

Beyond Convenience: Beyond Convexity

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**MINI-SYMPOSIUM ON COMPUTATION AND
OPTIMIZATION IN THE SCIENCES AND ENGINEERING**

Outline of the Talk

- Convex Optimization
- A Few Contemporary Applications
- Non-convex Optimization
- Robust Regression
- Applications of Robust Regression
- Robust PCA

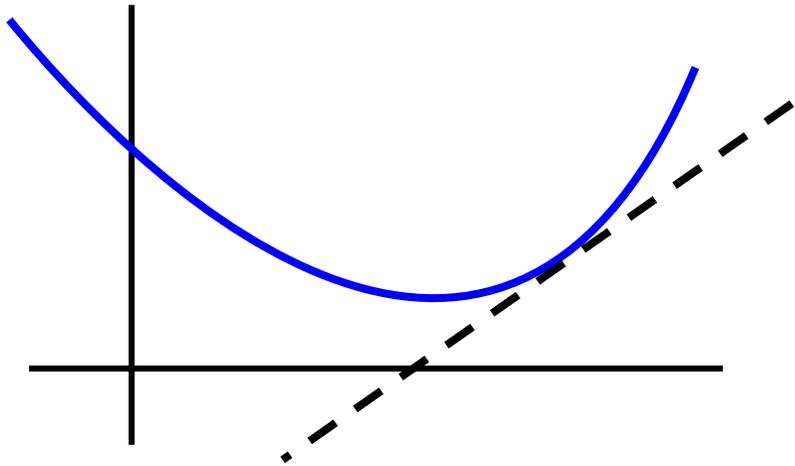
Convex Optimization

Convex Optimization

$$\min_{\mathbf{x} \in \mathcal{C}} f(\mathbf{x})$$

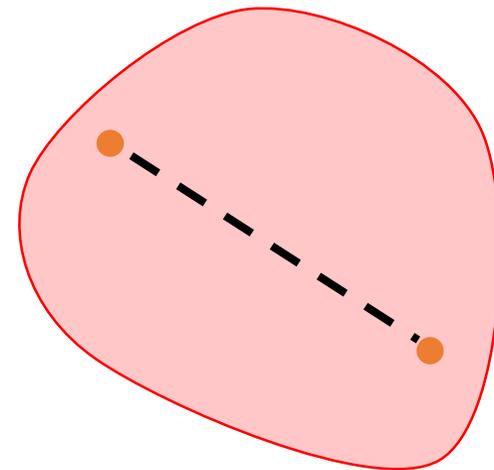
$$f : \mathbb{R}^d \rightarrow \mathbb{R}$$

Convex function



$$\mathcal{C} \subseteq \mathbb{R}^d$$

Convex set

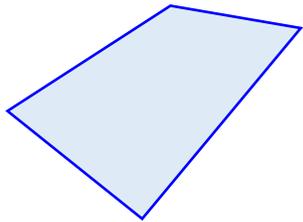


Examples

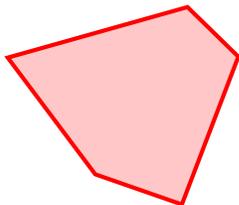
Linear Programming

$$\begin{aligned} \min_{\mathbf{x} \in \mathbb{R}^d} \quad & \mathbf{a}^\top \mathbf{x} \\ \text{s.t.} \quad & \mathbf{b}_i^\top \mathbf{x} \leq c_i \end{aligned}$$

f



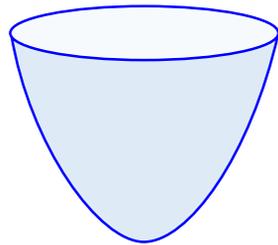
\mathcal{C}



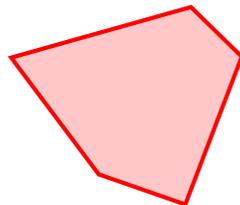
Quadratic Programming

$$\begin{aligned} \min_{\mathbf{x} \in \mathbb{R}^d} \quad & \frac{1}{2} \mathbf{x}^\top \mathbf{A} \mathbf{x} + \mathbf{a}^\top \mathbf{x} \\ \text{s.t.} \quad & \mathbf{b}_i^\top \mathbf{x} \leq c_i \end{aligned}$$

f



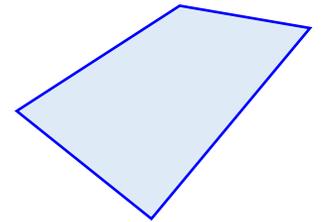
\mathcal{C}



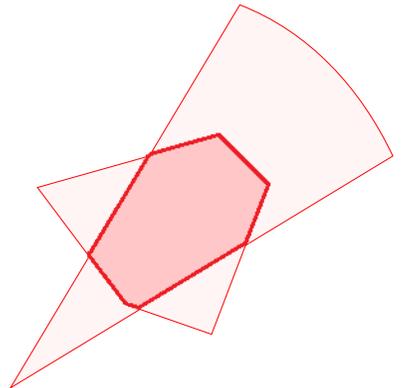
Semidefinite Programming

$$\begin{aligned} \min_{\mathbf{X} \succeq \mathbf{0}} \quad & \mathbf{A}^\top \mathbf{X} \\ \text{s.t.} \quad & \mathbf{B}_i^\top \mathbf{X} \leq c_i \end{aligned}$$

