Distributed Optimization for Machine Learning

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Machine Learning Methods to Analyze Large-Scale Data

Machine Learning

Optimization

Systems

Applications

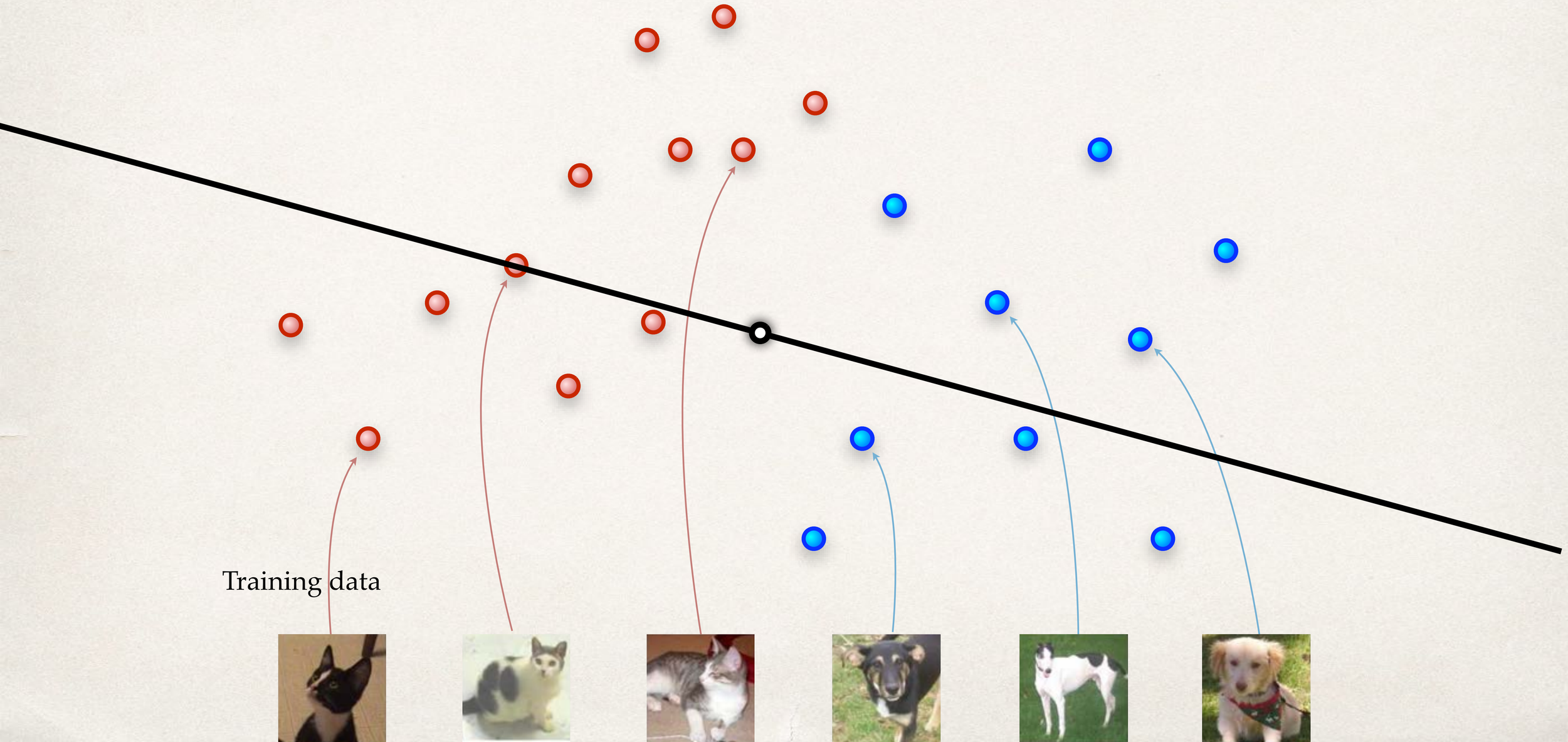
Machine Learning?

