Final Project

EE 546: Mathematics of High-dimensional Data

University of Southern California

You should work in groups of two (a few one/three size groups may also be allowed). If this is a problem, please let me know as soon as possible.

Possible project types:

1- **Literature Review.** Pick a research paper on a topic related to this course, read it carefully, and write a report that clearly and coherently explains the main ideas and results in your own words. This is your opportunity to read about a topic that goes beyond what we cover in lecture, and also to demonstrate your ability to decipher a research article in this area. You will also give an oral/poster presentation near the end of the semester, where you discuss the main ideas from the paper. In the case of paper that are very long you can discuss with me what parts of the paper are suitable for covering.

   A list of possible papers is given in this pdf. Once a paper gets picked by a group it will not be available for other groups. I will indicate in this pdf if the paper has been selected already so please check before sending me an email. You can also propose a paper not on the list, but you have to clear this with me well in advance.

2- **Original Research.** If you are inclined to do original research project, please talk to me first and pitch your ideas during office hours. Please note that the goal is to have mostly research projects rather that literature reviews. In case you pick the original research category you should still do a project proposal (where you state the problem and point to any prior/related work), a project report (think of it as a research paper with results that are a bit more preliminary and with language that can be a bit more informal), and also an oral/poster presentation.

Project Proposal:

One member of the group should send me an email, cc'ing the group members, stating (i) project group, and (ii) the paper you plan to cover. You can send this to me anytime before midnight November 8, 2020. Use the subject line "EE 546: Project proposal".

Project Report: Anytime before 2 PM December 9 2020, one member of each group should send the final report as a PDF file to me via email(again cc'ing other group members) with the subject "EE 546: Project Report". The report should not simply restate the text already in the paper. It should explain the key ideas in the paper. It does not have to go into every detail of the paper, but it should at least describe some key parts of the paper in moderate detail when needed. There are no page limits on the report. However, you should try to make it as clear and succinct as possible. You will be judged by clarity and brevity of writing and your ability to get across the main ideas. The report should not be longer than it needs to be. So avoid unnecessary "fluff". I expect most good reports will be at most 6-8 pages (single column and normal font size please see this paper for an example).

Possible Papers: (A few more papers might be added in a few days)

- Applied papers
  - End-to-End Variational Networks for Accelerated MRI Reconstruction
    `https://arxiv.org/abs/2004.06688`
  - CNN Denoisers As Non-Local Filters: The Neural Tangent Denoiser
    `End-to-End Variational Networks for Accelerated MRI Reconstruction`
  - Total Deep Variation for Linear Inverse Problems
    `https://arxiv.org/abs/2001.05005`
  - PULSE: Self-Supervised Photo Upsampling via Latent Space Exploration of Generative Models
    `https://arxiv.org/abs/2003.03808`
  - A Style-Based Generator Architecture for Generative Adversarial Networks
    `https://arxiv.org/abs/1812.04948`
  - Analyzing and Improving the Image Quality of StyleGAN
    `http://openaccess.thecvf.com/content_CVPR_2020/html/Karras_Analyzing_and_Improvin`
  - Image Augmentations for GAN Training
    `https://arxiv.org/abs/2006.02595`
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    `https://arxiv.org/abs/2006.02595`
  - Training Generative Adversarial Networks with Limited Data
    `https://arxiv.org/abs/2006.06676`
  - Differentiable Augmentation for Data-Efficient GAN Training
    `https://arxiv.org/abs/2006.10738`
  - iUNets: Fully invertible U-Nets with Learnable Up- and Downsampling
    `arxiv.org/abs/2005.05220`
  - GAN Compression: Efficient Architectures for Interactive Conditional GANs
    `https://arxiv.org/abs/2003.08936`
  - Medical Out-of-Distribution Analysis Challenge
    `http://medicalood.dkfz.de/web/`
  - Tuning-free Plug-and-Play Proximal Algorithm for Inverse Imaging Problems
    `https://proceedings.icml.cc/static/paper_files/icml/2020/4134-Paper.pdf`
  - Adversarially Learned Inference
    `https://arxiv.org/abs/1606.00704`
  - Perceptual Losses for Real-Time Style Transfer and Super-Resolution
    `https://arxiv.org/abs/1603.08155`
  - Adversarial Feature Learning
    `https://arxiv.org/pdf/1605.09782.pdf`

- Learning from Simulated and Unsupervised Images through AdversarialTraining
  https://arxiv.org/abs/1612.07828
- Distribution Matching Losses Can Hallucinate Features in Medical Image Translation
  https://arxiv.org/pdf/1805.08841.pdf
- Unsupervised image-to-image translation networks
  http://papers.nips.cc/paper/6672-unsupervised-image-to-image-translation-network
- Adversarial Discriminative Domain Adaptation
  http://openaccess.thecvf.com/content_cvpr_2017/papers/Tzeng_Adversarial_Discrimi
- Deep transfer learning with joint adaptation networks
  https://dl.acm.org/doi/pdf/10.5555/3305890.3305909
- Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks
  https://arxiv.org/pdf/1703.10593.pdf
- SimCLR
  https://arxiv.org/abs/2002.05709
- Learning Representations by Maximizing Mutual Information Across Views
  https://arxiv.org/abs/1906.00910
- MoCo: Momentum Contrast for Unsupervised Visual Representation Learning
  https://arxiv.org/abs/1911.05722

