Capstone project Meeting - 1113

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Contents

Important dates

1. Weeks 2.1 - 2.4: get a basic understanding of the project.
2. **Week 2.4 (Wednesday 3rd of December)**: submit a project plan.
3. Weeks 2.5 - 2.6: break.
4. **Weeks 2.7 (Monday 5th of January)**: submit revised project plan.
5. Weeks 2.7 - 2.9: project (work full time).
6. **Weeks 2.9 (Friday 23rd of January)**: submit their final deliverable (code, data, etc.)
7. **Week 2.10**: final presentation.

Introduction of topic

Two parts: Numerical analysis (NA) and Machine learning (ML).

1. NA: iterative methods for linear systems, preconditioning techniques.
2. ML: invertible neural networks (INNs).
3. Aim: using ML models (INNs) to address preconditioning problems in NA (preconditioner).

Project expectations

Knowledge expectations

1. NA: understanding iterative methods for linear systems and preconditioning techniques.
2. ML: implement INNs.
3. NA + ML (preconditioner learning): literature review (2-3 papers)
   PS: focus on the ML model (structure and loss function), numerical examples, etc.
   skip complex NA methods (e.g., Krylov, conjugate gradient, ...).
4. Consider the following questions:
   - Why use ML? why invertibility?(from NA's view)
   - Why choose INNs compared with fully connected networks (FCNs)?
   - What are the limitations of your model?
   - What could be done in future work?
   - ...

Project expectations - 2

Other expectations

1. **Timeline**: when (weeks), who, what(goals)
2. **Clear code structure**: e.g., 'data/', 'models/', 'utils/', 'main.py', requirements.txt, README.md
3. **Comparison**: your method vs. classical preconditioner (Jacobi, Gauss-Seidel)
   your method vs. FCN-based preconditioner

MoSCoW analysis

markdown.

Discussion and Questions? I

1. Package to use? (PyTorch or JAX?)
2. Generation of linear systems (NGSolve, code provided)
3. Weekly meeting schedule
4. Literature recommendation (preconditioner learning):
   - Chen, J., (2025). Graph Neural Preconditioners for Iterative Solutions of Sparse Linear Systems. Presented at the The Thirteenth International Conference on Learning Representations.
   - Giraud, L., Kruse, C., Mycek, P., Shpakovych, M., Xiang, Y., (2025). Neural network preconditioning: a case study for the solution of the parametric Helmholtz equation.
5. Literature (iterative methods):
   - Kelley, C. T. (1995). Iterative methods for linear and nonlinear equations. Society for Industrial and Applied Mathematics.
6. Literature (invertible neural networks):

Discussion and Questions? II

- Papamakarios, G., Nalisnick, E., Rezende, D. J., Mohamed, S., & Lakshminarayanan, B. (2021). Normalizing flows for probabilistic modeling and inference. Journal of Machine Learning Research, 22(57), 1-64.
- Teshima, T., Ishikawa, I., Tojo, K., Oono, K., Ikeda, M., & Sugiyama, M. (2020). Coupling-based invertible neural networks are universal diffeomorphism approximators. Advances in Neural Information Processing Systems, 33, 3362-3373.
- Meng, Y., Huang, J., & Qiu, Y. (2024). Koopman operator learning using invertible neural networks. Journal of Computational Physics, 501, 112795.

Questions?