

Learn 2 Warm Start

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Joint work with Brandon Amos, Georgina Hall, Bartolomeo Stellato

Real-time Convex Problem Applications

Robotics and Control



Energy grid



Finance



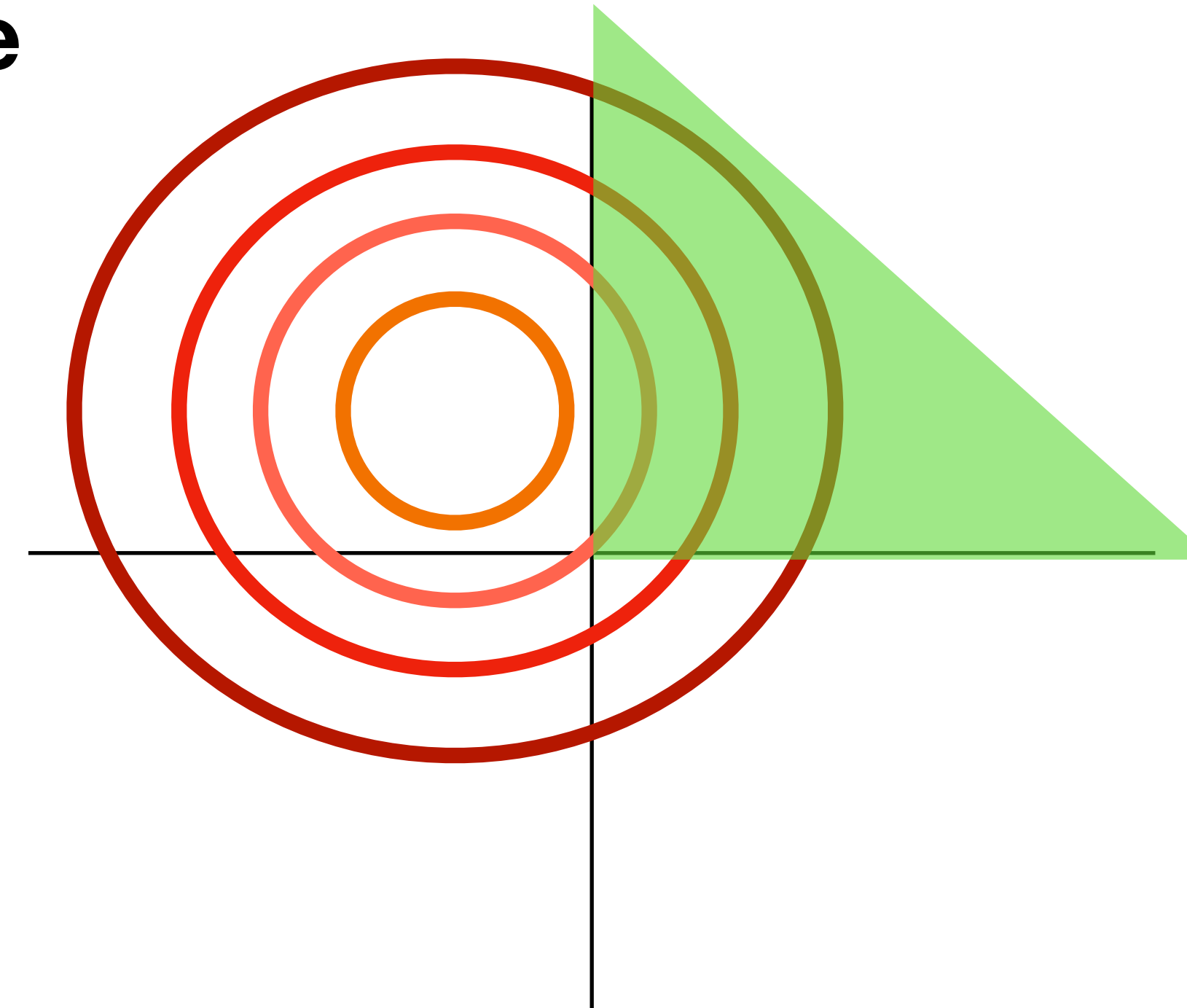
Convex Problems

minimize $f(x)$ \longleftarrow **Convex function**
 subject to $x \in \mathcal{X}$ \longleftarrow **Convex set**

