lecture 28.
  - Topics: Adversarial Attacks
- Apr 28, 2022. Lecture 29.
  - Topics: Conclusions

Grading Scale

This class is graded according to a set curve. Final grades will be distributed through a comparison among students based on the assignments outlined.

Attendance Policy

This course follows Purdue's academic regulations regarding attendance, which states that students are expected to be present for every meeting of the classes in which they are enrolled. When conflicts or absences can be anticipated, such as for many University-sponsored activities and religious observations, the student should inform the instructor of the situation as far in advance as possible. For unanticipated or emergency absences when advance notification to the instructor is not possible, the student should contact the instructor as soon as possible by email or phone. When the student is unable to make direct contact with the instructor and is unable to leave word with the instructor's department because of circumstances beyond the student's control, and in cases falling under excused absence regulations, the student or the student's representative should contact or go to the Office of the Dean of Students website to complete appropriate forms for instructor notification. Under academic regulations, excused absences may be granted for cases of grief/bereavement, military service, jury duty, and parenting leave. For details, see the Academic Regulations & Student Conduct section of the University Catalog website.

Guidance on class attendance related to COVID-19 are outlined on the Protect Purdue website.

Any student who has substantial reason to believe that another person is threatening the safety of others by not complying with Protect Purdue protocols is encouraged to report the behavior to and discuss the next steps with their instructor. Students also have the option of reporting the behavior to the Office of the Student Rights and Responsibilities. See also Purdue University Bill of Student Rights and the Violent Behavior Policy under University Resources in Brightspace.

Academic Guidance in the Event a Student is Quarantined/Isolated

If you must miss class at any point in time during the semester, please reach out to me via Purdue email so that we can communicate about how you can maintain your academic progress. If you find yourself too sick to progress in the course, notify your adviser and notify me via email or Brightspace. We will make arrangements based on your particular situation. Please note that, according to Details for Students on Normal Operations for Fall 2021 announced on the Protect Purdue website, "individuals who test positive for COVID-19 are not guaranteed remote access to all course activities, materials, and assignments."

Academic Integrity

Academic integrity is one of the highest values that Purdue University holds. Individuals are encouraged to alert university officials to potential breaches of this value by either emailing integrity@purdue.edu or by calling 765-494-8778. While information may be submitted anonymously, the more information is submitted the greater the opportunity for the university to investigate the concern.

Any action that might give a student unfair advantage on homework or exams will be considered as academic dishonesty. Examples include, but are not limited to:

- Communicating with others during the quizzes;
- Record and distribute the quiz materials and homework solutions;
- Requesting a re-grade of work that has been altered;
- Submitting work that is not your own.

If you work with another student on a homework, you must acknowledge the person(s) by writing their names on your submission. Regardless if you have worked with another classmate, you must write your own solution. **Write your own solution** means you write in your own words, write your own program, make your own plots. If we see two identical homework, both parties will receive zero.

Cheating in homework and exams will receive penalties including, but not limited to, partial or no credit for the respective work, and / or failing the course.

All cases of academic dishonesty will be reported to the Office of Student Rights and Responsibilities for review at the university level, and will result in punishment. Possible punishments include, but are not limited to, a score of zero on work related to the cheating incident, a failing grade for the course, and, in severe cases, expulsion from the university.

Nondiscrimination Statement

Purdue University is committed to maintaining a community that recognizes and values the inherent worth and dignity of every person; fosters tolerance, sensitivity, understanding, and mutual respect among its members; and encourages each individual to strive to reach his or her own potential. In pursuit of its goal of academic excellence, the University seeks to develop and nurture diversity. The University believes that diversity among its many members strengthens the institution, stimulates creativity, promotes the exchange of ideas, and enriches campus life. Link to Purdue's nondiscrimination policy statement.

Accessibility

Purdue University is committed to making learning experiences accessible. If you anticipate or experience physical or academic barriers based on disability, you are welcome to let me know so that we can discuss options. You are also encouraged to contact the Disability Resource Center at: drc@purdue.edu or by phone: 765-494-1247.

Mental Health Statement

If you find yourself beginning to feel some stress, anxiety and/or feeling slightly overwhelmed, try WellTrack. Sign in and find information and tools at your fingertips, available to you at any time.

If you need support and information about options and resources, please see the Office of the Dean of Students for drop-in hours (M-F, 8 am- 5 pm).

If you find yourself struggling to find a healthy balance between academics, social life, stress, etc., sign up for free one-on-one virtual or in-person sessions with a Purdue Wellness Coach at RecWell. Student coaches can help you navigate through barriers and challenges toward your goals throughout the semester. Sign up is completely free and can be done on BoilerConnect. If you have any questions, please contact Purdue Wellness at evans240@purdue.edu.

