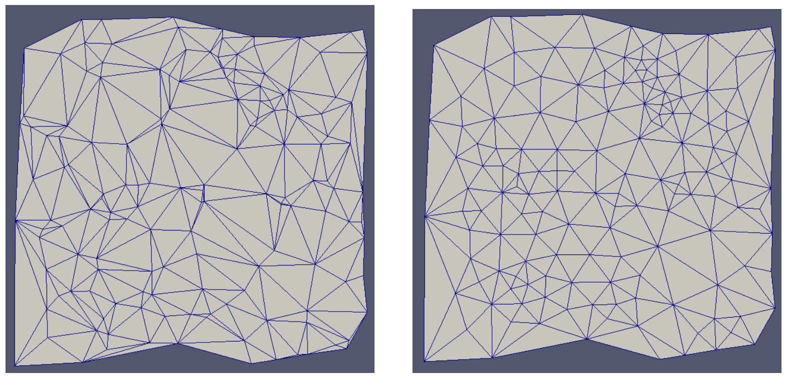
APPM 5630
"Advanced Convex Optimization"
Prof. Becker, spring 2021
Student projects

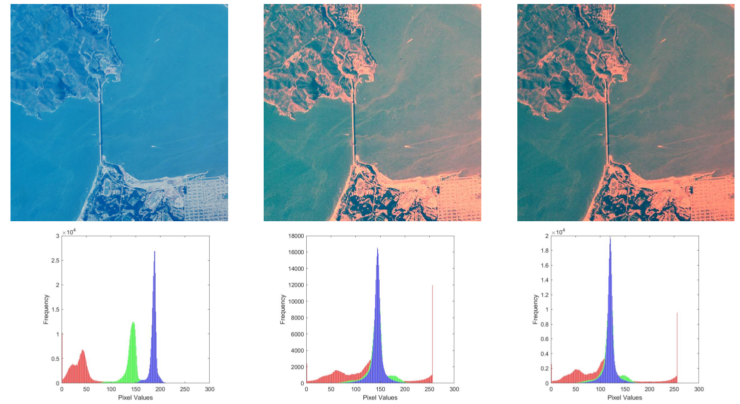
Student backgrounds:
- Applied Math (BS/MS, PhD)
- Computer Science (PhD)
- Aerospace Engineering (PhD)

Block Coordinate Descent for Mesh Quality Improvement
(Sachin Natesh)



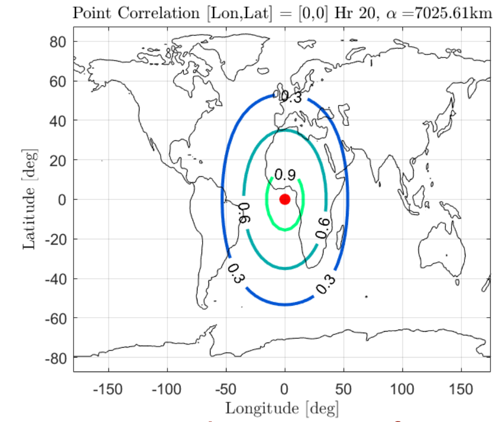
(a) Original Mesh 2 (b) Optimized Mesh 2

Image Optimization
(Jacob Spainhour, Damien Beecroft, Spas Angelov)

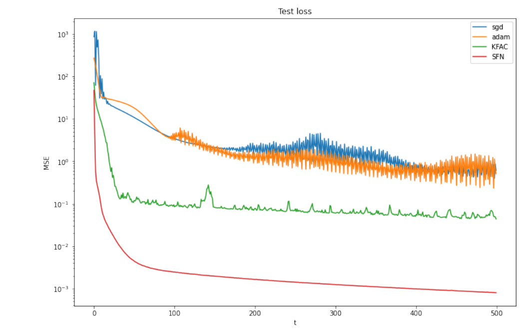


(a) Original (b) Linear Scaling (c) Intensity Preservation

Electron Density Localization
(Nick Dietrich)



Approximating the Natural Gradient
(Mike McCabe)



An overview of sparse recovery with convex optimization
(Mike Huffman, Steven Kordonowy)

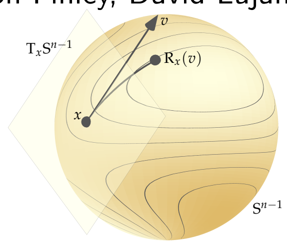
Theorem 1. *(Theorem 1.3 in [1]) Assume e is supported on a set S of size k. If $\delta_k + \delta_{2k} + \delta_{3k} < 1$, then e is the unique solution to (P_1).*

In order to prove Theorem 1, we prove the existence of a dual variable with helpful properties and then show that our solutions to (P_1) must be unique. We argue there exists a dual variable ν that obeys

1. $\langle \nu, v_j \rangle = sgn(e_j)$ for $j \in S$
2. $|\langle \nu, v_j \rangle| \leq 1$ for all $j \notin S$