software that can

learn from data

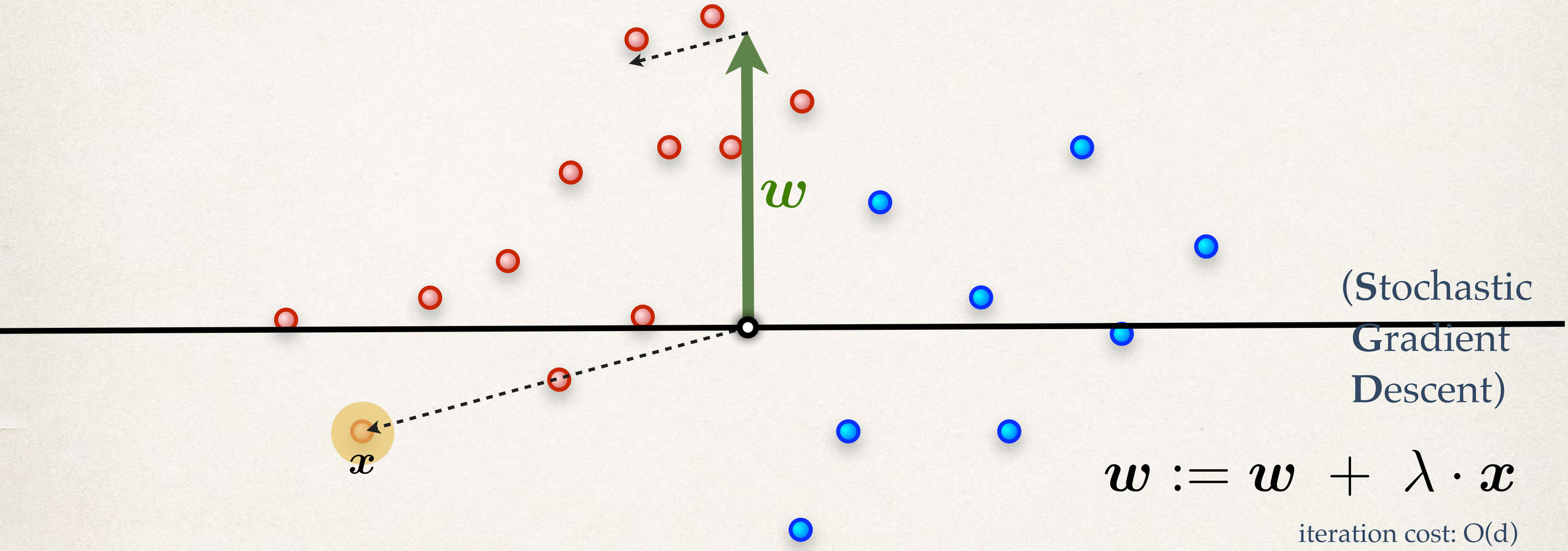
image source

Machine Learning Example



The Learning Algorithm

$\boldsymbol{x}_i \in \mathbb{R}^d$



(Stochastic Gradient Descent)

$$\boldsymbol{w} := \boldsymbol{w} + \lambda \cdot \boldsymbol{x}$$

iteration cost: O(d)

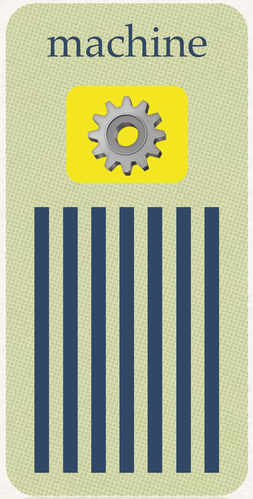
Perceptron

(Rosenblatt 1957)

Support-Vector-Machine

(Cortes & Vapnik 1995)

Machine Learning Systems



Machine Learning Systems

What if the data does not fit onto one computer anymore?

