Korea Advanced Institute of Science and Technology
Department of Electrical Engineering & Computer Science

EE531 Statistical Learning Theory
Fall 2019 Project Outline

Issued: Nov 07 2019,
Due: Dec 19 2019

Policy

This course has introduced essential concepts in machine learning such as PAC learning, agnostic PAC learning, Uniform convergence, VC-dimension, No-free lunch, Graphical Models, Expectation Maximization, Regression, Large Margin Classification, Fairness, and Deep Learning. This project will provide students with the opportunity to make use of these concepts and also experience current machine learning research. Students are encouraged to work in groups but it is not a requirement. The group size will be limited to 2.

This project will cover two recent interesting areas: Fairness and Graph. Every group will review two papers. The project will be conducted in a fixed format. (1. Project Proposal) Groups will submit a list of 3 papers on fairness and 3 papers on graph that they wish to review. Each group should provide a 3-page reasons for their choices. Course staffs will assign one paper for each topic from the list. (2. Progress Video) Two weeks later, groups will submit a 30-minute progress video detailing the project and narrating the progress. Groups should also submit presentation material along with the video. (3. Final Presentation) (In the final week, groups will present the reviews of each paper in front of the course staffs. Groups should submit a 6-page final report at the presentation. The presentation will be evaluated based on clarity and reproduction of the experimental result.

Schedule & grading

Task	Submission date	Percentage
Group association & project proposal	Nov 14	30%
Progress video	Nov 28	30%
Final presentation	Dec 17, 19	40%

1. 3-page project proposal
   Each group should submit a **3-page project proposal in pdf format**. The project proposal should include the following items.

   (a) Clearly and concisely describe in mathematical terms, the problem which the paper is trying solve. If the paper is proposing an algorithm, state the mathematical objective of the algorithm in terms of input and output.

   (b) If the paper is not proposing an algorithm but giving a proof about a theorem, please summarize the theorem and significance of the theorem.

(c) If implementing an algorithm, you should prepare a slide clearly describing the input/output, io relationship, and separately describe the training and inference process.

(d) If the paper is providing a proof about a theorem, please provide an example of the theorem, and use the example in the proof.

(e) Describe any novelty and significant facts about the algorithm/theorem.

(f) Should include performance comparison among algorithms. Describe experiment in detail.

(g) State group members' responsibilities

2. 30-minute progress video and presentation material used in the video
   Each group will be submit a 30-minute project progress video in the format stated below. The video should give a short introduction along with background then state clearly the problem the project is considering and the machine learning algorithm to solve the problem in a very clear manner. Student should include **powerpoint presentation material** used in the video. The video and presentation material will count 30% of your project grade.

   (a) software for making video: "https://www.apowersoft.com/free-online-screen-recorder"

   (b) format: AVI

   Above screen recorder is is free open source problem which enables the recording of screen. First, you should launch the webcam and microphone which feeds the video of your presentation. Second, your recording should include the powerpoint presentation material and your feed of video. Third, record your presentation and save as AVI format and send it to TAs.

3. Project presentation and final 6-page report
   Each group consisting of no more than 2 students delivers a 20-minute project presentation. Students should turn-in (1) powerpoint presentation material including comments and a (2) 6-page report to TAs by e-mail (*sunghun.kang@kaist.ac.kr, tungluu2202@kaist.ac.kr, hobincar@kaist.ac.kr*) until Dec 19. Final presentation and report will count 40% of your project grade.

Paper lists on following topics

1. Fairness

   - When Worlds Collide: Integrating Different Counterfactual Assumptions in Fairness (C Russell et al. NeurIPS 2017)
   - Fair Clustering Through Fairlets (F Chierichetti et al. NeurIPS 2017)
   - On Fairness and Calibration (G Pleiss et al. NeurIPS 2017)
   - Recycling Privileged Learning and Distribution Matching for Fairness (N Quadrianto et al. NeurIPS 2017)
   - From Parity to Preference-based Notions of Fairness in Classification (MB Zafar et al. NeurIPS 2017)
   - Beyond Parity: Fairness Objectives for Collaborative Filtering (S Yao et al. NeurIPS 2017)
   - Counterfactual Fairnesss (MJ Kusner et al. NeurIPS 2017)
   - Fairness Behind a Veil of Ignorance: A Welfare Analysis for Automated Decision Making (H Heidari et al. NeurIPS 2018)
   - Enhancing the Accuracy and Fairness of Human Decision Making (I Valera et al. NeurIPS 2018)
   - Online Learning with an Unknown Fairness Metric (S Gillen et al. NeurIPS 2018)
   - Empirical Risk Minimization Under Fairness Constraints (M Donini et al. NeurIPS 2018)
   - Fairness Through Computationally-Bounded Awareness (MP Kim et al. NeurIPS 2018)
   - Predict Responsibly: Improving Fairness and Accuracy by Learning to Defer (D Madras et al. NeurIPS 2018)
   - The Everlasting Database: Statistical Validity at a Fair Price (B Woodworth et al. NeurIPS 2018)
   - The Price of Fair PCA: One Extra dimension (S Samadi et al. NeurIPS 2018)
   - Meritocratic Fairness for Cross-Population Selection (M Kearns et al. ICML 2017)
   - Nonconvex Optimization for Regression with Fairness Constraints (J Komiyama et al. ICML 2018)
   - Fairness Without Demographics in Repeated Loss Minimization (TB Hashimoto et al. ICML 2018)
   - Fair and Diverse DPP-Based Data Summarization (LE Celis et al. ICML 2018)
   - Scalable Deletion-Robust Submodular Maximization: Data Summarization with Privacy and Fairness Constraints (E Kazemi et al. ICML 2018)
   - Residual Unfairness in Fair Machine Learning from Prejudiced Data (N Kallus et al. ICML 2018)
   - Delayed Impact of Fair Machine Learning (LT Liu et al. ICML 2018)
   - Learning Adversarially Fair and Transferable Representations (D Madras et al. ICML 2018)
   - Blind Justice: Fairness with Encrypted Sensitive Attributes (N Kilbertus et al. ICML 2018)
   - A Reductions Approach to Fair Classification (A Agarwal et al. ICML 2018)