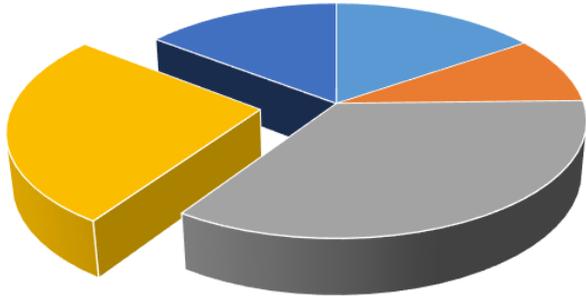
f



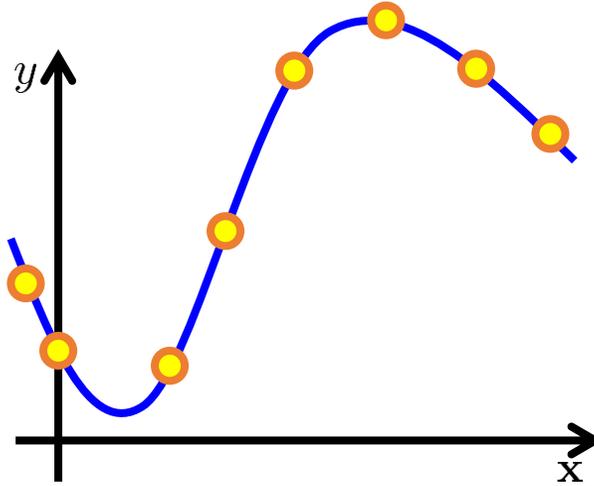
\mathcal{C}



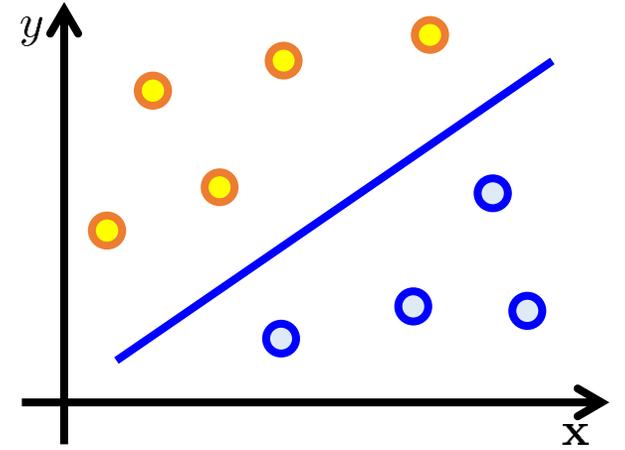
Applications



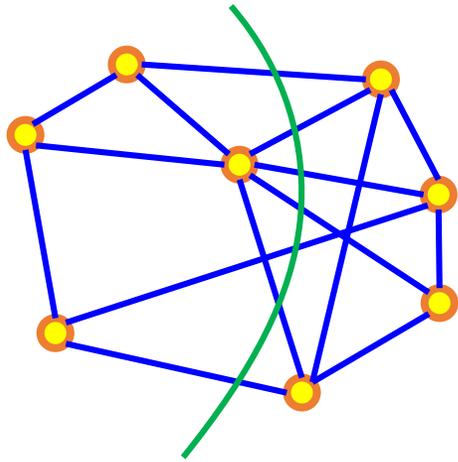
Resource Allocation



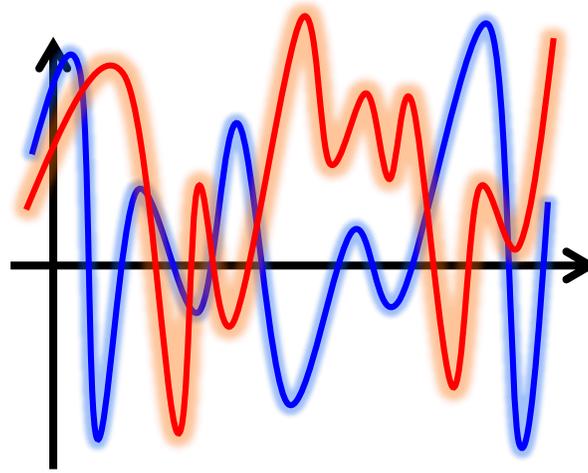
Regression



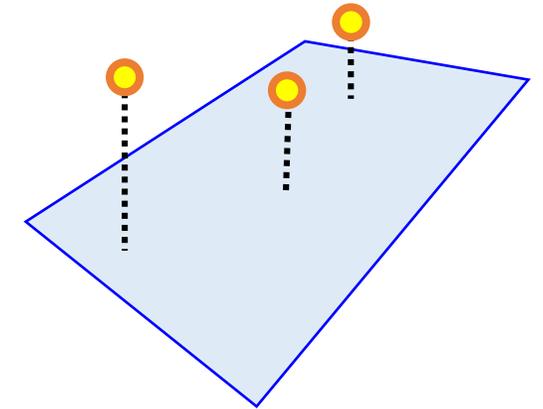
Classification



Clustering/Partitioning



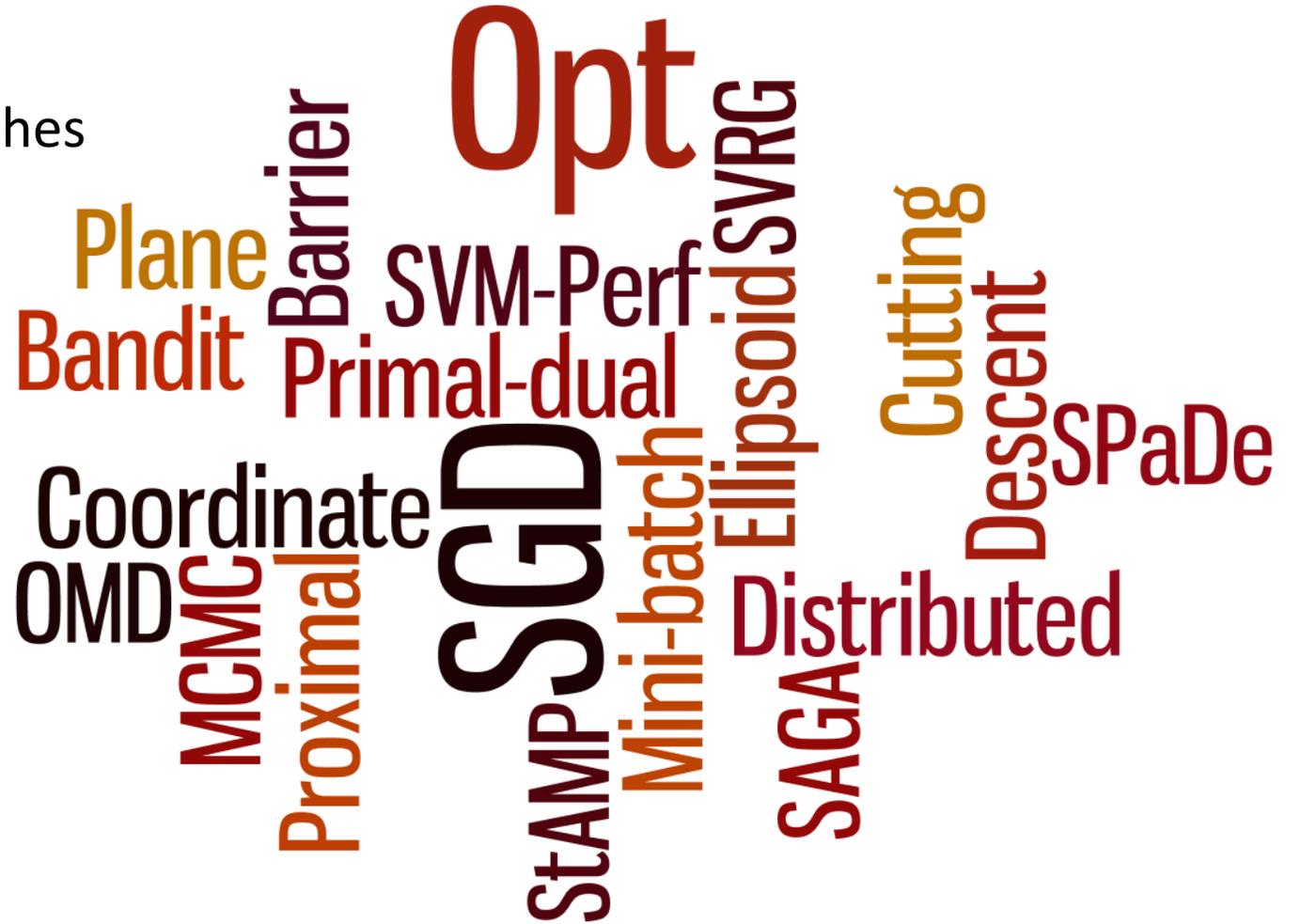
Signal Processing



Dimensionality Reduction

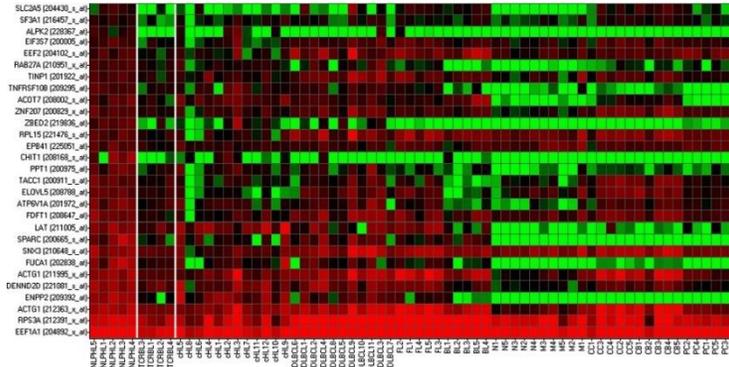
Techniques

- Projected (Sub)gradient Methods
 - Stochastic, mini-batch variants
 - Primal, dual, primal-dual approaches