If you're struggling and need mental health services: Purdue University is committed to advancing the mental health and well-being of its students. If you or someone you know is feeling overwhelmed, depressed, and/or in need of mental health support, services are available. For help, such individuals should contact Counseling and Psychological Services (CAPS) at 765-494-6995 during and after hours, on weekends and holidays, or by going to the CAPS office of the second floor of the Purdue University Student Health Center (PUSH) during business hours.

CAPS also offers resources specific to COVID-19 on its website. Topics range from "Adjusting to the New Normal" to "How to Talk with Professors about Personal Matters."

Basic Needs Security

Any student who faces challenges securing their food or housing and believes this may affect their performance in the course is urged to contact the Dean of Students for support. There is no appointment needed and Student Support Services is available to serve students 8 a.m.-5 p.m. Monday through Friday. Considering the significant disruptions caused by the current global crisis as it relates to COVID-19, students may submit requests for emergency assistance from the Critical Need Fund.

Emergency Preparation

In the event of a major campus emergency, course requirements, deadlines and grading percentages are subject to changes that may be necessitated by a revised semester calendar or other circumstances beyond the instructor's control. Relevant changes to this course will be posted onto the course website or can be obtained by contacting the instructors or TAs via email or phone. You are expected to read your @purdue.edu email on a frequent basis.

Course Evaluation

During the last two weeks of the course, you will be provided with an opportunity to evaluate this course and your instructor. Purdue uses an online course evaluation system. You will receive an official email from evaluation administrators with a link to the online evaluation site. You will have up to two weeks to complete this evaluation. Your participation is an integral part of this course, and your feedback is vital to improving education at Purdue University. I strongly urge you to participate in the evaluation system.

Homeworks

Submitting Your Homework

Due Date / Time: Homework is due **4:59pm** Eastern Time on the due day. Please submit your homework through Gradescope.

Late homework will not be accepted.

Due Dates

- Homework 0 (PDF.) Do not hand in.
- Homework 1. Due: Jan. 26, 2022 Thursday. 4:59pm Eastern Time.
- Homework 2. Due: Feb. 9, 2022 Thursday. 4:59pm Eastern Time.
- Homework 3. Due: Feb. 23, 2022 Thursday. 4:59pm Eastern Time.
- Homework 4. Due: Mar. 9, 2022 Thursday. 4:59pm Eastern Time.
- Homework 5. Due: Mar. 30, 2022 Thursday, 4:59pm Eastern Time.
- Homework 6. Due: Apr. 13, 2022 Thursday, 4:59pm Eastern Time.

Online Homework Submission

- Go to Gradescope
- Login
- Go to Assignment
- Upload your homework
- Please either type using the LaTeX template posted on this website, or photo-scan the solution

Grading

Homework will be graded on a coarse basis. For each homework, you will receive:

- 2 points. Complete
- 1 points. Partially complete
- 0 points. You do not hand in homework.

Quizzes

There will be six quizzes, and the worst one will be dropped. Each quiz is 60 minutes long. Each quiz will carry 8%. The quizzes are conducted right after the due date of the homework. You will be given a 48-hour window to complete the 60-min quiz, completely online. During the quiz, I will ask you lecture questions. I will also ask you homework questions. For example, if in the homework I ask you to plot a figure, I may ask you to change a parameter and re-plot the figure. Quizzes will be open-book, open-note, open-computer. However, with only 60 minutes, you probably will not have time to read anything besides answering the questions. So, please do the homework. On the contrary, if you attend the lecture and do your homework, you will find 60 mins to be much more than enough for the quiz.

Quiz 0. Don't count in the grade.

- Time: Jan 12 (Thur) 5pm ET to Jan 14 (Sat) 5pm ET.
- Length of quiz: 60 minutes.
- Access through gradescope.
- Coverage: Homework 0.

Quiz 1 (8%).

- Time: Jan 26 (Thur) 5pm ET to Jan 28 (Sat) 5pm ET.
- Length of quiz: 60 minutes.
- Access through gradescope.
- Coverage: Homework 1, and materials I posted before the quiz.

Quiz 2 (8%).

- Time: Feb 9 (Thur) 5pm ET to Feb 11 (Sat) 5pm ET.
- Length of quiz: 60 minutes.
- Access through gradescope.
- Coverage: Homework 2, and materials I posted before today's lecture and after the last quiz.

Quiz 3 (8%).

- Time: Feb 23 (Thur) 5pm ET to Feb 25 (Sat) 5pm ET.
- Length of quiz: 60 minutes.
- Access through gradescope.

- Coverage: Homework 3, and materials I posted before today's lecture and after the last quiz.

Quiz 4 (8%).

