CS182 - Introduction to Machine Learning, Fall 2022-23
Course Projects

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One of main goals of CS182 is to prepare you to utilize machine learning techniques to solve real-world problems, and this course project provides a good opportunity for you to start in this direction.

I. Specifications

As a part of evaluation of CS182, you are required to complete a course project based on this instruction. Your project can be theory-based or application-based. In a theory-based project, you can try to develop novel machine learning models and/or algorithms. You can also choose to compare different algorithms with possible improvement for a specific cutting-edge machine learning topic. In an application-based project, you can pick an interesting dataset or application, applying one or more well-known machine learning algorithms as baselines, and extending these baselines in creative and innovative ways. The general guidelines are listed as follows.

- Projects should be completed in groups, each of which is composed of **1-2** students.
- Each project consists of two major parts: one final writeup and the source code.
  - **Final writeup**: You are expected to submit a final writeup summarizing your findings, ideas, and contributions. Final writeup must be in the form of a NeurIPS paper and **no longer than 9 pages** for the body of the writeup with additional pages for references. Only the hard copy in **pdf**, rather than the source latex code, should be submitted.
  - **Source code**: For the sake of convenience, it is highly recommended to use Python or Matlab to implement your ideas and algorithms in the project. However, any other programming languages are allowed. It is your responsibility to make sure the source code is executable and contains no severe bugs. Please submit the code in a separate **zip** file.

II. Structure of the Written Report

In order to make the evaluation of the project as objective as possible, the written report should strictly adhere to the following structure with the sections (a penalty will be applied if the report is not organized according to the guideline):

Abstract: 10% grade

1) Introduction: 10% grade
2) Overview of existing work (with unified notation): 30% grade
3) Criticism of the existing work: 10% grade
4) New contribution (if any): 5% grade
5) Numerical results: 20% grade
6) Conclusions: 10% grade

References: 5% grade

III. Schedule and Submission

Please follow the deadlines below. They are strict deadlines and there will be penalties for not respecting them. In particular, the final reports late by 1 day will be penalized with 20% of the grade, late by 2 days will be penalized with 40% of the grade, and late by 3 days is most likely a Fail.

1) *Group member and Topic:* By **Nov. 6th, 2022 (CST)**, you need to form your group (if you want), choose a topic (either inspired on the list of topics below or not, preferably the student will come up with a topic of his/her interest), and report these information to the link:

https://docs.qq.com/sheet/DTm9aQUFaSFlydEJ3?tab=BB08J2
Note: Every group member should fill in the form.

2) *Final report:* By **Dec. 18th 11pm, 2022 (CST)**, submit your final report with filename

{stu_name_1_in_Chinease}–{stu_name_2_in_Chinease}–project_name.pdf

with the source codes and all the cited references (optional) with filename

{stu_name_1_in_Chinease}–{stu_name_2_in_Chinease}–project_name.zip

to the link:
http://pan.shanghaitech.edu.cn/cloudservice/outerLink/decode?c3Vnb24xNjY2Mjc5OTI4ODY2c3Vnb24
Note: Only one group member is supposed to submit the project, tag the rest of group members, and make sure the member-specific contributions.

IV. Project Topics

The first task for you is to pick one interesting project topic. There are many avenues that you may pursue for this project, and we encourage you to be brave and creative even if you don't think you'll necessarily get "good" results. Here are some preliminary topics[1]:

- Topic: Graph Machine Learning
  1) On the Equivalence Between Temporal and Static Equivariant Graph Representations, ICML 2022
  2) Optimization-Induced Graph Implicit Nonlinear Diffusion, ICML 2022
  3) SpeqNets: Sparsity-Aware Permutation-Equivariant Graph Networks, ICML 2022
  4) Descent Steps of a Relation-Aware Energy Produce Heterogeneous Graph Neural Networks, NIPS 2022
  5) Ordered Subgraph Aggregation Networks, NIPS 2022
  6) Graph Neural Networks as Gradient Flows, ICLR 2023 Submission
  7) DiGress: Discrete Denoising Diffusion for Graph Generation, ICLR 2023 Submission
- Topic: Reduced-Rank Regression
  1) Fast Algorithms for Sparse Reduced-Rank Regression, AISTATS 2019
  2) Reduced Rank Regression via Adaptive Nuclear Norm Penalization, Biometrika 2013
  3) Envelopes and Reduced-Rank Regression, Biometrika 2015
  4) Robust Reduced-Rank Regression, Biometrika 2017
  5) Sparse PCA: Optimal Rates and Adaptive Estimation, The Annals of Statistics 2013
  6) Fast and Privacy Preserving Distributed Low-Rank Regression, ICASSP 2017
  7) Accelerated Sparse Linear Regression via Random Projection, AAAI 2016
  8) Robust Reduced-Rank Modeling via Rank Regression, Journal of Statistical Planning and Inference 2017
- Topic: Blind Deconvolution
  1) Short-and-Sparse Deconvolution Via Rank-One Constrained Optimization (Roco), ICASSP 2022
  2) Manifold Gradient Descent Solves Multi-Channel Sparse Blind Deconvolution Provably and Efficiently, IEEETIT 2021
  3) Blind Deconvolution Using Modulated Inputs, IEEETSP 2020
  4) Compressive Blind Image Deconvolution, IEEETIP 2013
  5) Near-Optimal Compressed Sensing of a Class of Sparse Low-Rank Matrices via Sparse Power Factorization, IEEETIT 2018

[1] You can pick any topic that is related to our course and interests you.