 - Coordinate update techniques
- Interior Point Methods
 - Barrier methods
 - Annealing methods
- Other Methods
 - Cutting plane methods
 - Accelerated routines
 - Proximal methods
 - Distributed optimization
 - Derivative-free optimization



A Few Contemporary Applications

Gene Expression Analysis



DNA micro-array gene expression data

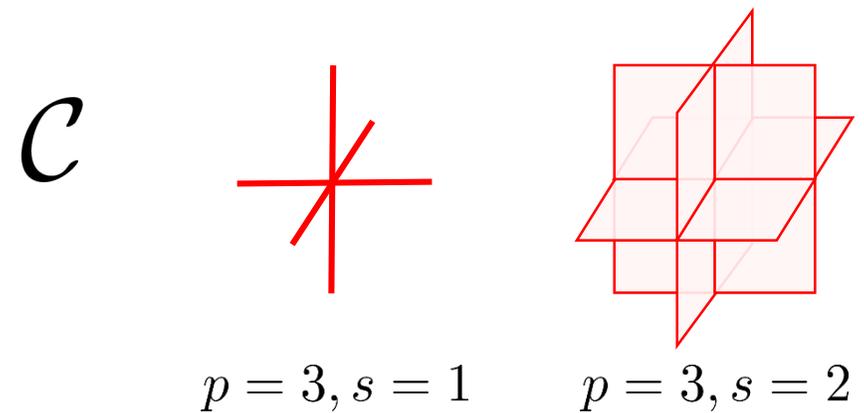
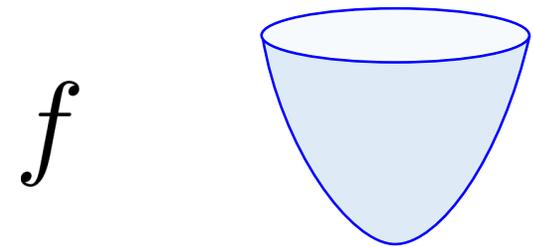


 $i = (\mathbf{x}_i, y_i) \in \mathbb{R}^p \times \mathbb{R}$

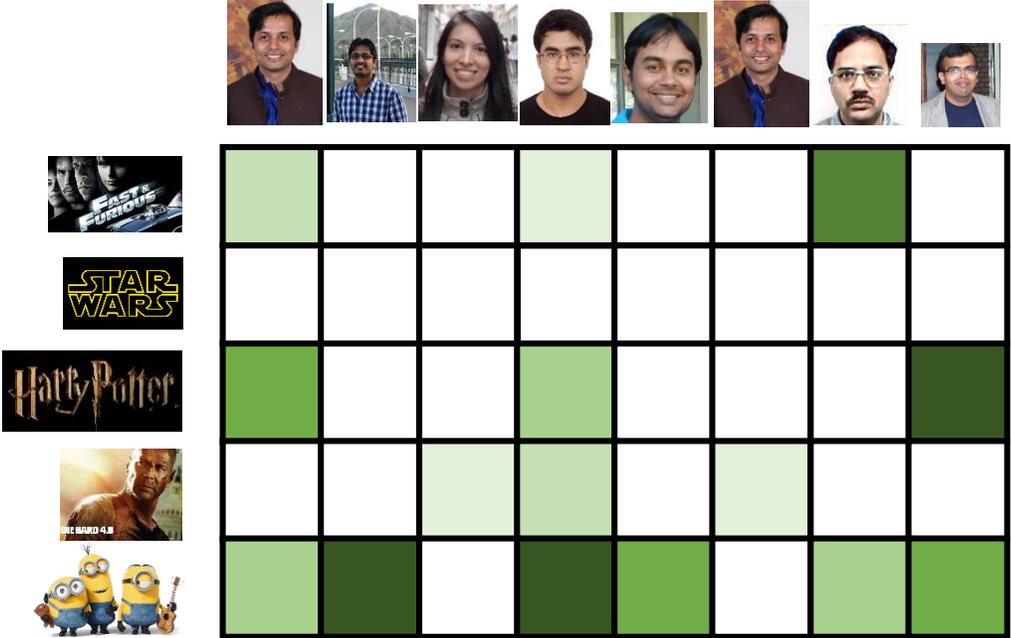
Linear model: $y_i = \mathbf{x}_i^\top \mathbf{w}^*$

Challenge: \mathbf{w}^* is sparse!