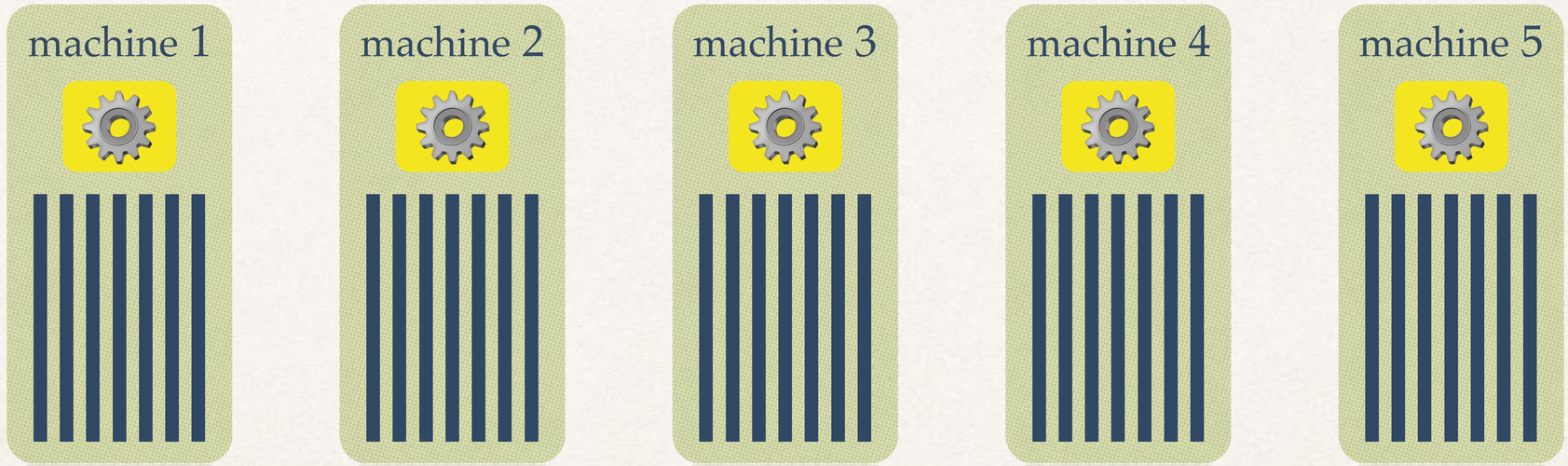
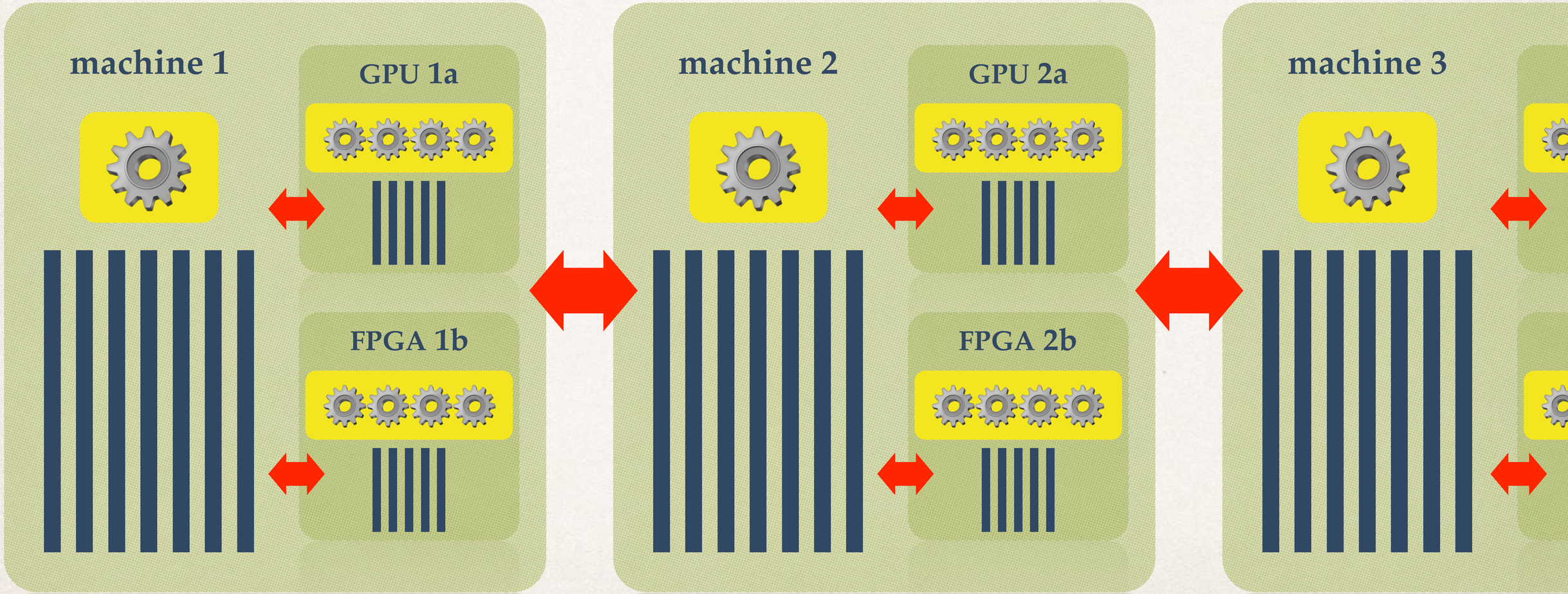


Foto: Florian Hirzinger

Machine Learning Systems



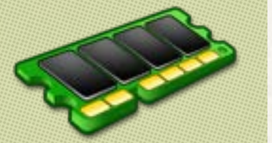
Challenge

The Cost of Communication

$\boldsymbol{v} \in \mathbb{R}^{100}$

- Reading $\boldsymbol{v}$ from memory (RAM)

