

CMSC838B/CMSC498Z: Differentiable Programming Reading List

Differentiation, Jacobian and higher-order derivatives

- The Matrix Calculus You Need For Deep Learning (<https://arxiv.org/pdf/1802.01528>)
- Differentiation of Functions of Several Variables ([https://math.libretexts.org/Bookshelves/Calculus/Calculus_\(OpenStax\)/14:_Differentiation_of_Functions_of_Several_Variables](https://math.libretexts.org/Bookshelves/Calculus/Calculus_(OpenStax)/14:_Differentiation_of_Functions_of_Several_Variables))
- The Matrix Cookbook (<https://www.math.uwaterloo.ca/~hwolkowi/matrixcookbook.pdf>)
- On the calculation of Jacobian matrices by the Markowitz rule (<https://www.osti.gov/servlets/purl/5933713>)
- Optimal accumulation of Jacobian matrices by elimination methods on the dual computational graph (<https://link.springer.com/article/10.1007/s10107-003-0456-9>)
- Edge Pushing is Equivalent to Vertex Elimination for Computing Hessians (<https://par.nsf.gov/servlets/purl/10039361>)
- Efficient Symbolic Differentiation for Graphics Applications (<https://www.microsoft.com/en-us/research/wp-content/uploads/2016/02/main-65.pdf>)
- Lazy Multivariate Higher-Order Forward-Mode AD (<https://engineering.purdue.edu/~qobi/papers/popl2007a.pdf>)
- Greedy Algorithms for Optimizing Multivariate Horner Schemes (<https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.330.7430&rep=rep1&type=pdf>)

Automatic Differentiation

- Automatic Differentiation in Machine Learning: A survey (<https://arxiv.org/pdf/1502.05767>)
- Differentiable Programming from Scratch (<https://thenumb.at/Autodiff/>)
- Automatic Differentiation: The most criminally underused tool in the potential machine learning toolbox? (<https://justindomke.wordpress.com/2009/02/17/automatic-differentiation-the-most-criminally-underused-tool-in-the-potential-machine-learning-toolbox/>)
- Introduction to Automatic Differentiation (<https://alexey.radul.name/ideas/2013/introduction-to-automatic-differentiation/>)
- Wengert 1964 “A Simple Automatic Derivative Evaluation Program” (<https://www.cs.princeton.edu/courses/archive/fall19/cos597C/files/wengert1964.pdf>)
- Fast reverse-mode automatic differentiation using expression templates in C++ (<http://www.met.reading.ac.uk/~swrhgnrj/publications/adept.pdf>)
- ADrien: an implementation of automatic differentiation in Maple (<https://dl.acm.org/doi/10.1145/309831.309941>)
- Hierarchical Approaches to Automatic Differentiation (<https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.49.2929&rep=rep1&type=pdf>)
- Simon Peyton Jones, “Automatic Differentiation for Dummies” (<https://2019.ecoop.org/details/ecoop-2019-papers/11/Automatic-Differentiation-for-Dummies>)
 - Not really for dummies but it covers how functional programming people think about this problem.
- Geometric Deep Learning: Grids, Groups, Graphs, Geodesics, and Gauges (<https://arxiv.org/abs/2104.13478>, <https://www.youtube.com/watch?v=w6Pw4MOzMuo>, <https://towardsdatascience.com/geometric-foundations-of-deep-learning-94cdd45b451d>)
- Randomized Automatic Differentiation (<https://arxiv.org/abs/2007.10412>)

- Perturbation confusion confusion (<http://blog.sigfpe.com/2011/04/perturbation-confusion-confusion.html>)
- Automatic Differentiation: Inverse Accumulation Mode (<https://openreview.net/forum?id=Bygj2Ys6IS>)
- Issues in Parallel Automatic Differentiation (<https://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.57.2468>)
- Who Invented the Reverse Mode of Differentiation? (https://ftp.gwdg.de/pub/misc/EMIS/journals/DMJDMV/vol-ismv/52_griewank-andreas-b.pdf)

Systems & Libraries

- PyTorch: An Imperative Style, High-Performance Deep Learning Library (<https://arxiv.org/abs/1912.01703>)
- How Usability Improves Performance in Pytorch (<https://slideslive.com/38955641/how-usability-improves-performance-in-pytorch?ref=account-84635-latest>)
- Tangent: Automatic differentiation using source-code transformation for dynamically typed array programming (<https://arxiv.org/abs/1809.09569>)
- Differentiable Programming for Image Processing and Deep Learning in Halide (https://people.csail.mit.edu/tzuma/gradient_halide/)
- Enoki (https://rgl.s3.eu-central-1.amazonaws.com/media/papers/NimierDavidVicini2019Mitsuba2_7.pdf)
- Opt (<http://optlang.org/>)
- Enzyme (<https://enzyme.mit.edu/>)
- The ADIFOR 2.0 System for the Automatic Differentiation of Fortran 77 Programs (<https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.31.399&rep=rep1&type=pdf>)
- Recipes for Adjoint Code Construction (TAMC) (http://twister.caps.ou.edu/OBAN2019/Giering_recipe4adjoint.pdf)
- KotlinV: A shape-safe DSL for differentiable programming (<https://openreview.net/forum?id=SkluMSZ08H>)
- CasADi: a software framework for nonlinear optimization and optimal control (<https://link.springer.com/article/10.1007/s12532-018-0139-4>)
- The Tapenade automatic differentiation tool (<https://hal.inria.fr/hal-00913983/PDF/tapenadeRefV2.pdf>)
- Relay: A New IR for Machine Learning Frameworks (<https://arxiv.org/pdf/1810.00952.pdf>)