- Preventing Fairness Gerrymandering: Auditing and Learning for Subgroup Fairness (M Kearns et al. ICML 2018)
- Probably Approximately Metric-Fair Learning (GN Rothblum et al. ICML 2018)
- Scalable Fair Clustering (A Backurs et al. ICML 2019)
- Training Well-Generalizing Classifiers for Fairness Metrics and Other Data-Dependent Constraints (A Cotter et al. ICML 2019)
- The Implicit Fairness Criterion of Unconstrained Learning (LT Liu et al. ICML 2019)
- Fairwashing: the risk of rationalization (U Aïvodji et al. ICML 2019)
- Compositional Fairness Constraints for Graph Embeddings (AJ Bose et al. ICML 2019)
- Learning Optimal Fair Policies (R Nabi et al. ICML 2019)
- Fairness-Aware Learning for Continuous Attributes and Treatments (J Mary et al. ICML 2019)
- Fairness risk measures (RC Williamson et al. ICML 2019)
- Proportionally Fair Clustering (X Chen et al. ICML 2019)
- Stable and Fair Classification (L Huang et al. ICML 2019)
- Flexibly Fair Representation Learning by Disentanglement (E Creager et al. ICML 2019)
- Fair Regression: Quantitative Definitions and Reduction-Based Algorithms (A Agarwal et al. ICML 2019)
- Fairness without Harm: Decoupled Classifiers with Preference Guarantees (B Ustun et al. ICML 2019)
- Differentially Private Fair Learning (M Jagielski et al. ICML 2019)
- Obtaining Fairness using Optimal Transport Theory (P Gordaliza et al. ICML 2019)
- Repairing without Retraining: Avoiding Disparate Impact with Counterfactual Distributions (H Wang et al. ICML 2019)
- On the Long-term Impact of Algorithmic Decision Policies: Effort Unfairness and Feature Segregation through Social Learning (H Heidari et al. ICML 2019)
- Making Decisions that Reduce Discriminatory Impacts (M Kusneret al. ICML 2019)
- Fair k-Center Clustering for Data Summarization (M Kleindessner et al. ICML 2019)
- Guarantees for Spectral Clustering with Fairness Constraints (M Kleindessner et al. ICML 2019)

2. Graph

- Learning Steady-States of Iterative Algorithms over Graphs (Hanjun Dai et al. ICML 2018)
- Contextual graph markov model: A deep and generative approach to graph processing (Davide Bacciu et al., ICML 2018)
- Stochastic Training of Graph Convolutional Networks with Variance Reduction (Jianfei Chen et al., Oral, ICML 2018)
- Learning deep generative models of graphs (Yujia Li et al. ICML 2018)
- GraphRNN: Generating Realistic Graphs with Deep Auto-regressive Models (Jiaxuan You et al., Oral ICML 2018)
- Adaptive graph convolutional neural networks (Ruoyu Li et al. AAAI 2018)

