

# Neural Fixed-Point Acceleration for Convex Optimization

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## Overview

Fixed-point problems are often computational bottleneck in large systems

**Acceleration** of fixed-point iterations: use knowledge of prior iterates to improve future iterates

Classically done without machine learning, e.g. Anderson Acceleration (AA)

Fixed-point problems repeatedly solved in application likely share structure

**Neural fixed-point acceleration**: leverage shared structure to accelerate distribution over problem instances using learning

Challenge: Complex fixed-point mappings result in subtleties with interweaving model updates with fixed-point computations, differentiating through mappings

## Main Application: Convex Cone Programming

Accelerate Splitting Conic Solver, called SCS (state-of-the-art cone solver)

## Neural SCS Design

**Model:**

- MLPs for initial prediction
- LSTMs/GRUs for prediction of sequence iterates

**Differentiating through SCS Fixed-Point Iterations:**

- Implicit differentiation for linear system solve
- Cone projection derivatives for zero, non-negative, second-order and PSD cones based on prior work.

**Loss function:**

- Tau normalization: Removing iterate-scaling factor from loss essential for good solution

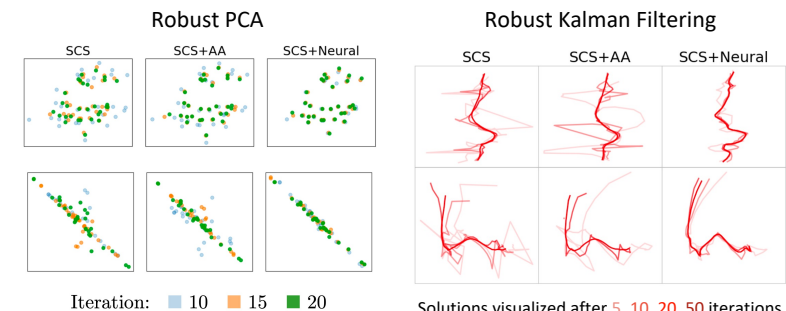
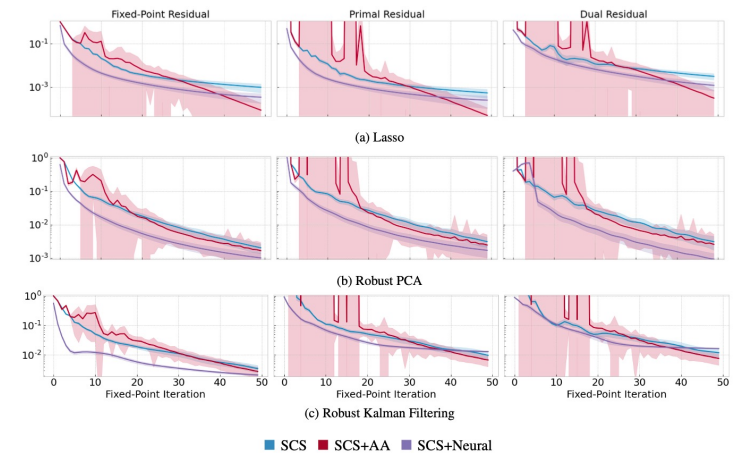
## Neural Fixed-Point Acceleration Framework

**Algorithm 1** Neural fixed-point acceleration augments standard fixed-point computations with a learned initialization and updates to the iterates.

```
Inputs: Context  $\phi$ , parameters  $\theta$ , and fixed-point map  $f$ .  
[ $x_1, h_1$ ] =  $g_\theta^{\text{init}}(\phi)$       ▷ Initial hidden state and iterate  
for fixed-point iteration  $t = 1..T$  do  
     $\tilde{x}_{t+1} = f(x_t; \phi)$       ▷ Original fixed-point iteration  
     $x_{t+1}, h_{t+1} = g_\theta^{\text{acc}}(x_t, \tilde{x}_{t+1}, h_t)$       ▷ Acceleration  
end for
```

## Experiments and Visualizations

Faster convergence to a good solution than SCS and SCS + Anderson Acceleration (default acceleration) on 3 problems: Lasso, Robust PCA, Robust Kalman Filtering



Visualizing iterates also shows that Neural-accelerated SCS stabilizes to a solution much faster than SCS/SCS+AA