EE 270 - Project Ideas

Below is a list of recent papers on randomized matrix computation and optimization algorithms. They can be good starting points for the project. Please send an e-mail to the instructor and CA for more information.

Sketching convex neural networks
https://stanford.edu/~pilanci/papers/NNConvex.pdf

Sketching Gauss Newton Method for training non-convex model
https://drive.google.com/file/d/1x_ft76LXMD9-OKGnkdcJWcFLyXaPxo2x/view

Sketching methods for reinforcement learning and bandit problems

Effective sketching methods for value function approximation
Y Pan, ES Azer, M White
https://arxiv.org/pdf/1708.01298

Contextual Bandits with Random Projection
X Yu
https://arxiv.org/pdf/1903.08600

Variance reduction methods for stochastic gradient descent

https://arxiv.org/pdf/1805.02632

Random sampling and sketching for differential Equations

Random Sampling and Efficient Algorithms for Multiscale PDEs
K Chen, Q Li, J Lu, SJ Wright
https://arxiv.org/pdf/1807.08848

Sketching recurrent neural networks
Random Sketching, Clustering, and Short-Term
Memory in Spiking Neural Networks
https://drops.dagstuhl.de/opus/volltexte/2020/11708/pdf/LIPIcs-ITCS-2020-23.pdf

Sketching methods for semidefinite programming

Scalable Semidefinite Programming

A Yurtsever, JA Tropp, O Fercoq, M Udell
https://arxiv.org/pdf/1912.02949

Sketching for global non-convex optimization

Computing Active Subspaces Efficiently with Gradient Sketching
PG Constantine, A Eftekhari
https://ieeexplore.ieee.org/iel7/7377772/7383717/07383809.pdf

Randomized tensor decompositions

A practical randomized CP tensor decomposition
C Battaglino, G Ballard, TG Kolda
https://epubs.siam.org/doi/pdf/10.1137/17M1112303

Fast and guaranteed tensor decomposition via sketching
Y Wang, HY Tung, AJ Smola
http://papers.nips.cc/paper/5944-fast-and-guaranteed-tensor-decomposition-via-sketching.pdf

Almost optimal tensor sketch
TD Ahle, JBT Knudsen
https://arxiv.org/pdf/1909.01821

Randomized alternating least squares for canonical tensor decompositions: application to a PDE with random data
MJ Reynolds, A Doostan, G Beylkin
https://epubs.siam.org/doi/pdf/10.1137/15M1042802

Randomized Finite Element Methods

https://scholarworks.umass.edu/cgi/viewcontent.cgi?article=1731&context=dissertations_2

Adaptive and learning based random projection methods

Learning-Based Frequency Estimation Algorithms
CY Hsu
https://openreview.net/pdf?id=r1lohoCqY7

Projecting" better than randomly": How to reduce the dimensionality of very large datasets in a way that outperforms random projections

M Wojnowicz, D Zhang, G Chisholm
https://ieeexplore.ieee.org/iel7/7795280/7796876/07796904.pdf

Stochastic optimization using random projections
Scalable Adaptive Stochastic Optimization Using Random Projections
Gabriel Krummenacher, Brian McWilliams, Yannic Kilcher, Joachim M. Buhmann, Nicolai Meinshausen
https://arxiv.org/abs/1611.06652

11. Dimension reduction methods for linear programs
Using the Johnson-Lindenstrauss lemma in linear and integer programming Vu Khac Ky1 , Pierre-Louis Poirion, Leo Liberti
https://pubsonline.informs.org/doi/pdf/10.1287/moor.2017.0894

https://arxiv.org/pdf/1507.00990.pdf

12. Fast Hessian spectrum calculations for deep learning
https://arxiv.org/pdf/1912.07145.pdf

13. Low-rank batch representations for memory-constrained training
Analyze and implement (at low level) neural network training using SGD with noisy gradients that are random, unbiased, low-rank approximations of batches of true gradients.

Optimal Kronecker-Sum Approximation of Real Time Recurrent Learning
http://proceedings.mlr.press/v97/benzing19a/benzing19a.pdf

14. Acceleration methods for iterative sketching

https://arxiv.org/pdf/1609.09419.pdf