- An end-to-end deep learning architecture for graph classification (Muhan Zhang et al. AAAI 2018)
- Deeper insights into graph convolutional networks for semi-supervised learning (Qimai Li et al. AAAI 2018)
- Geniepath: Graph neural networks with adaptive receptive paths (Ziqi Liu et al. AAAI 2018)
- Inductive Representation Learning on Large Graphs (William L. Hamilton et al. NIPS 2017)
- Adaptive sampling towards fast graph representation learning (Wenbing Huang et al. NIPS 2018)
- Hierarchical graph representation learning with differentiable pooling (Zhitao Ying et al. NIPS 2018)
- Out of the Box: Reasoning with Graph Convolution Nets for Factual Visual Question Answering (Medhini Narasimhan et al., NIPS 2018)
- Beyond Vector Spaces: Compact Data Representation as Differentiable Weighted Graphs (Denis Mazur et al, NIPS 2019)
- GNNExplainer: Generating Explanations for Graph Neural Networks (Rex Ying et al., NIPS 2019)
- Learning Graphical State Transitions (Daniel D. Johnson, ICLR 2017)
- Semi-supervised classification with graph convolutional networks (Thomas N. Kipf et al., ICLR 2017)
- Graph attention networks (Petar Veličković et al. ICLR 2018)
- Covariant Compositional Networks For Learning Graphs (Risi Kondor et al., ICLR 2018)
- Fastgcn: fast learning with graph convolutional networks via importance sampling (Jie Chen et al., ICLR 2018)
- NerveNet: Learning Structured Policy with Graph Neural Networks (Tingwu Wang et al., ICLR 2018)
- Few-Shot Learning with Graph Neural Networks (Victor Garcia et al., ICLR 2018)
- Learning to Represent Programs with Graphs (Miltiadis Allamanis et al., ICLR 2018)
- Deep graph infomax (Petar Veličković et al., ICLR 2019)
- Generative Code Modeling with Graphs (Marc Brockschmidt et al., ICLR 2019)
- Adversarial Attacks on Graph Neural Networks via Meta Learning (Daniel Zügner et al., ICLR 2019)
- How powerful are graph neural networks (Keyulu Xu et al. ICLR 2019)
- DyRep: Learning Representations over Dynamic Graphs (Rakshit Trivedi et al., ICLR 2019)
- Generative Code Modeling with Graphs (Marc Brockschmidt et al., ICLR 2019)
- Two-Stream Adaptive Graph Convolutional Networks for Skeleton-Based Action Recognition (Lei Shi et al., CVPR 2019)
- Rethinking Knowledge Graph Propagation for Zero-Shot Learning (Michael Kampffmeyer et al., CVPR 2019)
- Semi-Supervised Learning With Graph Learning-Convolutional Networks (Bo Jiang et al., CVPR 2019)

- An End-To-End Network for Generating Social Relationship Graphs (Arushi Goel et al., CVPR 2019)
- A Convex Relaxation for Multi-Graph Matching (Paul Swoboda et al., CVPR 2019)
- Explainability Methods for Graph Convolutional Neural Networks (Phillip E. Pope et al., CVPR 2019)
- Video Relationship Reasoning Using Gated Spatio-Temporal Energy Graph (Yao-Hung Hubert Tsai et al., CVPR 2019)
- Data Representation and Learning With Graph Diffusion-Embedding Networks (Bo Jiang et al., CVPR 2019)
- Graph Attention Convolution for Point Cloud Semantic Segmentation (Lei Wang et al., CVPR 2019)
- Learning Actor Relation Graphs for Group Activity Recognition (Jianchao Wu et al., CVPR 2019)
- Label Efficient Semi-Supervised Learning via Graph Filtering (Qimai Li et al., CVPR 2019)
- Explore-Exploit Graph Traversal for Image Retrieval (Cheng Chang et al., CVPR 2019)
- Spatial-Aware Graph Relation Network for Large-Scale Object Detection (Hang Xu et al., CVPR 2019)
- Exploiting Edge Features for Graph Neural Networks (Liyu Gong et al., CVPR 2019)
- Neural Task Graphs: Generalizing to Unseen Tasks From a Single Video Demonstration (De-An Huang et al., CVPR 2019)
- Explainable and Explicit Visual Reasoning Over Scene Graphs (Jiaxin Shi et al., CVPR 2019)
- Edge-labeling Graph Neural Network for Few-shot Learning (Jongmin Kim et al., CVPR 2019)
- Generating Classification Weights with GNN Denoising Autoencoders for Few-Shot Learning (Spyros Gidaris et al., CVPR 2019)
- Zero-shot Recognition via Semantic Embeddings and Knowledge Graphs (Xiaolong Wang et al., CVPR 2018)
- Rethinking Knowledge Graph Propagation for Zero-Shot Learning (Michael Kampffmeyer et al., CVPR 2018)
- Multi-Label Zero-Shot Learning with Structured Knowledge Graphs (Chung-Wei Lee et al., CVPR 2018)
- Dynamic Graph Generation Network: Generating Relational Knowledge from Diagrams (Haoyu Wang et al., CVPR 2018)
- Dynamic Graph CNN for Learning on Point Clouds (Yue Wang et al., CVPR 2018)
- PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation (Charles R. Qi et al., CVPR 2018)
- Iterative Visual Reasoning Beyond Convolutions (Xinlei Chen et al., CVPR 2018)
- Geometric deep learning on graphs and manifolds using mixture model cnns (Federico Monti et al., CVPR 2017)
- The More You Know: Using Knowledge Graphs for Image Classification (Kenneth Marino et al., CVPR 2017)

- Graph-Structured Representations for Visual Question Answering (Damien Teney et al., CVPR 2017)
- 3D Graph Neural Networks for RGBD Semantic Segmentation (Xiaojuan Qi et al., CVPR 2017)
- Dynamic Edge-Conditioned Filters in Convolutional Neural Networks on Graphs (Martin Simonovsky et al., CVPR 2017)