Example

$$f(x) = \left\| x - \begin{bmatrix} -1 \\ 1 \end{bmatrix} \right\|_2^2$$

$$\mathcal{X} = \{x \mid \mathbf{1}^T x \leq 1, x \geq 0\}$$



Primal

minimize $\frac{1}{2}x^T P x + c^T x$
 subject to $Ax + s = b$

$$s \in \mathcal{K}$$

Conic constraint

Example Cones

$$\{s \mid s \geq 0\}$$

$$\{(s, t) \mid \|s\|_2 \leq t\}$$

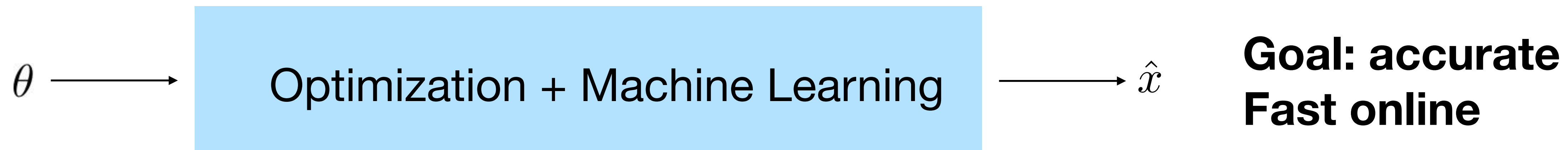
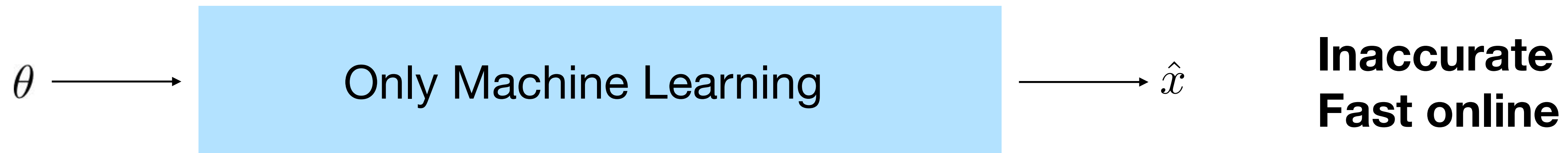
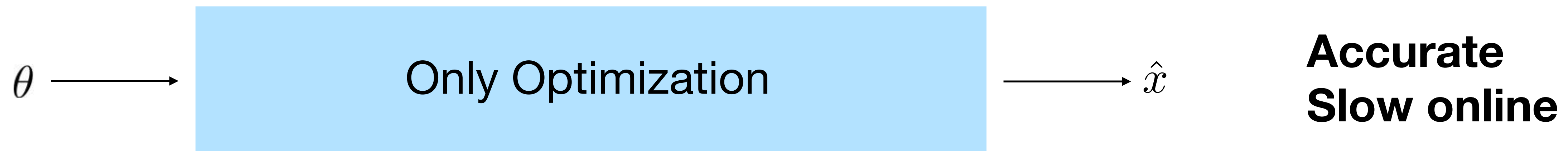
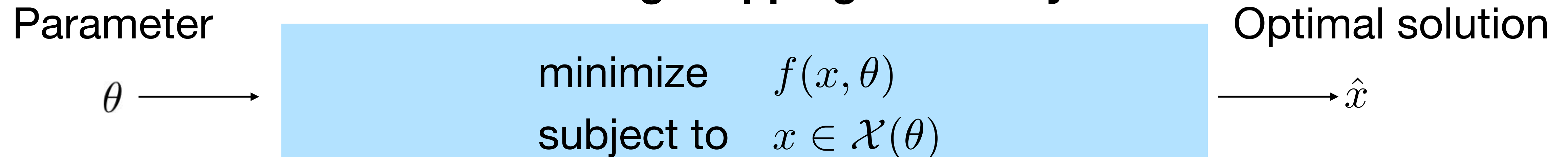
$$\{S \mid S \succeq 0\}$$