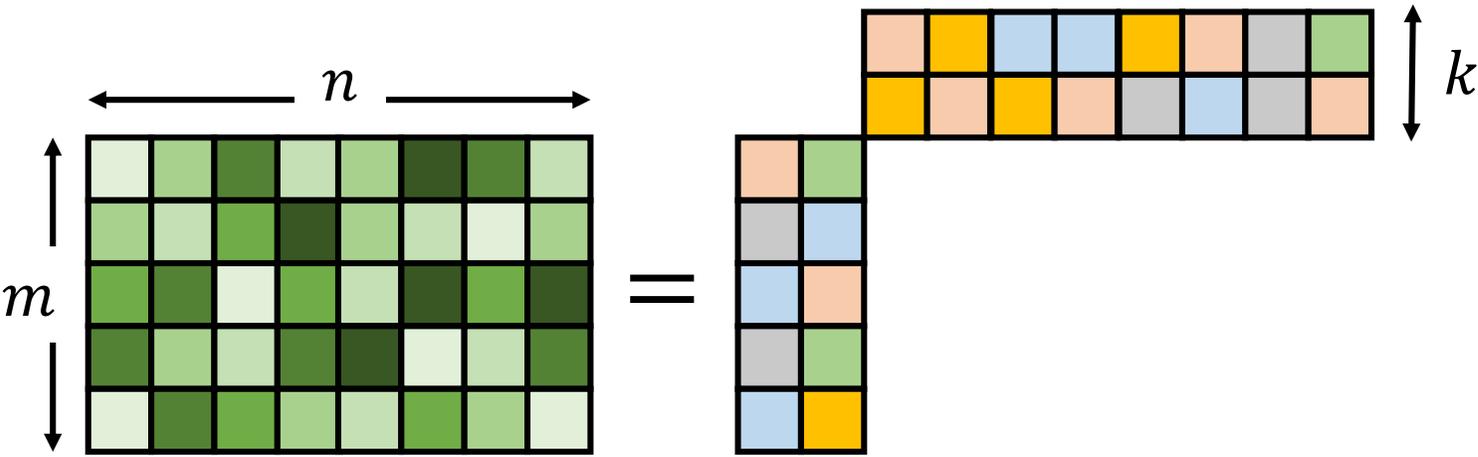
$$\min_{\mathbf{w} \in \mathcal{B}_0^p(s)} \sum_{i=1}^n (y_i - \mathbf{x}_i^\top \mathbf{w})^2$$



