

Introduction to Mathematical Optimization

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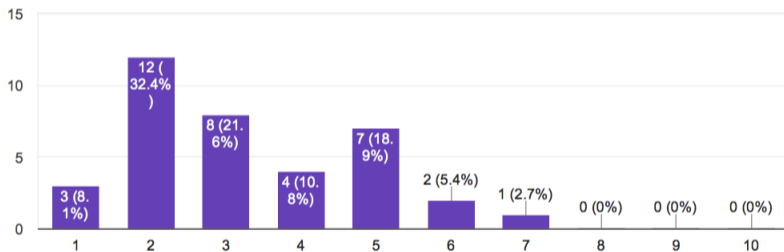


- ▶ *Background*
 - ▶ PhD Aeronautics & Astronautics, 2011, Stanford University (PhD Minor in CME)
 - ▶ Harry S Truman Postdoctoral Fellow, Sandia National Laboratories, 2011–2014
 - ▶ Principal Member of Technical Staff, Sandia National Laboratories, 2014–
- ▶ *Research interests*: nonlinear model reduction, computational mechanics, machine learning, uncertainty quantification, numerical optimization, Krylov-subspace methods, time-parallel methods

Pre-course feedback

Rate your current knowledge of mathematical optimization

37 responses

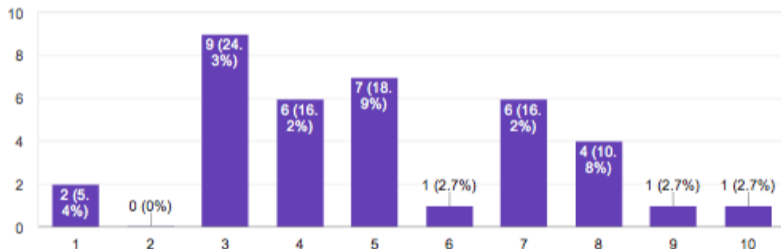


- ▶ I will not assume you have any previous knowledge
- ▶ Yet, we will cover some advanced topics and tools for the 5-7 people

Pre-course feedback

Rate your experience level with Python

37 responses

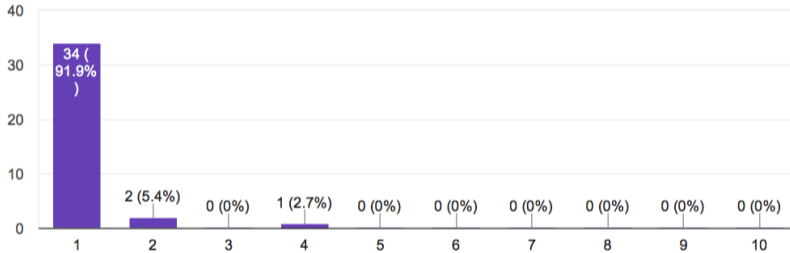


- ▶ Provided ipython notebooks that can be run without experience with Python
- ▶ Those with Python experience can quickly figure out how to use optimization tools

Pre-course feedback

Rate your experience level with CVXPY

37 responses

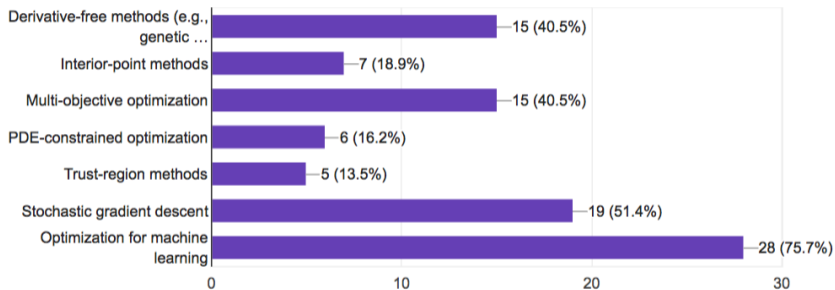


- ▶ No previous knowledge is needed
- ▶ CVXPY has a shallow learning curve: designed to allow you to “express your problem in a natural way”

Pre-course feedback

Which special topics most interest you?

37 responses



- ▶ We will briefly cover optimization aspects of machine learning
 - ▶ stochastic gradient descent
 - ▶ neural networks
 - ▶ distributed optimization

Pre-course feedback



- ▶ Lots of interest in machine learning, Python, general knowledge

Course materials

- ▶ You may download the course materials from <https://goo.gl/CbuBwm>
- ▶ These include:
 1. Slides
 2. iPython notebooks
 3. html exports of iPython notebooks
- ▶ html exports are useful for following along if you don't want to run code interactively, weren't able to install CVXPY, etc.

Rough outline

Session 1: 9:00am–10:30am

- ▶ Introduction to optimization (2_introduction.pdf)
- ▶ Unconstrained optimization (3_unconstrained.pdf)

Session 2: 10:45am–12:00pm

- ▶ Optimization in Python (4_optimization-in-python.pdf)
- ▶ Constrained optimization (5_constrained.pdf)

Session 3: 2:00pm–3:15pm

- ▶ Optimization for machine learning (6_optimization-for-ml.pdf)

Session 4: 3:15pm–4:45pm

- ▶ Convex optimization (7_convexity.pdf)
- ▶ Convex-optimization examples (8_modeling.pdf)

ICME at Stanford



- ▶ Home at Stanford for a critical multidisciplinary field that uses advanced mathematical and computing capabilities to understand and solve big, complex problems
- ▶ Over 50 faculty affiliated from 20+ departments
- ▶ MS and PhD students apply studies to wide range of domains
- ▶ MS tracks in Data Science, Computational Finance, Geoscience, Imaging Sciences
- ▶ World-class Facilities, such as the HIVE Immersive Visualization Environment, and High Performance GPU Cluster
- ▶ Offering MS and PhD degrees in computational mathematics for over 30 years: first as part of CS; then 14 years ago ICME spun off into separate institute
- ▶ Over 60 courses for graduate students as well as some undergraduates

ICME at Stanford: external partners

- ▶ These Fundamentals of Data Science workshops are part of the ICME program for **external partners**.
- ▶ We have events throughout the year around computational math, data science, machine learning and related fields.
- ▶ If you want your company to be involved in ICME collaboration, let us know!
- ▶ My organization (Sandia National Laboratories) has close connections with Stanford ICME

References

- ▶ J. Nocedal and S. J. Wright. *Numerical Optimization*, Springer, 1999.
- ▶ S. Boyd and L. Vadenberghe. *Convex Optimization*, Cambridge University Press, 2004. (available online)
 - ▶ Excellent lectures by S. Boyd online
 - ▶ Class notes and lectures for EE364a, EE364b online
 - ▶ CVX101 MOOC
- ▶ P.E. Gill, W. Murray, and M.H. Wright, *Practical Optimization*, London, Academic Press, 1981.
- ▶ Bottou, L., Curtis, F.E. and Nocedal, J., 2018. Optimization methods for large-scale machine learning. *SIAM Review*, 60(2), pp.223-311. (available on the arXiv)
 - ▶ Advanced recent review article