- Time: Mar 9 (Thur) 5pm ET to Mar 11 (Sat) 5pm ET.
- Length of quiz: 60 minutes.
- Access through gradescope.
- Coverage: Homework 4, and materials I posted before today's lecture and after the last quiz.

Quiz 5 (8%).

- Time: Mar 30 (Thur) 5pm ET to Apr 1 (Sat) 5pm ET.
- Length of quiz: 60 minutes.
- Access through gradescope.
- Coverage: Homework 5, and materials I posted before today's lecture and after the last quiz.

Quiz 6 (8%).

- Time: Apr 13 (Thur) 5pm ET to Apr 15 (Sat) 5pm ET.
- Length of quiz: 60 minutes.
- Access through gradescope.
- Coverage: Homework 6, and materials I posted before today's lecture and after the last quiz.

Final Project

Learning objectives of the final project

- Understands the machine learning theory behind the method
  - Can clearly describe the method using rigorous mathematical language in the final report.
- Can reimplement the method from scratch
  - The student should be able to reimplement the method using only basic Python packages.

    - The student should be able to identify, describe, and analyze the effect of different engineering practices, e.g., implementation tricks and parameter/hyperparameter choices, using scientific languages.
    - The student should be able to train the implemented model using the dataset they select, and identify and solve issues that prevent the model from convergence.
- Can use the implemented method for custom applications
    - The student should be able to identify a target application of their implemented method and discover the datasets they will use for the project.
    - The student can identify baseline methods as comparison
    - The student should be able to analyze the experimental behaviors of their model on the target application

Logistics

The final project will be a critical pillar of this course. As the lecture and homework will mostly focus on the mathematical foundation of the machine learning models, the final project will help you combine the mathematical foundation with the practical domain of these machine learning models, by writing a machine learning model and a paper yourself.

The topic of the final project are restricted to the ten papers listed on this website. These papers are carefully selected, and contain the most famous and useful machine learning models nowadays. I understand you might want to have a more open-ended project. Unfortunately, we will be unable to provide useful feedbacks for you to learn and ensure fairness given the size of the class. However, you are encouraged to bring your own data to your project to tested your implemented machine learning model.

The final project will be **individual**, meaning everyone needs to write their own code and final report. Do not panic and feel you are on your own. As our final project will be restricted to ten papers, for each project, there will be 8 to 10 students working on it. You are encouraged to form study groups with those working on the same project. We allow and encourage discussion among students, sharing useful online resources, and providing peer-reviews of final reports. You just need to acknowledge all the help you receive. However, it is NOT allowed to use code written by other students in the class, and everyone needs to write their own report. You need to write an acknowledge section in your final report (not counted towards 10 pages) to list all help you receive from other students in the class. Every report will be graded using the same criteria.

Requirements

The final projects requires you to re-implement the machine learning method described in the the paper we assign you, use your re-implementation to perform experiments of your choice to demonstrate the re-implementation is successful, and write a report.

There will be code for these papers online, and you are encouraged to first play with these codes before implementing your own. Do not copy or modify any code from these existing implementations as your final project; we will be able to use code plagiarism detectors to find it. The purpose of requiring you write everything from scratch is to help you learn how to overcome practical problems that people never talk about in their papers. It is not enough to only understand the mathematical insight of a machine learning model. To build a machine learning model that works in real life, you will face a lot of problems that are not reflected in the mathematical derivation, and need to know how to tackle them.

We understand that everyone has a different background in the field. Therefore, you can simplify the problem based on your capability. For example, you can have extra assumptions on the data your model will work on, or you can reduce the complexity of your re-implemented machine learning model, etc. You will have to clearly state what kind of simplification you have made in your final report. Don't overclaim. In academia, your integrity reputation will be severely damaged if you overstate what you can do. In his class, we will **heavily penalize** overstatement.

Your final report will be in the form of an academic paper that needs to be in the format below. Your submitted final report will be independently reviewed by the teaching staff, and rated according to the following criteria:

- Does the paper clearly state the problem that the implemented machine learning model targets? You will have to use your own language to describe the problem. **Heavy penalty** will be added for copying (with moderate modification of) the original paper.

- Does the paper identify and clearly descirbe similar works in the related work, and lists their advantages and disadvantages?

- Does the paper explain the mathematical derivation well? You will have to use your own language to form the mathematical derviation. **Heavy penalty** will be added for copying (with moderate modification of) the original paper.

- Does the paper clearly state the technical difficulties in the reimplementation and possible solutions?