  100 ns



- Sending $\boldsymbol{v}$ to another machine

  500'000 ns

- Typical Map-Reduce iteration

  10'000'000'000 ns

Challenge

Usability

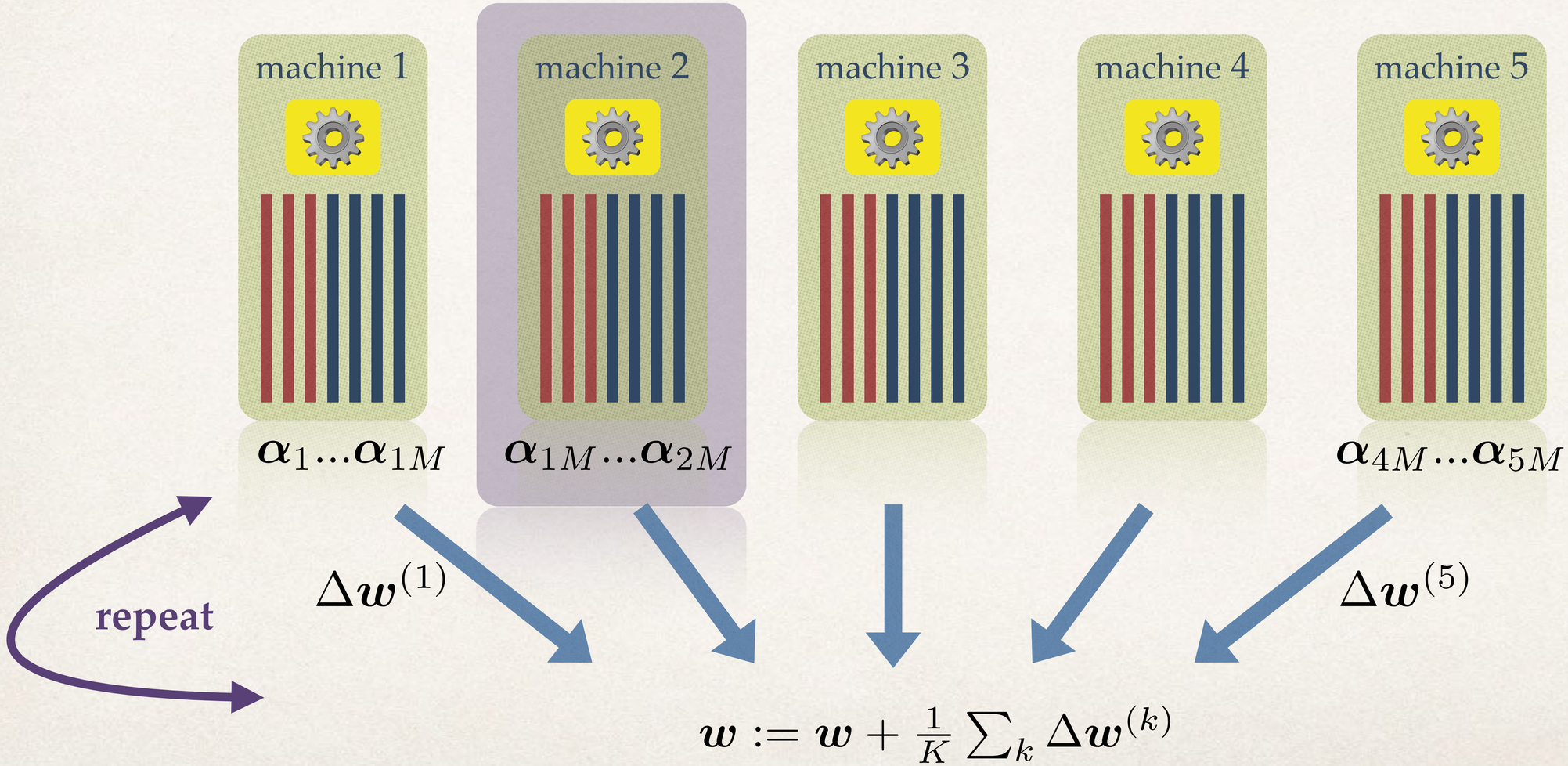
Parallel Programming is Hard

- no **reusability** of good
  single machine algorithms & code

Problem class

$$\min_{\boldsymbol{\alpha} \in \mathbb{R}^n} \quad f(A\boldsymbol{\alpha}) \; + \; g(\boldsymbol{\alpha})$$