6) Efficient Blind Deblurring under High Noise Levels, ISPA 2019

- Topic: Latent Variable Gaussian Graphical Model
  1) Alternating direction methods for latent variable Gaussian graphical model selection, Neural Computation 2013
  2) Learning latent variable Gaussian graphical models, ICML 2014
  3) Precision matrix estimation in high dimensional Gaussian graphical models with faster rates, AISTATS 2016
  4) Copula Gaussian graphical models with hidden variables, ICASSP 2012
  5) Speeding up latent variable Gaussian graphical model estimation via nonconvex optimization, NIPS 2017
  6) Low-rank and sparse structure pursuit via alternating minimization, PMLR2016
  7) Partial Gaussian graphical model estimation, IEEETIT 2014
- Topic: Nonconvex Statistical Optimization
  1) Graphical Nonconvex Optimization via an Adaptive Convex Relaxation, ICML 2018
  2) Nonconvex Sparse Graph Learning under Laplacian Constrained Graphical Model, NIPS 2019
  3) Towards Faster Rates and Oracle Property for Low-Rank Matrix Estimation, ICML 2016
  4) On Quadratic Convergence of DC Proximal Newton Algorithm in Nonconvex Sparse Learning, NIPS 2017
  5) Statistical sparse online regression: A diffusion approximation perspective, ICML 2018
  6) On Fast Convergence of Proximal Algorithms for SQRT-Lasso Optimization: Don't Worry About its Nonsmooth Loss Function, UAI 2019
- Topic: Robust Covariance Estimation
  1) An l-infinity eigenvector perturbation bound and its application to robust covariance estimation, JMLR 2018
  2) Group symmetric robust covariance estimation, IEEETSP 2015
  3) Defense against backdoor attacks via robust covariance estimation, ICML 2021
  4) Faster algorithms for high-dimensional robust covariance estimation, COLT 2019
  5) Robust Gaussian covariance estimation in nearly-matrix multiplication time, NIPS 2020
  6) Robust shrinkage estimation of high-dimensional covariance matrices, IEEETSP 2011
- Topic: Machine Learning for Combinatorial Optimization
  1) Machine learning for combinatorial optimization: a methodological tour d'horizon, arXiv 2018
  2) Combinatorial optimization with graph convolutional networks and guided tree search, NIPS 2018
  3) Learning mixed-integer convex optimization strategies for robot planning and control, CDC 2020
  4) Learning combinatorial optimization algorithms over graphs, NIPS 2017
  5) Learning cut selection for Mixed-intergerliner programming via hierarchical sequence model, ICLR 2023
  6) A GNN-guided predict-and-search framework for mixed-integer linear programming, ICLR 2023
  7) Configuring mixed-integer linear programming solvers with deep metric learning, ICLR 2023
- Topic: Robust Mean Estimation
  1) Robust and differentially private mean estimation, NIPS 2021
  2) Recent Advances in Algorithmic High-Dimensional Robust Statistics, arxiv 2019
  3) Outlier Robust Mean Estimation with Subgaussian Rates via Stability, NIPS 2020
  4) High-Dimensional Robust Mean Estimation in Nearly-Linear Time, SODA 2019

5) High-dimensional Robust Mean Estimation via Gradient Descent, ICML 2020
6) Mean Estimation and Regression Under Heavy-Tailed Distributions: A Survey, Foundations of Computational Mathematics 2019
7) Robust Online and Distributed Mean Estimation Under Adversarial Data Corruption, arXiv 2022
8) Robust Sparse Mean Estimation via Sum of Squares, COLT 2022

- Topic: GARCH Estimation
  1) A GARCH Model with Artificial Neural Networks, Information 2020
  2) AI algorithms for fitting GARCH parameters to empirical financial data, Physica A: Statistical Mechanics and Its Applications 2022
  3) Estimating value at risk: LSTM vs. GARCH, arXiv 2022
  4) Estimating GARCH models using support vector machines, Quantitative Finance 2003
  5) Support Vector Machine-Based GARCH-type Models: Evidence from ASEAN-5 Stock Markets, Data Science for Financial Econometrics 2021
  6) Estimating GARCH models using kernel machine learning, Journal of the Korean Data and Information 2010
  7) Estimation of GARCH models and performance analysis of volatility trading system using Support Vector Regression, Journal of Intelligence and Information Systems 2017

In addition to the ideas listed above, you might also refer to some recent machine learning research papers. Some top-tier conferences in machine learning are NeurIPS, ICML, ICLR, AISTATS, and UAI. Some top-tier journals in machine learning and signal processing are JMLR, TMLR, IEEE TPAMI, IEEE TSP, IEEE TIP, and IEEE TIT.

V. After CS182

An excellent CS182 project will be publishable or nearly-publishable piece of work. After completing CS182, if you would like to continue working on your project along this direction as your graduation project, or submit your work to a machine learning (or other appropriate non-machine learning) conference or journal, please feel free to talk with me. I am happy to give you some guidance and support your further work.