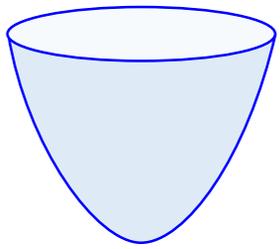
Recommender Systems



$$\min_{L \in \mathcal{M}_k^{m,n}} \|X_\Omega - L_\Omega\|_F^2$$



f



\mathcal{C}

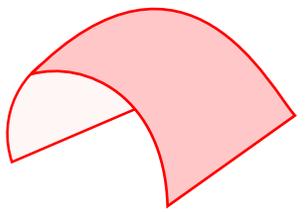


Image Reconstruction and Robust Face Recognition

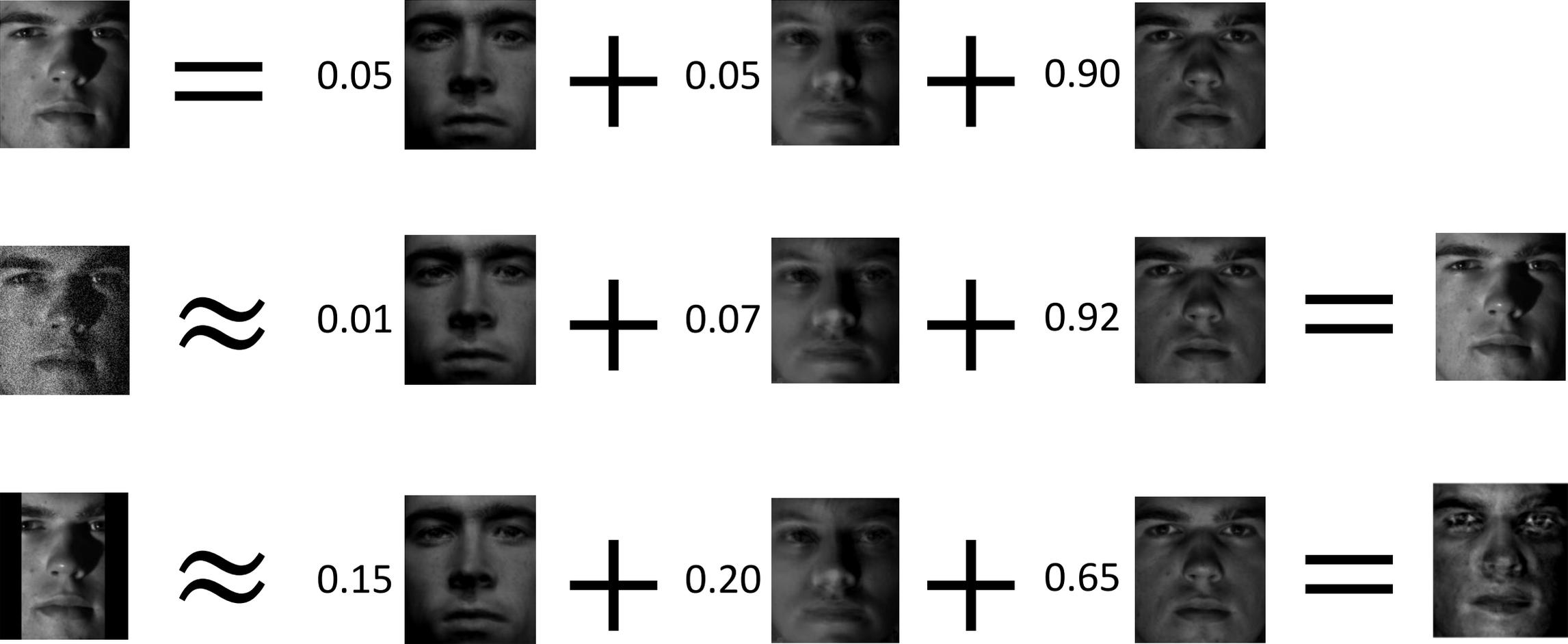
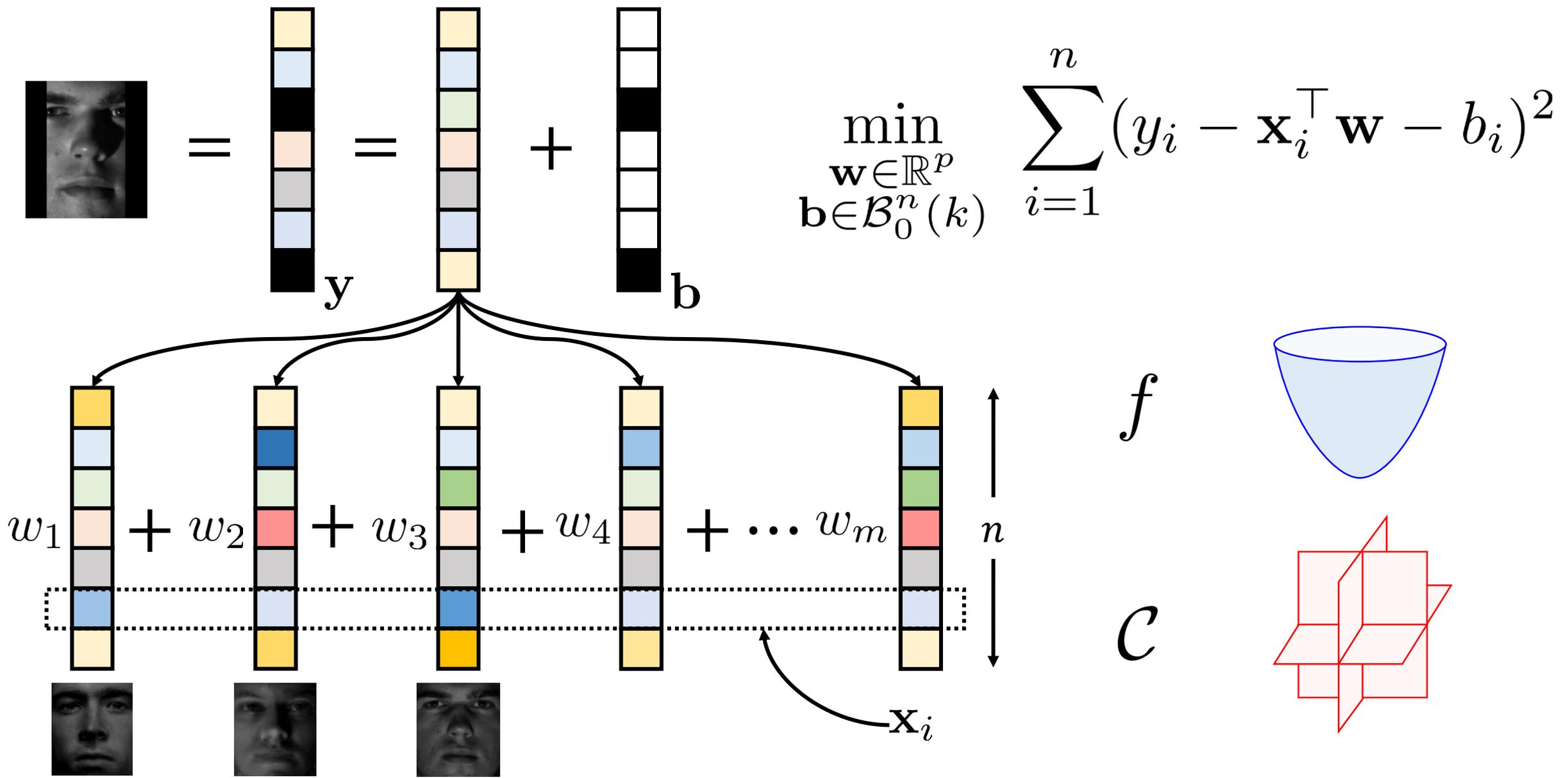
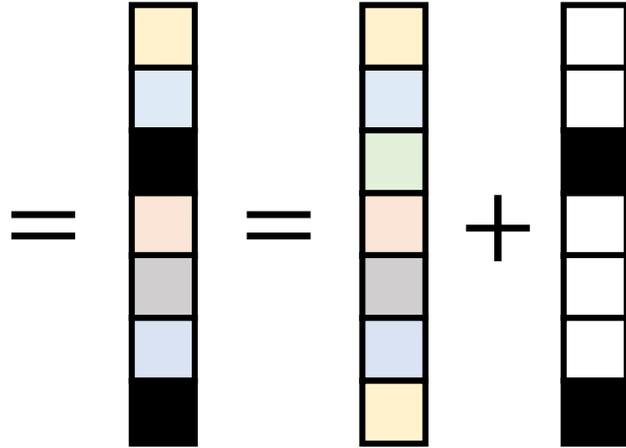


