Speedup Techniques for Hyperparameter Optimization

Overview of Multi-Fidelity Optimization

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Motivating Example

- One possible cheap approximation of an expensive function: use a data subset
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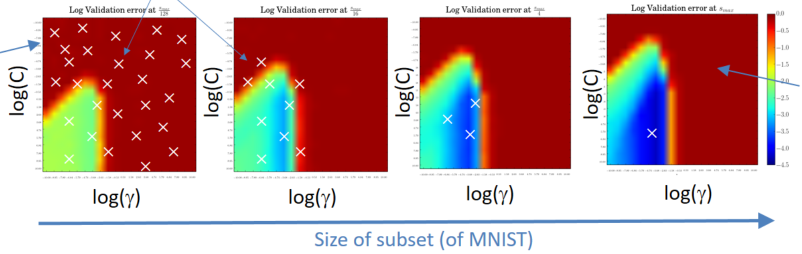
- E.g.: Support Vector Machines (SVM) on MNIST dataset (hyperparameters: C, γ)

× denotes evaluated hyperparameter settings

Log validation error (red:bad; green:OK; blue:good) when trained on subset of 390 data points (takes few seconds to compute)



Log validation error when trained on full dataset of 50.000 data points (takes several hours to compute)

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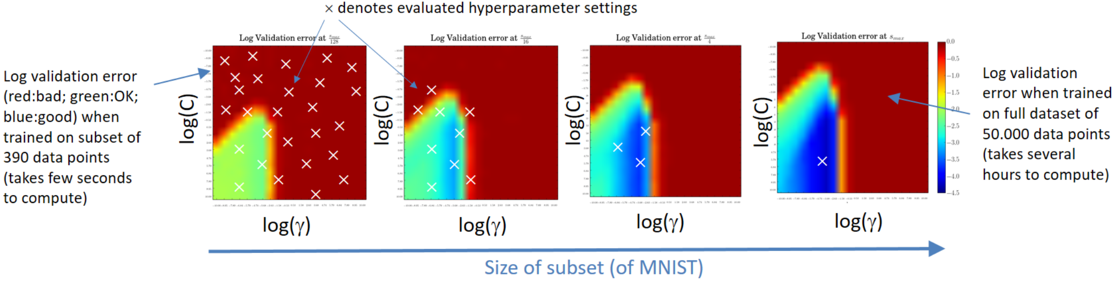
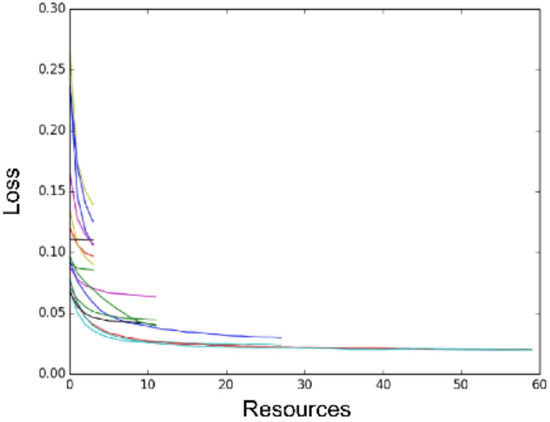


$\rightarrow$ up to 1000x speedups over blackbox optimization on full data [Klein et al, AISTATS 2017]

Motivating Example 2: Shorter Runs of Anytime Algorithms

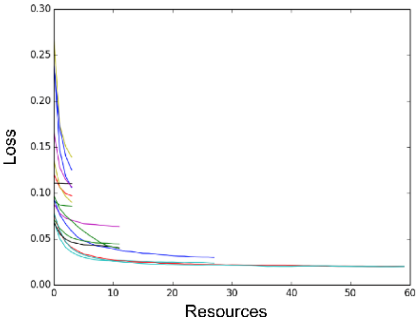
- Performance with shorter runs of an anytime algorithm (such as SGD):



Multi-Fidelity Optimization In General

Exploit cheap approximations of an expensive blackbox function $\rightarrow$ afford more configurations

- Idea: eliminate poor configurations early, allocate more resources to promising ones.



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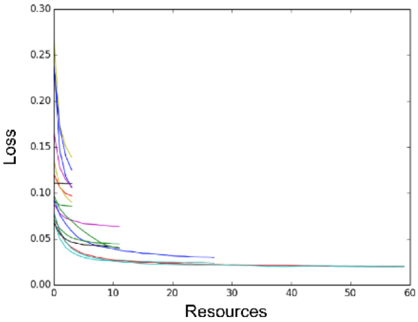

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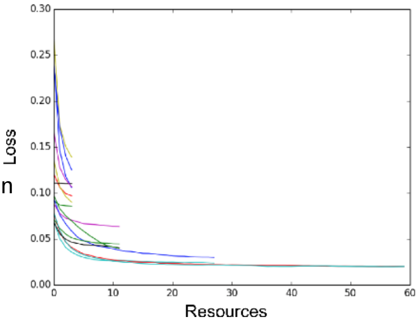

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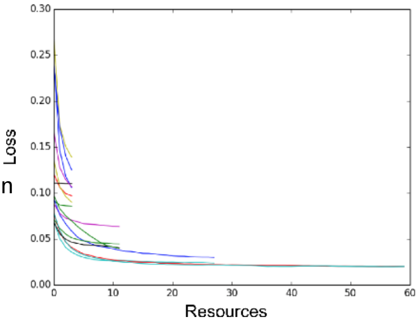

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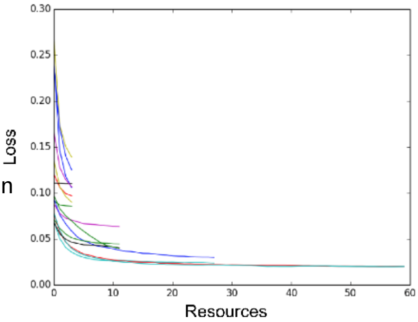

  - General concept, applicable even in fields outside ML, e.g., fluid simulation:
    - ★ Number of particles
    - ★ Time scale of simulation

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- In the simplest case: good with low resources $\leftrightarrow$ good with high resources.
  - In practice, this is of course not always true

How Useful is the Cheap Approximation? The Rank Correlation

Given:

- A set of configurations $\mathbf{\Lambda} = \{\boldsymbol{\lambda}_1, ..., \boldsymbol{\lambda}_n\}$
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- The performances $g(\boldsymbol{\lambda}_1), ..., g(\boldsymbol{\lambda}_n)$ on a cheap approximation of the black box

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We compute the Spearman rank correlation between $[f(\boldsymbol{\lambda}_1), ..., f(\boldsymbol{\lambda}_n)]$ and $[g(\boldsymbol{\lambda}_1), ..., g(\boldsymbol{\lambda}_n)]$

- If this is high (in the extreme: 1), the relative ranking of the configurations is the same on f and g
  - In that case, we can optimize cheaply on g and also obtain an optimum for f
- If it is low (≈ 0), optimizing g does not tell us anything about f

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Goal: find approximations g that are very cheap but have high rank correlations with f

Questions to Answer for Yourself / Discuss with Friends

- Repetition. Which cheap approximation is better in this hypothetical case?
  - Downscaling images (5x cheaper, rank correlation of 0.8)
  - Less epoch of SGD (4x cheaper, rank correlation of 0.75)

- Discussion. Can you think of an application of your interest
  where you would likely have a good multi-fidelity approximation?