In many cases, solvers are not fast enough

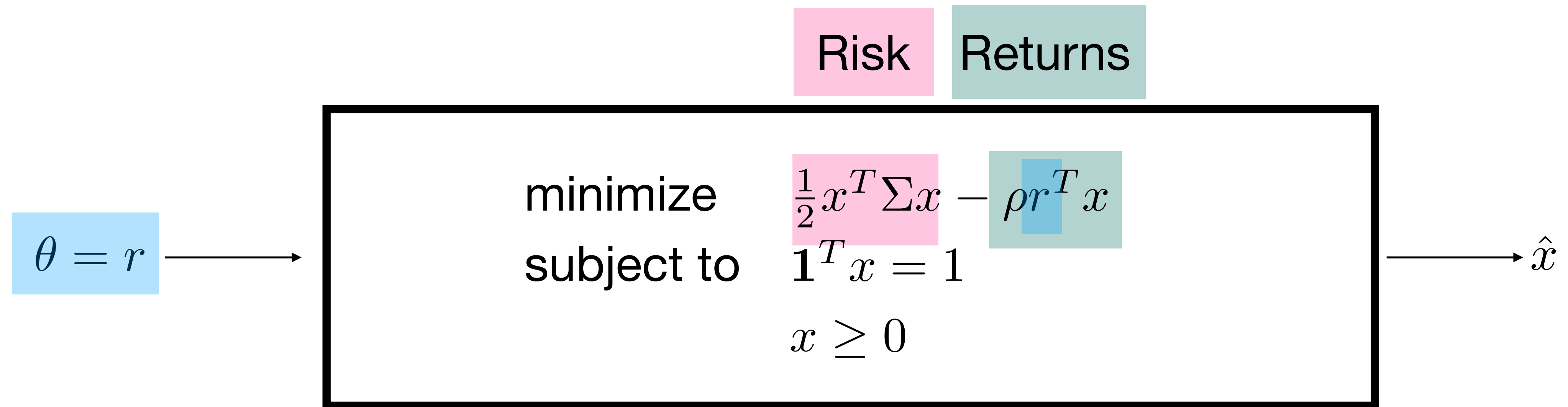
Parametric Convex programs

Often, we solve **parametric** convex problems from the same family

Goal: Learning mapping efficiently



Running Example: Markowitz



Σ : Covariance matrix

r : returns vector

ρ : weighting hyperparameter

Need to Decide

1. Solver choice

Rewrite KKT conditions as a linear complementarity problem

Algorithm: Douglas-Rachford Splitting

First order method

Fixed point iterations $z^{i+1} = T(z^i)$

Details in next 2 slides

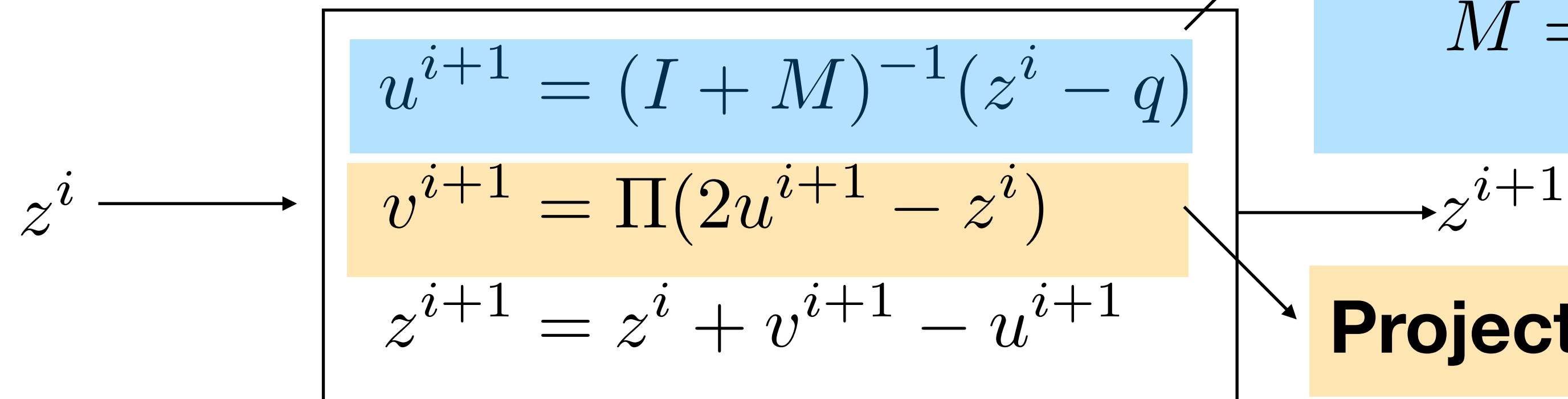


2. Learning method with this solver

Fixed Point Iterates

$$\begin{array}{ll}\text{minimize} & \frac{1}{2}x^T P x + c^T x \\ \text{subject to} & Ax + s = b \\ & s \in \mathcal{K}\end{array}$$

Fixed point iterate



Linear system solve

$$M = \begin{bmatrix} P & A^T \\ -A & 0 \end{bmatrix} \quad q = (c, b)$$

Projection onto \mathcal{K}^*

Repeat until $\|z^{i+1} - z^i\|_2$ is small

Markowitz Example

$$\begin{aligned} &\text{minimize} && \frac{1}{2}x^T \Sigma x - \rho r^T x \\ &\text{subject to} && \mathbf{1}^T x = 1 \\ &&& x \geq 0 \end{aligned}$$