- Does the paper identify, describe, and analyze the effect of different engineering practices, e.g., implementation tricks and parameter/hyperparameter choices, using scientific languages?
- Does the student train the implemented model using the dataset they select, and identify and solve issues that prevent the model from convergence?
- Does the paper analyze the experimental behaviors of their model on selected application and compare with baselines?
- Are there sufficient experiments demonstrating the success of re-implementation?
- Are the limitations/assumptions clearly stated in the paper? Are there overclaim? **Heavy penalty** will be added for overclaim.
- The amount of work in the reimplementation.
- Is the paper easy to read? Are your ideas elaborated clearly?

Instructions

Your report (aka paper) should have the following sections.

Introduction. In the introduction section, you need to define the problem, and justify why it is a valuable problem to investigate. In each of the topics below, you are likely going to pick one or two sub-topics to investigate. In the introduction, I want to see your explanation of why do you pick those sub-problems. You can explain their significance, e.g., by solving this problem we will gain certain insights. Think about a conference reviewer. Why would somebody accept your paper? It has to be relevant, and useful.

Related work. This is the literature review section. Demonstrate to me that you have read several papers, and you are able to summarize them into meaningful categories. A good literature survey should articulate the limitations of the existing work, and highlight the new findings of your work. Try not to give a laundry list of papers, because they are not very useful.

Method. The heading of this section is up to you. I call it “method”, but you can call it whatever you want. This is the main part of your paper. If you are proposing a new idea, you need to explain your idea. If you are studying some phenonomenon, you need to explain the insights behind the phenonomenon. A good method section should contain a few very carefully drawn figures to illustrate your ideas. Depending on the nature of your project, you may want to combine this section with the experiment section. If this appears necessary for your work, please make your best judgement.

Experiment. As the heading suggests, this is the place where you put all your experimental results. If you are comparing with other methods, you need to define the evaluation metric. If you conduct an ablation study, explain why your ablation study is fair and meaningful. Memember, experiments are presented in order to show evidence of anything you claim. If you claim something, you'd better have an experiment to support.

Conclusion. People are sometimes confused about the conclusion section. In my opinion, conclusion is not the same as summary. Yes, you need to summarize the paper in this section. But more importantly, you want to explain the limitations of your findings. You also need to suggest future directions of your work. Sometimes, you may have found some unexpected outcomes. Then in the conclusion you may want to comment on them.

Acknowledgement. Acknowledge all the help you receive from others throughout the project.

Every paper is unique, and so you need to make the best judgement of what to include and what not to include in the paper. The above outline is recommended, but not mandatory. However, based on my past experience in reviewing papers, serving as program chairs and journal editors, the recommended outline is quite robust. So if it is your first time writing, please consider it.

Deadlines

Apr 30, Sunday, **4:59pm** Eastern Time.

Hard deadline. No extension.

This is the paper that we will grade.

Please submit through gradescope.

Submission Format

Please use the official ICML 2021 LaTeX template to type your report. You can download the template at https://icml.cc/Conferences/2021/StyleAuthorInstructions

Page length: no more than 10 pages. References do not count towards the 10 pages.

No supplementary materials. All reports have to be self contained.

Do not change the margin, font size, etc.

Topics

Neural Ordinary Differential Equations
Paper: https://arxiv.org/abs/1806.07366
Note: Using machine learning models to describe differential processes

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks
Project page: https://junyanz.github.io/CycleGAN/
Note: Unpaired supervised learning for generative models

Conditional Generative Adversarial Networks
Paper: https://arxiv.org/abs/1411.1784
Note: The generative-adversarial network that allow you to specify a label for the data you want to generate

Adaptive Convolutions with Per-pixel Dynamic Filter Atom
Paper: https://arxiv.org/abs/2108.07895
Note: Improving the convolutional architecture of CNNs using adaptive convolution kernels

Learning to Reweight Examples for Robust Deep Learning
Paper: https://arxiv.org/abs/1803.09050
Note: a method to dynamically generate weights for samples when the dataset is not balanced

Learning with Noisy Labels
Paper:
https://proceedings.neurips.cc/paper/2013/file/3871bd64012152bfb53fdf04b401193f-Paper.pdf
Note: a robust machine learning method when your supervised dataset has noisy labels

Graduated Non-Convexity for Robust Spatial Perception: From Non-Minimal Solvers to Global Outlier Rejection
Paper: https://arxiv.org/pdf/1909.08605.pdf
Note: a theoretical paper that describes an uncertainty-aware model fitting method

Plug-and-Play ADMM for Image Restoration: Fixed Point Convergence and Applications

Paper: https://arxiv.org/abs/1605.01710
Note: an elegant method for image restoration problems in general

Practical Bayesian Optimization of Machine Learning Algorithms
Paper: https://arxiv.org/abs/1206.2944
Note: a very useful tool for finding optimal architecture for neural networks

Optimization as a model for few shot learning
Paper: https://openreview.net/forum?id=rJY0-Kcll
Note: a door-opening work on metalearning