Image Denoising and Robust Face Recognition

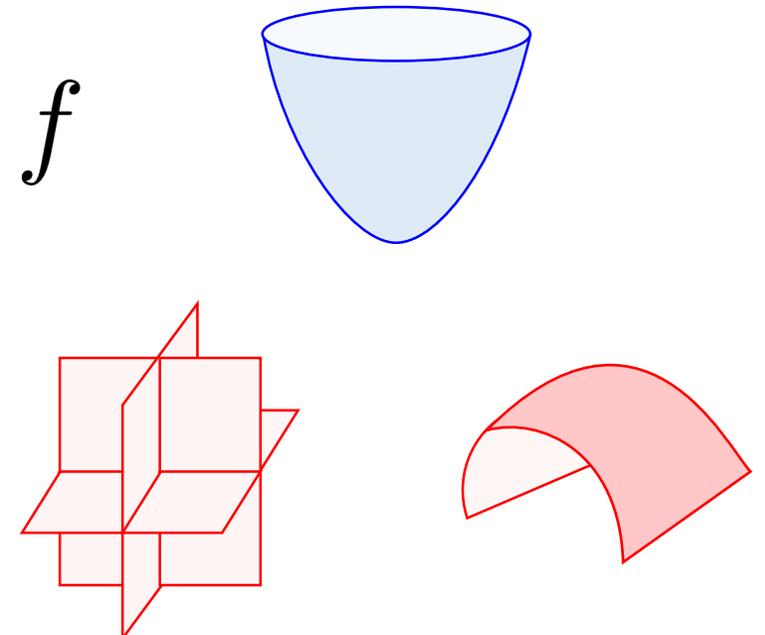
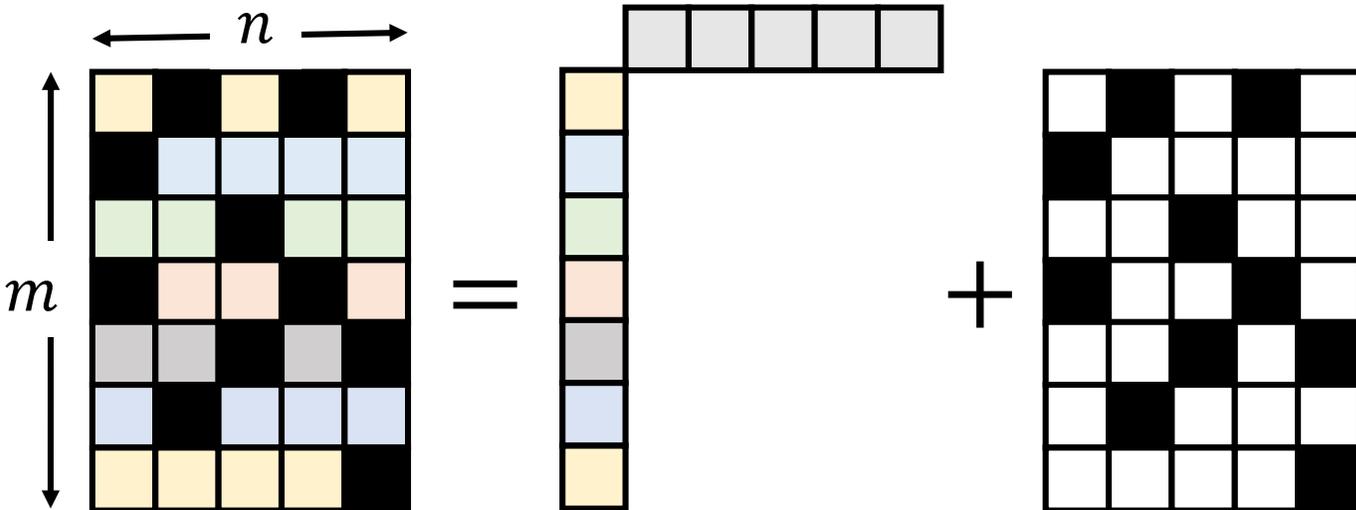


Large Scale Surveillance

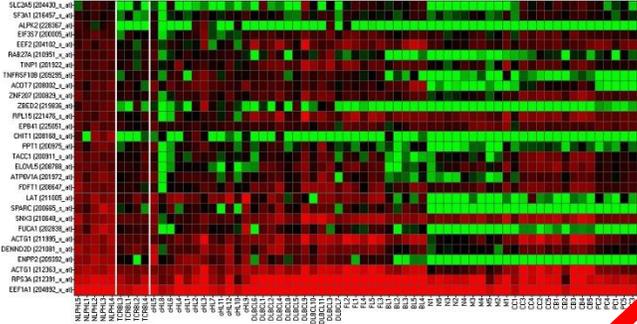
- Foreground-background separation



$$\min_{\substack{L \in \mathcal{M}_k^{m,n} \\ S \in \mathcal{B}_0^{m,n}(s)}} \|X - (L + S)\|_F^2$$



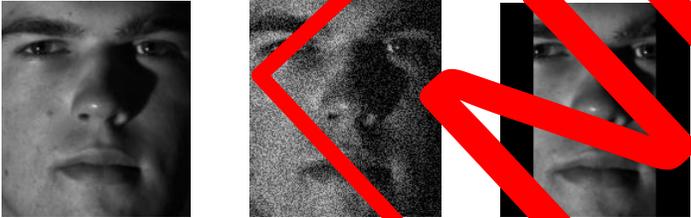
Non Convex Optimization



Sparse Recovery



Matrix Completion



Robust Regression



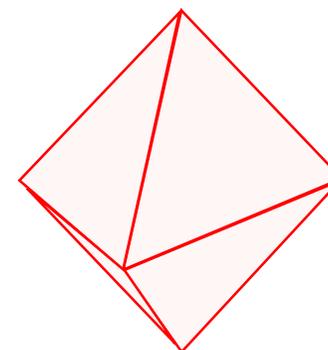
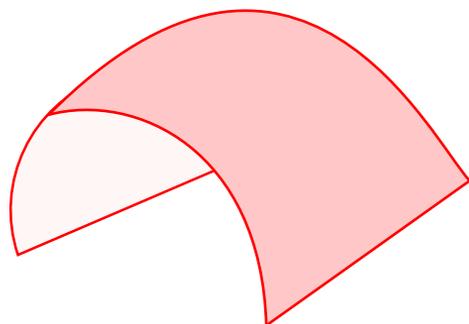
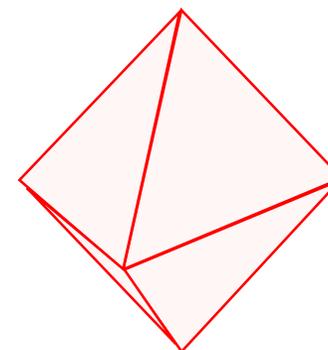
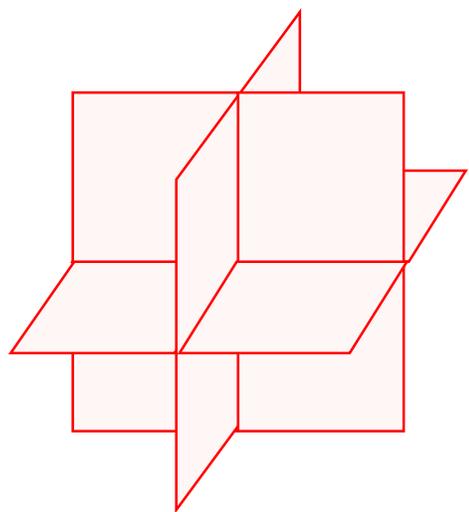
Robust PCA

