SI231B - Matrix Computations, Fall 2024

Course Project

1 Specifications

Some specifications for the project:

- The length should be at least 5 single-column pages with 10pt font. Be brief and to the point.
- The project should be written using LaTeX (use an IEEE paper style or similar) and submitted in PDF format (do not use Word!).
- Keep a pdf copy of all the cited references (submit them along with the final project).
- The student should read around 8 research papers on the chosen topic and cite at least 8 related papers.
- The project should start with a description of the problem: this should not be a separate overview of each of the papers one after another; instead, it should contain a unified problem formulation, explaining how each of the related papers fits within the general formulation.
- The related papers should be criticized: the student should have an opinion on the papers that he/she read; the student should be able to comment on the contributions and limitations of each paper.
- Independent research: after the problem formulation and overview of the state of the art, the student should try to propose something new that improves on the existing approaches based on the contents learnt from this course.
- Numerical simulations: the student should design numerical experiments in order to justify his/her points of view.
- No plagiarism or self-plagiarism is allowed. (The student is never allowed to reuse his/her own published or submitted papers as the final project.)

2 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):

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

References: 10% grade

3 Schedule and submission

By January 9th, 2025 at 11:59 PM, submit your final report with all the cited references (required) and codes (optional) with filename YourChineseName_YourStudentID.zip to the link: https://epan.shanghaitech.edu.cn/l/LFr9S6. This is a strict deadline and there will be penalties for not respecting them. In particular, the final report late by 1 day will be penalized with 30% of the grade, late by more than 1 days will be a FAIL.

4 List of topics

You need to choose a topic from the following list, and cite at least one paper below the topic.

- Covariance matrix estimation:
  - Augmented Covariance Matrix Reconstruction for DOA Estimation Using Difference Coarray, IEEE Transactions on Signal Processing, 2021.
  - Coupled Regularized Sample Covariance Matrix Estimator for Multiple Classes, IEEE Transactions on Signal Processing, 2021.
- QR decomposition:
  - A Fast Tensor Completion Method Based on Tensor QR Decomposition and Tensor Nuclear Norm Minimization, IEEE Transactions on Computational Imaging, 2021.
  - Solving Complex-Valued Time-Varying Linear Matrix Equations via QR Decomposition With Applications to Robotic Motion Tracking and on Angle-of-Arrival Localization, IEEE Transactions on Neural Networks and Learning Systems, 2022.
- Reduced-rank regression:
  - Sparse Reduced-Rank Regression for Simultaneous Dimension Reduction and Variable Selection, Journal of the American Statistical Association, 2012.
  - Multi-View Facial Expression Recognition Based on Group Sparse Reduced-Rank Regression, IEEE Transactions on Affective Computing, 2014.
- Signal compression:
  - Riemannian Low-Rank Model Compression for Federated Learning With Over-the-Air Aggregation, IEEE Transactions on Signal Processing, 2023.
  - Graph Signal Compression by Joint Quantization and Sampling, IEEE Transactions on Signal Processing, 2022.
- Singular value decomposition (SVD):
  - Multilinear Generalized Singular Value Decomposition (ML-GSVD) and Its Application to Multiuser MIMO Systems, IEEE Transactions on Signal Processing, 2022.
  - On Properties and Structure of the Analytic Singular Value Decomposition, IEEE Transactions on Signal Processing, 2024.
- Positive semi-definite matrix (PSD):
  - Block Factor-Width-Two Matrices and Their Applications to Semidefinite and Sum-of-Squares Optimization, IEEE Transactions on Automatic Control, 2023.
  - 1-Bit compressed sensing of positive semi-definite matrices via rank-1 measurement matrices, IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2016.

- Low-rank matrix approximation:
  - Multiscale Decomposition in Low-Rank Approximation, IEEE Signal Processing Letters, 2017.
  - Fast Nonnegative Matrix/Tensor Factorization Based on Low-Rank Approximation, IEEE Transactions on Signal Processing, 2012.
- Principal component analysis:
  - An Efficient Randomized Low-Rank Matrix Factorization with Application to Robust PCA, IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC), 2021.
  - Sparse Principal Component Analysis With Preserved Sparsity Pattern, IEEE Transactions on Image Processing, 2019.
- Matrices for graphs:
  - Fastest Mixing Markov Chain on Graphs with Symmetries, SIAM Journal on Optimization, 2009.
  - Convex optimization of graph Laplacian eigenvalues, Proceedings of the International Congress of Mathematicians, 2006.
- MIMO optimization:
  - A Unified MIMO Optimization Framework Relying on the KKT Conditions, IEEE Transactions on Communications, 2021.
- Orthogonalization:
  - Generalized orthogonalization: a unified framework for Gram-Schmidt orthogonalization, SVD and PCA, IEEE International Conference on Systems, Man, and Cybernetics (SMC), 2022.
- Eigen-decomposition:
  - Faster proximal algorithms for matrix optimization using Jacobi-based eigenvalue methods, Neural Information Processing Systems, 2021.
  - Eigendecomposition-Free Training of Deep Networks for Linear Least-Square Problems, IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021.