* Deep learning theory papers
  - The generalization error of random features regression: Precise asymptotics and double descent curve https://arxiv.org/abs/1908.05355
  - Approximation and Estimation Bounds for Artificial Neural Networks, Andrew R. Barron
  - Universal Approximation Bounds for Superpositions of a Sigmoidal Function, Andrew R. Barron
  - http://www-bcf.usc.edu/ soltanol/overparam.pdf
  - A mean field view of the landscape of two-layer neural networks, Song Mei, Andrea Montanari, and Phan-Minh Nguyen
  - https://arxiv.org/pdf/1810.02032.pdf
  - https://arxiv.org/pdf/1810.02281.pdf
* Stochastic gradients
  - Stephen J. Wright, Coordinate Descent Algorithms.
  - Richtarik and Takac, Iteration Complexity of Randomized Block-Coordinate Descent Methods for Minimizing a Composite Function.

- Hazan, Levy, Shai Shalev-Shwartz, On Graduated Optimization for Stochastic Non-Convex Problems.
- Shalev-Schwartz, Shamir, and Sridharan, Learning kernel-based half-spaces with the 0-1 loss.
- Coordinate Descent Converges Faster with the Gauss-Southwell Rule Than Random Selection.
- Hazan, Levy, Shalev-Shwartz, Beyond Convexity: Stochastic Quasi-Convex Optimization.
- Johnson and Zhang, Accelerating Stochastic Gradient Descent using Predictive Variance Reduction.
- The following two papers: Shamir, A Stochastic PCA and SVD Algorithm with an Exponential Convergence Rate and Shamir, Convergence of Stochastic Gradient Descent for PCA.
- Hogwild!: A Lock-Free Approach to Parallelizing Stochastic Gradient Descent.

• Kmeans Clustering
  - `https://www.samuelbhopkins.com/clustering.pdf`
  - Arthur and Vassilvitskii. k-means++: The advantages of careful seeding.
  - Langberg and Schulman. Universal ϵ-approximators for integrals
  - Balcan, Blum, and Gupta. Clustering under Approximation Stability.
  - Telgarsky and Dasgupta, Moment-based uniform deviation bounds for k-means and friends
  - Kumar, Sabharwal, and Sen, Linear-time approximation schemes for clustering problems in any dimensions
  - Kanungo, Mount, Netanyahu, Piatko, Silverman, and Wu, A local search approximation algorithm for k-means clustering
  - Ostrovsky, Rabini, Schulman, and Swamy, The effectiveness of Lloyd-type methods for the k-means problem Feldman and Langberg, A unified framework for approximating and clustering data

• Spectral Clustering and Community Detection
  - Guedon and Vershynin, Community detection in sparse networks via Grothendieck's inequality.
  - The two papers together: Oymak and Hassibi, Finding Dense Clusters via "Low Rank + Sparse" and Korlakai Vinayak, Oymak, and Hassibi, Decomposition and sharp performance bounds for graph clustering via convex optimization.
  - Le, Levina, and Vershynin, Sparse random graphs: regularization and concentration of the laplacian.
  - Le and Vershynin, Concentration and regularization of random graphs.

- Hajek, Wu, and Xu, Achieving Exact Cluster Recovery Threshold via Semidefinite Programming.
- Hajek, Wu, and Xu, Achieving Exact Cluster Recovery Threshold via Semidefinite Programming: Extensions.
- Abbe and Sandon, Community detection in general stochastic block models: fundamental limits and efficient recovery algorithms.

• High dimensional statistical estimation

- El Karoui, Bean, Bickel, Lim, Yu. On robust regression with high-dimensional predictors
- El Karoui, Asymptotic behavior of unregularized and ridge-regularized high-dimensional robust regression estimators : rigorous results
- Donoho and Montanari, High Dimensional Robust M-Estimation: Asymptotic Variance via Approximate Message Passing.
- Donoho and Montanari, Variance Breakdown of Huber (M)-estimators: $n/p \to m \in (1, \infty)$
- Gavish and Donoho, Optimal shrinkage of Singular Values.

• Light Field (If you pick one of the light field papers you should also provide some background on light field in addition to the paper itself)

- Levoy, Ng, Adams, Footer, and Horowitz, Light Field Microscopy.
- Shi, Hassanieh, Davis, Katabi, and Durand, Light Field Reconstruction Using Sparsity in the Continuous Fourier Domain.
- Wetzstein, Lanman, Hirsch, Raskar, Tensor Displays: Compressive Light Field Synthesis using Multilayer Displays with Directional Backlighting.

• Learning mixture models

- Dasgupta and Schulman, A probabilistic analysis of EM for mixtures of separated, spherical Gaussians.
- Achlioptas and McSherry, On spectral learning of mixtures of distributions
- Hsu and Kakade, Learning mixtures of spherical Gaussians: moment methods and spectral decompositions
- Ge, Huang, and Kakade, Learning mixtures of Gaussians in high dimensions

• Tensor decompositions

- “Spectral algorithms for tensor completion,” A. Montanari, N. Sun, 2016.