Sparsity-based algorithms for inverse problems

Ganguly, P.S.

Propositions

Propositions accompanying the thesis "**Sparsity-based algorithms for inverse problems**".

1. Reconstruction results from different implementations of fast algorithms can be made more quantitatively similar to each other without knowledge of the underlying details of each implementation (Chapter 2).

2. Pixel- and voxel-based discretization are not always the most appropriate discretizations of an imaging problem, especially when physical or chemical knowledge of the system dictates otherwise (Chapter 3).

3. Model assumptions built into inference algorithms may not always hold in practice. However, practical heuristics are often able to steer algorithms to a good solution (Chapters 3 and 4).

4. The dynamics of multicellular biological systems can be modelled using a partial differential equation with a few terms. Learning-based methods that make use of the sparsity of terms can recover this dynamics from limited data (Chapter 5).

5. New algorithms for solving inverse problems often rely on the revival of older optimization techniques, such as the Frank-Wolfe method, and illustration of their applicability to a larger class of problems (*Revisiting Frank-Wolfe: Projection-free sparse convex optimization*, Jaggi, 2013).

6. Proper utilization of existing prior knowledge, such as the use of atomic models, is crucial for designing effective learning-based methods that minimize the need for additional error-prone steps (*Exploring generative atomic models in cryo-EM reconstruction*, Zhong et al., 2021).

7. Simulation paradigms such as the TEM-simulator provide a useful way to test the properties and shortcomings of an inference algorithm on close-to-realistic data and allow for small changes in simulation settings not easily accessible to experiments (*Simulation of transmission electron microscope images of biological specimens*, Rullgård et al., 2011).

8. Evaluating the performance of state-of-the-art algorithms on benchmark datasets must go hand in hand with interrogating current practices around dataset creation and splitting (*Parallel-beam X-ray CT datasets of apples with internal defects and label balancing for machine learning*, Coban et al., 2020).

9. Understanding why a method fails to give a desired result can be more insightful than a demonstration of cases where it succeeds; scientific "results" that question and debunk are much rarer – and therefore deserve more importance – than those that showcase improved performance.

10. There is no better way for a teacher to understand and correct their own misconceptions about a topic than conversing and interacting with a group of students.

Poulami Somanya Ganguly,
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