Fixed point iterate

$$u^{i+1} = (I + M)^{-1}(z^i - q)$$

$$v^{i+1} = \Pi(2u^{i+1} - z^i)$$

$$z^{i+1} = z^i + v^{i+1} - u^{i+1}$$

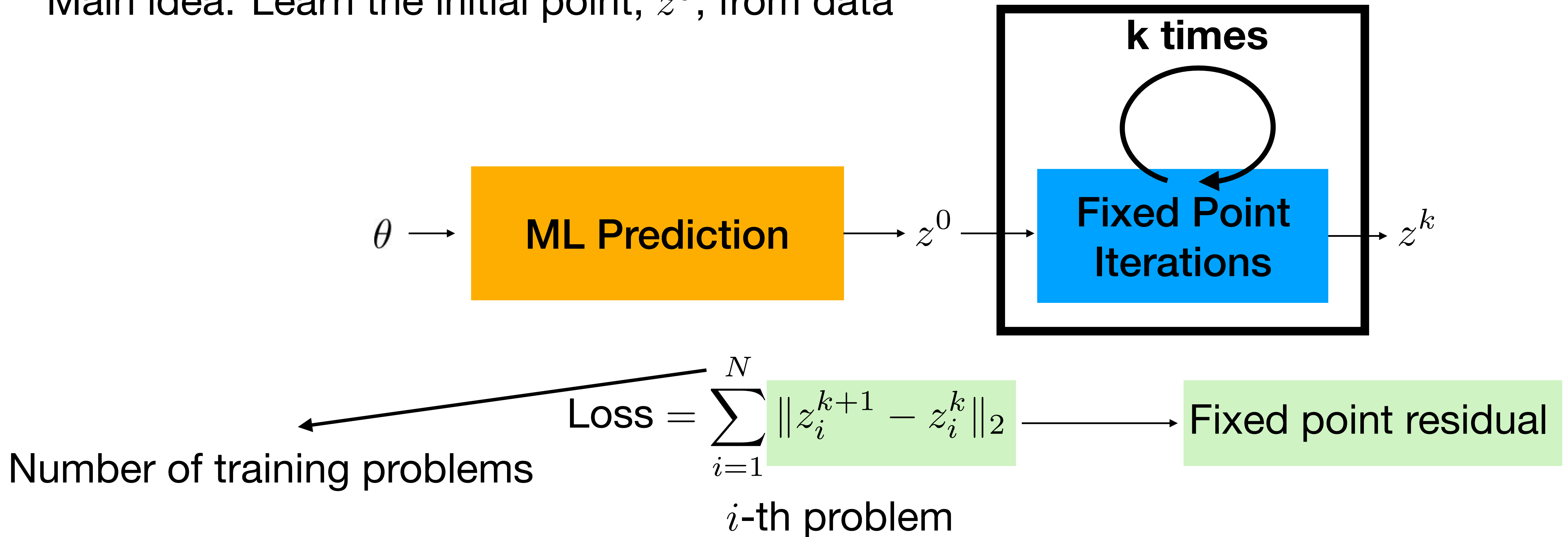
Linear system

$$M = \begin{bmatrix} \Sigma & \mathbf{1} \\ -\mathbf{1}^T & 0 \end{bmatrix} \quad q = (\rho r, 1)$$

Projection: clip negative values

Our Neural Network Architecture

Main idea: Learn the initial point, z^0 , from data

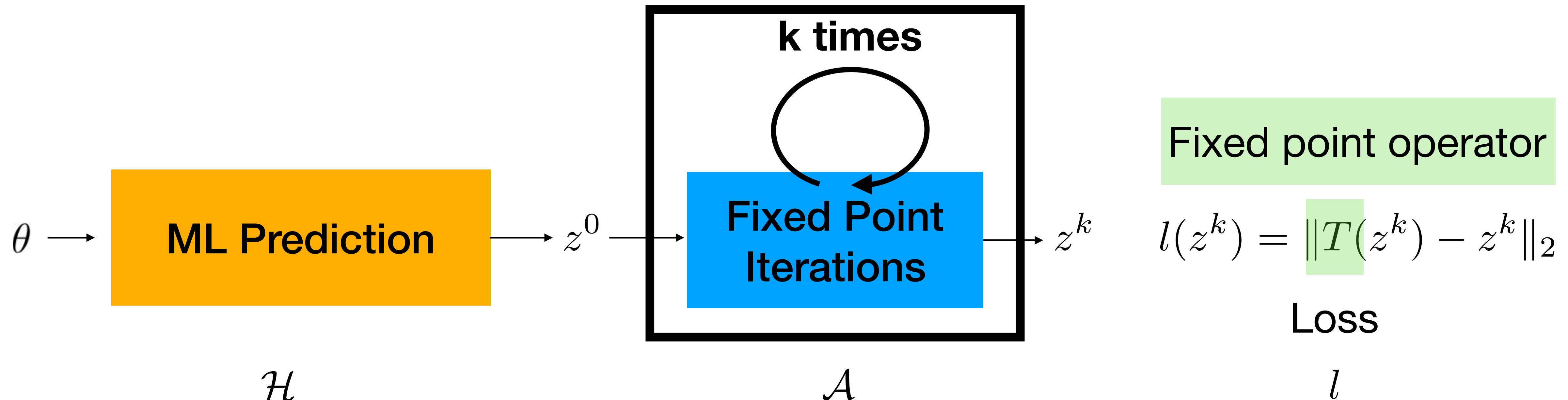


Minimize the loss w.r.t. the weights in the ML Prediction block

Apply a gradient-based method

Generalization Bounds

Generalization error can be bounded in terms of the Rademacher complexity



$$T \text{ } \kappa\text{-contractive} \longrightarrow \hat{\mathcal{R}}_N(\mathcal{H} \circ \mathcal{A} \circ l) \leq 2\sqrt{2}\kappa^k \hat{\mathcal{R}}_N(\mathcal{H}) \quad O\left(\frac{1}{\sqrt{k}}\right) \text{ if } T \text{ is averaged}$$

Learn 2 warm start: Generalization bounds improve with both N and k

Markowitz Numerical Example

$$\begin{aligned} &\text{minimize} && \frac{1}{2}x^T \Sigma x - \rho \bar{r}^T x \\ &\text{subject to} && \mathbf{1}^T x = 1 \\ &&& x \geq 0 \end{aligned}$$