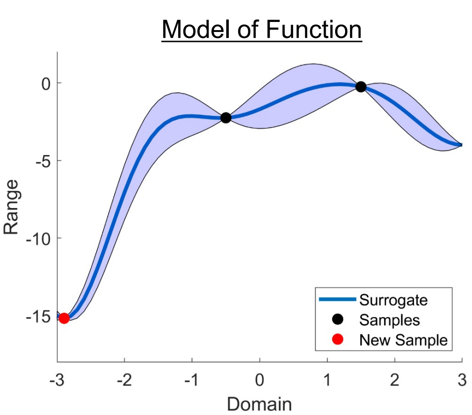
Lagrangian optimality conditions for (P_1) provides some intuition as to where these properties arise. The Lagrangian of (P_1) is given by $\mathcal{L}(d, \nu) = ||d||_1 + \nu^T F(d - e)$. $\mathcal{L}$ is not differentiable at $d = 0$, so we focus on subgradients. In order to satisfy stationarity of the KKT conditions, we must

An Exploration of Optimization on Smooth Manifolds
(Brandon Finley, David Lujan)



Retraction $R_x(v) = \frac{x+v}{\|x+v\|}$ on the sphere.

Bayesian Optimization: A Class of Zero-th Order Optimization Algorithms
(Kevin Doherty, Killian Wood)



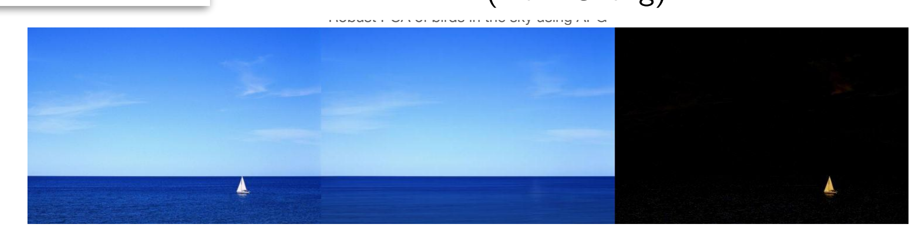
Mirror Descent Learning in Continuous Games
(Maneesha Papireddygari)

Theorem 1. *For any $\delta > 0$, $\exists T(\delta)$, such that for any $t \geq T(\delta)$, if $x^t \in \widetilde{B}(x^*, \delta)$, then $x^{\tilde{t}} \in \widetilde{B}(x^*, \delta)$, $\forall \tilde{t} \geq t$.*

Proof. Assume that for a $t \geq T(\delta)$, $x^t \in \widetilde{B}(x^*, \delta)$.
This implies, $\exists y^t$ such that, $x^t = C(y^t)$ and $F(x^*, y^t) < \delta$.
Let $\exists y^{t+1}$ such that, $x^{t+1} = C(y^{t+1})$. We need to show that $F(x^*, y^{t+1}) < \delta$.
Firstly we note a few equalities and inequalities that are helpful -

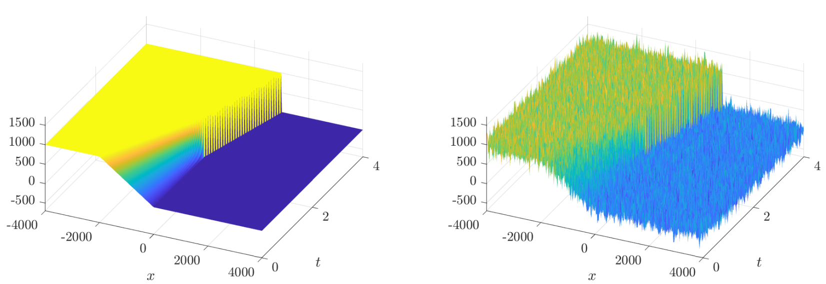
$$t_i^{t+1} = y_i^t + \alpha^t v_i(x^t) \qquad (1)$$

Robust Principal Component Analysis with Background Modeling Application
(Noki Cheng)

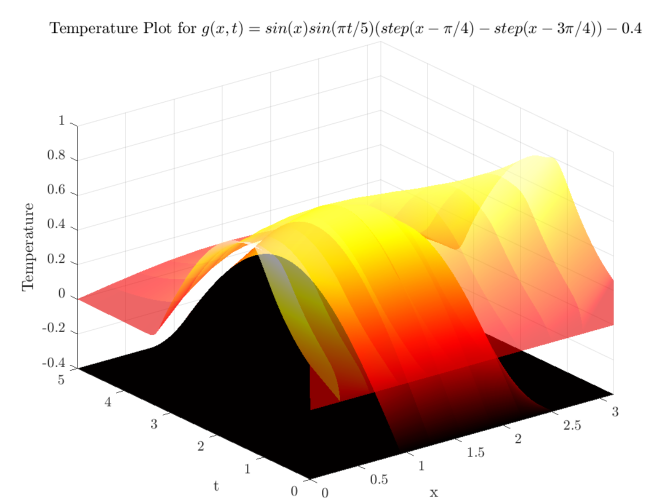


Robust PCA of boats in the sea using APG

WSINDy and Asymptotic Consistency
(Daniel Messenger)



Heat Transfer Optimization in 1D
(David Perkins)



Approximate Hessian Based ARC for Deep Learning
(Cooper Simpson, Jaden Wang)