NP-hard

Non-convex Optimization

Relaxation-based Techniques

- “Convexify” the feasible set



SLOW

Alternating Minimization

$$\begin{aligned} \min f(\mathbf{x}, \mathbf{y}) \\ \text{s.t. } \mathbf{x} \in \mathcal{C}_1 \\ \mathbf{y} \in \mathcal{C}_2 \end{aligned}$$

- ▷ Initialize $\mathbf{x}^0, \mathbf{y}^0$
- ▷ For $t = 1, 2, \dots$
 - ▷ $\mathbf{x}^t = \arg \min_{\mathbf{x} \in \mathcal{C}_1} f(\mathbf{x}, \mathbf{y}^{t-1})$
 - ▷ $\mathbf{y}^t = \arg \min_{\mathbf{y} \in \mathcal{C}_2} f(\mathbf{x}^t, \mathbf{y})$

Matrix Completion

$$\begin{aligned} \min_{L \in \mathcal{M}_k^{m,n}} \|X_\Omega - L_\Omega\|_F^2 \\ \equiv \min_{\substack{U \in \mathbb{R}^{m \times k} \\ V \in \mathbb{R}^{n \times k}}} \|X_\Omega - (UV^\top)_\Omega\|_F^2 \end{aligned}$$

Robust PCA

$$\min_{\substack{L \in \mathcal{M}_k^{m,n} \\ S \in \mathcal{B}_0^{m,n}(s)}} \|X - (L + S)\|_F^2$$

... also Robust Regression, coming up

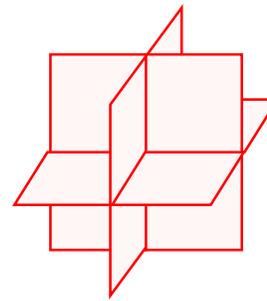
Projected Gradient Descent

$$\begin{aligned} \min f(\mathbf{x}) \\ \text{s.t. } \mathbf{x} \in \mathcal{C} \end{aligned}$$

- ▷ Initialize \mathbf{x}^0
- ▷ For $t = 1, 2, \dots$
 - ▷ $\mathbf{z}^t = \mathbf{x}^{t-1} - \eta_t \cdot \nabla f(\mathbf{x}^{t-1})$
 - ▷ $\mathbf{x}^t = \Pi_{\mathcal{C}}(\mathbf{z}^t)$

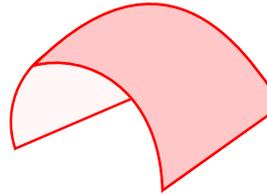
$$\Pi_{\mathcal{C}}(\mathbf{z}) = \arg \min_{\mathbf{x} \in \mathcal{C}} \|\mathbf{z} - \mathbf{x}\|_2^2$$

Non-convex
Projection



$$\mathcal{B}_0^p(s)$$

Top s elements by magnitude



$$\mathcal{M}_k^{m,n}$$

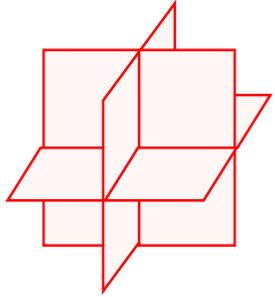
Perform k -truncated SVD

Sparse Recovery

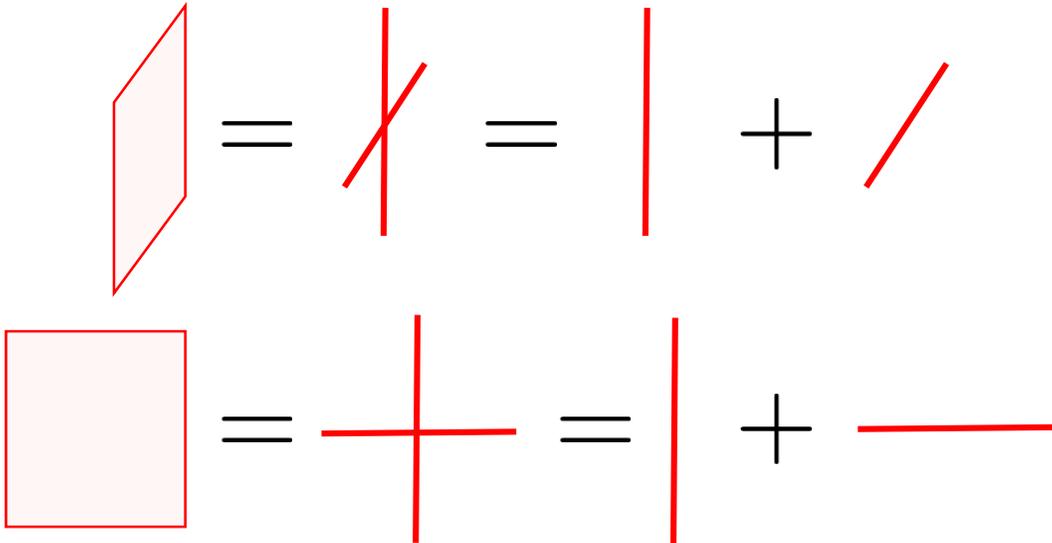
$$\min_{\mathbf{w} \in \mathcal{B}_0^p(s)} \sum_{i=1}^n (y_i - \mathbf{x}_i^\top \mathbf{w})^2$$