Sampled from noisy returns

\bar{r} changes for each problem

10000 training problems

5000 testing problems

Used Russell index data

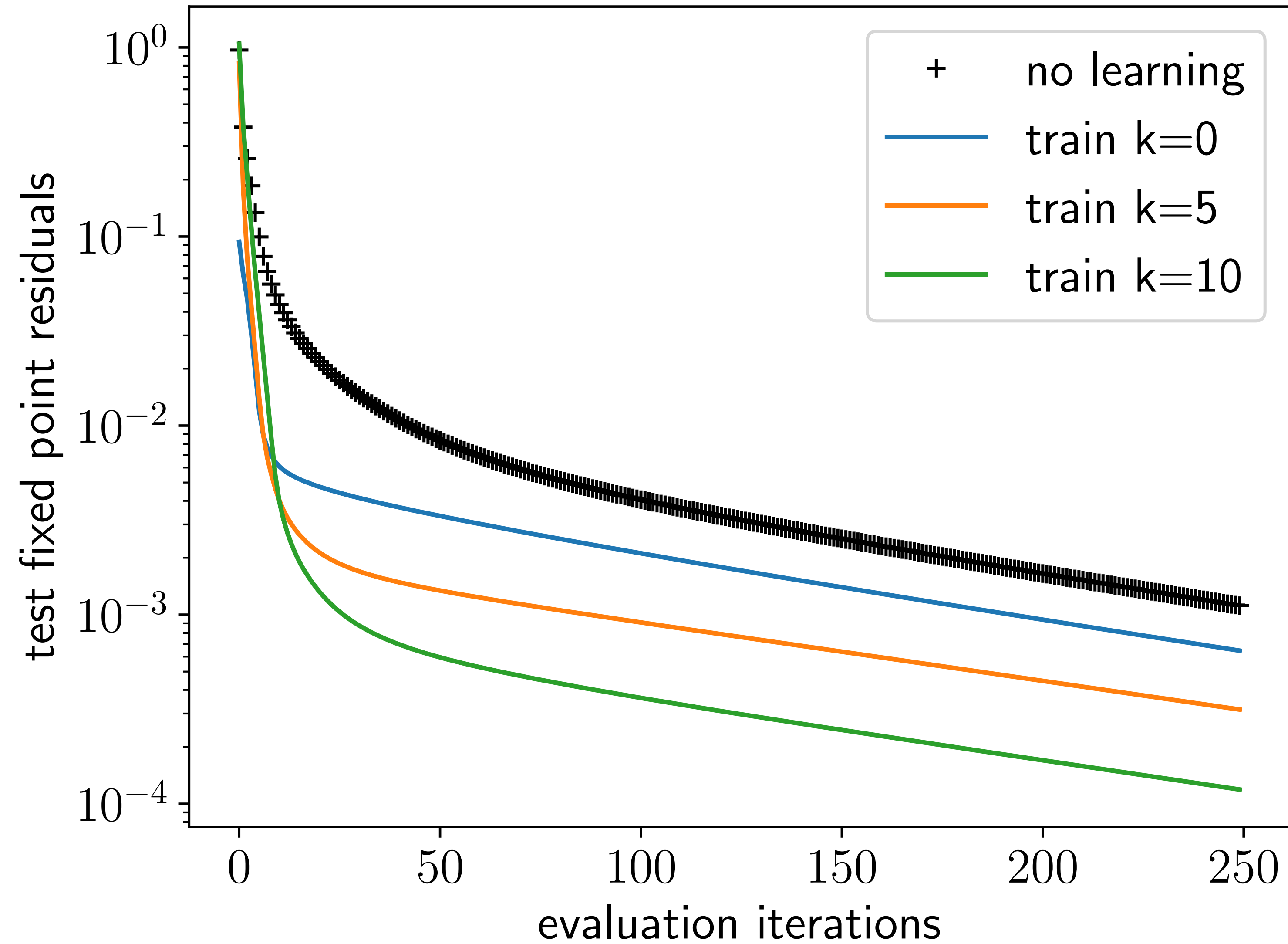
3000 assets

ML Prediction block

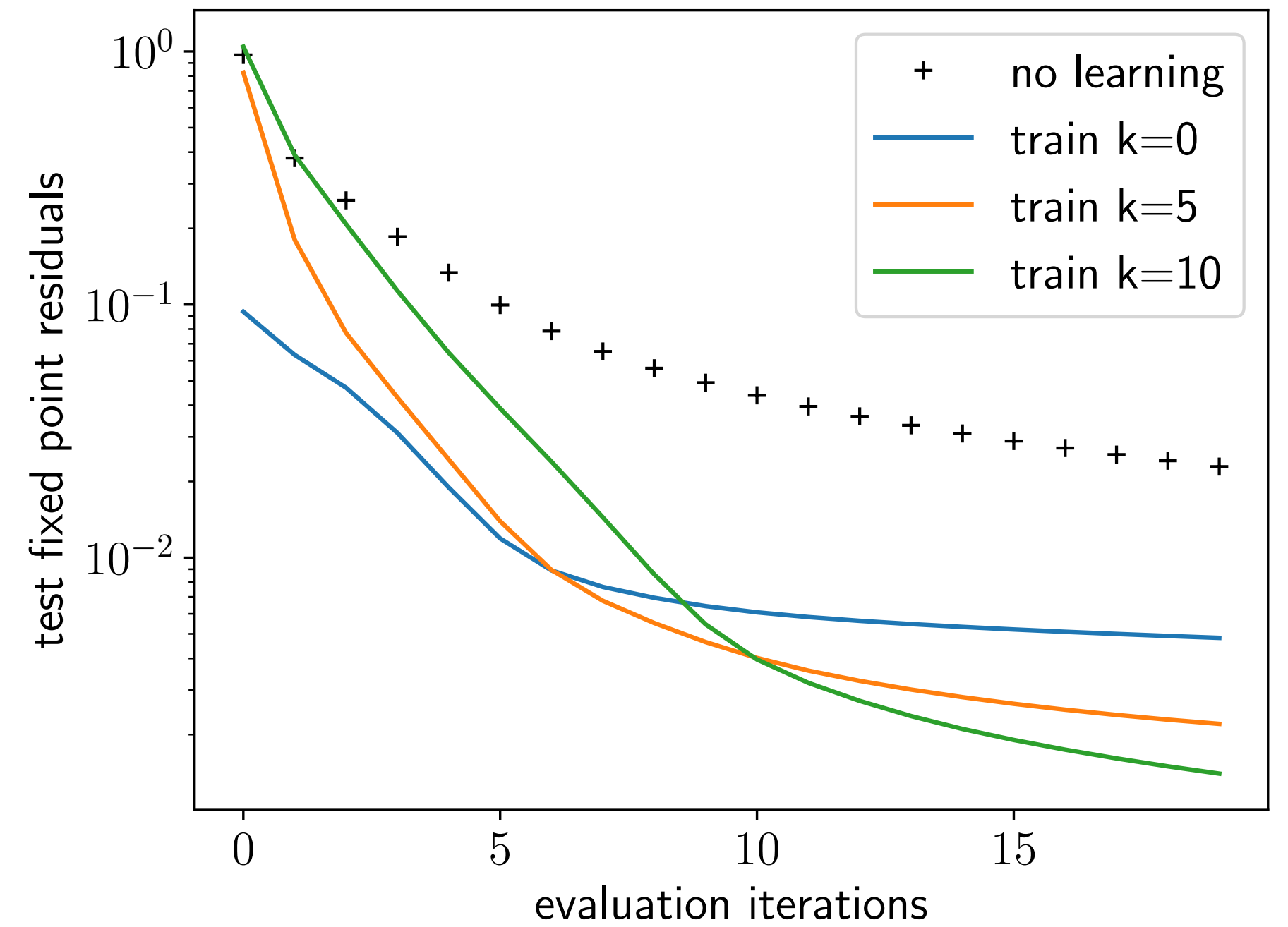
2 hidden layer neural network

ReLU activation

Markowitz Results



Learning significantly decreases the number of iterations



SCS implementation in C

Warm start	Time (sec)
Learn 2 warm start	0.62
None	3.20

Our contributions

Solve Convex problems in real time

End-to-end learning to accelerate fixed point algorithms

Generalization bounds in terms of N and k



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