Pursuit and Greedy Methods

$$\begin{aligned} \min f(\mathbf{x}) \\ \text{s.t. } \mathbf{x} \in \mathcal{C} \end{aligned}$$



Sparse Recovery



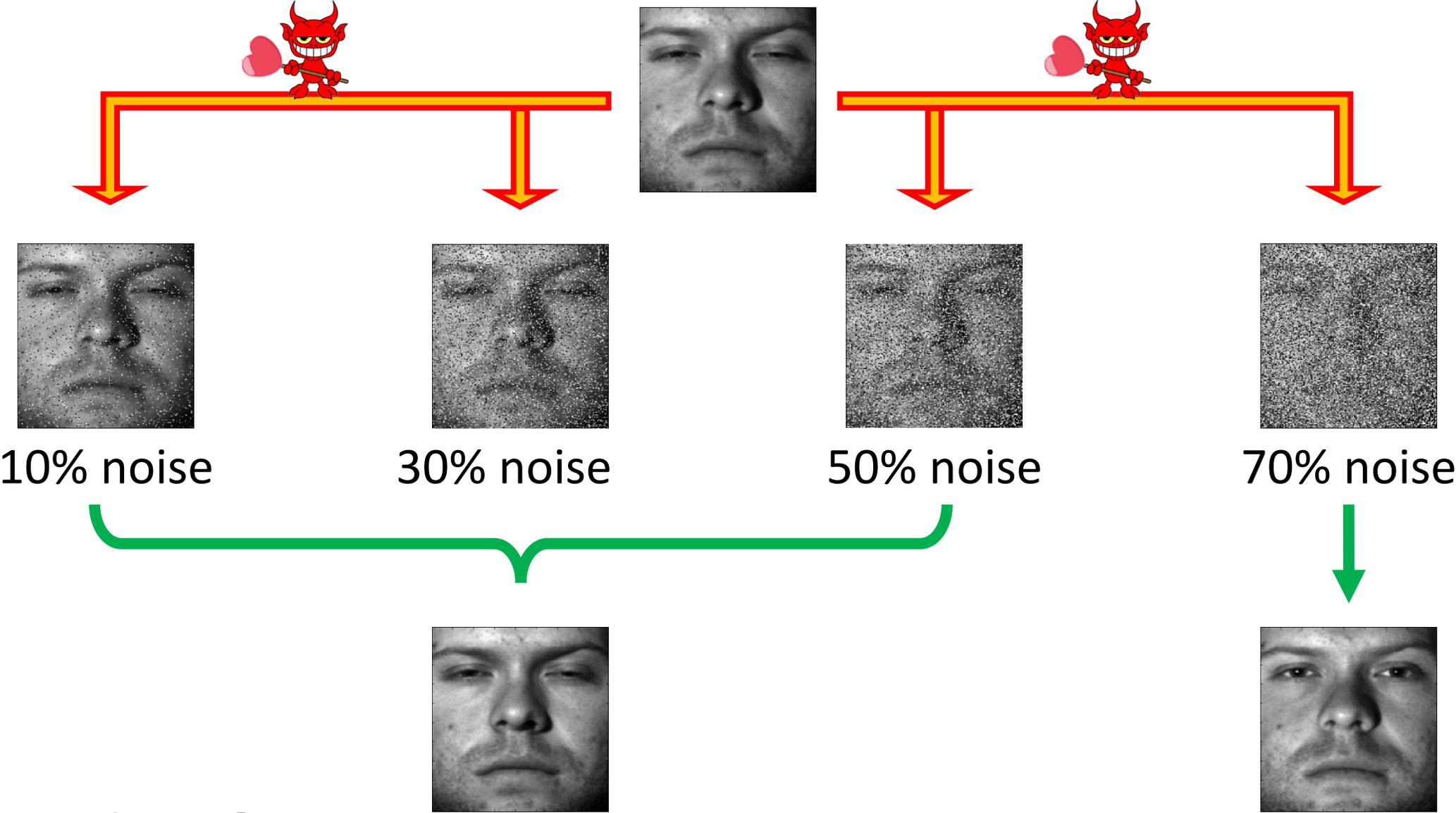
\mathcal{A} Set of “atoms”

$$\mathcal{C} = \left\{ \mathbf{x} = \sum_{i=1}^s \mathbf{a}_i : \mathbf{a}_i \in \mathcal{A} \right\}$$

- ▷ Initialize $S^0 = \phi$
- ▷ For $t = 1, 2, \dots$
 - ▷ \mathbf{a}^t = “best” greedy choice
 - ▷ $S^t = S^{t-1} \cup \{\mathbf{a}^t\}$
 - ▷ $\mathbf{x}^t = \arg \min_{\mathbf{x} \in \text{conv}(S^t)} f(\mathbf{x})$

Applications of NCOpt

Face Recognition



[Bhatia *et al* 2015]

Image Reconstruction



Original



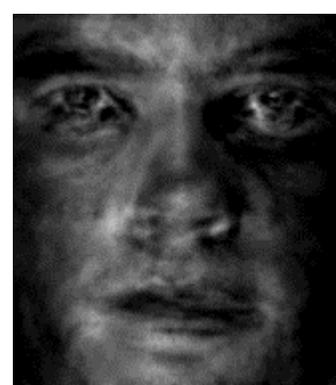
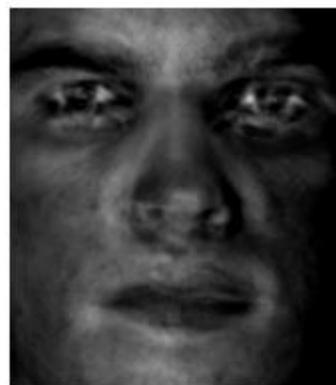
Input



Ordinary LS



Alt-Min



[Bhatia *et al* 2015]

Foreground-background Separation

Convex Relaxation. Runtime: 1700 sec



Alt-Proj. Runtime: 70 sec



Concluding Comments

Non-convex optimization is an exciting area

Widespread applications

- Much better modelling of problems
- Much more scalable algorithms
- Provable guarantees

So ...

- Full of opportunities
- Full of challenges

Acknowledgements

<http://research.microsoft.com/en-us/projects/altmin/default.aspx>

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Microsoft Research



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Microsoft Research



Ambuj Tewari
U. Michigan, Ann Arbor

Questions?