CoCoA - Communication Efficient Distributed Optimization



NIPS '14, ICML '15, arxiv.org/abs/1611.02189

Optimization: Primal-Dual Context

$$A_{\text{loc}}\Delta\boldsymbol{\alpha}_{[k]} + \boldsymbol{w}$$

$$\min_{\boldsymbol{\alpha}\in\mathbb{R}^n} \quad \Big[\ \mathcal{O}_A(\boldsymbol{\alpha}) := f(A\boldsymbol{\alpha}) + g(\boldsymbol{\alpha})\ \Big]$$

primal Lasso
dual L2-reg SVM/Log-Regr
primal L1-reg SVM/Log-Reg

correspondence

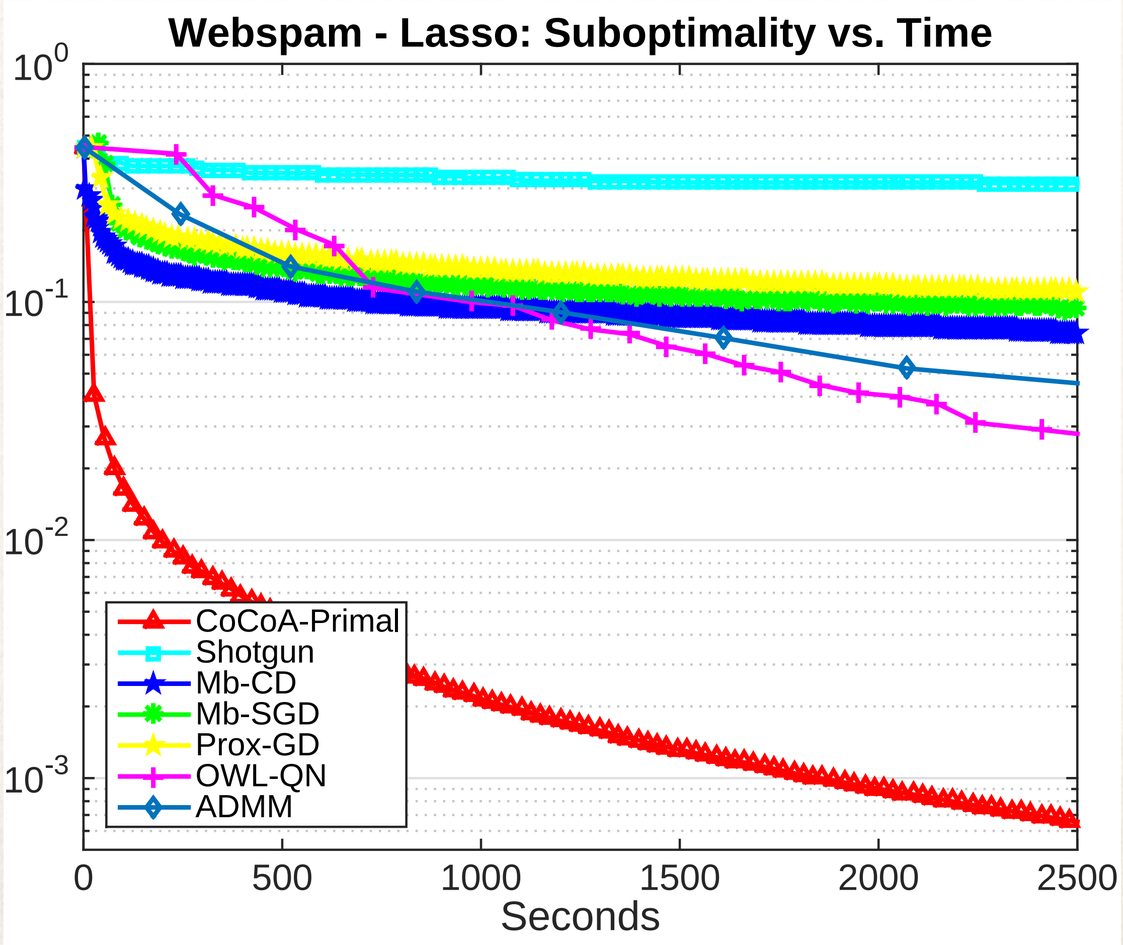
$$\boldsymbol{w} := \nabla f(A\boldsymbol{\alpha})$$

$$\min_{\mathbf{w}\in\mathbb{R}^d} \quad \Big[\ \mathcal{O}_B(\mathbf{w}) := g^*(-A^\top\mathbf{w}) + f^*(\mathbf{w})\ \Big]$$

Distributed Experiments

Sparse Linear Regression

Dataset	Training	Features	Sparsity
url	2,396,130	3,231,961	3.5e-3%
epsilon	400,000	2,000	100%
kddb	19,264,097	29,890,095	9.8e-5%
webspam	350,000	16,609,143	0.02%



NIPS 2014, ICML 2015,
arxiv.org/abs/1611.02189

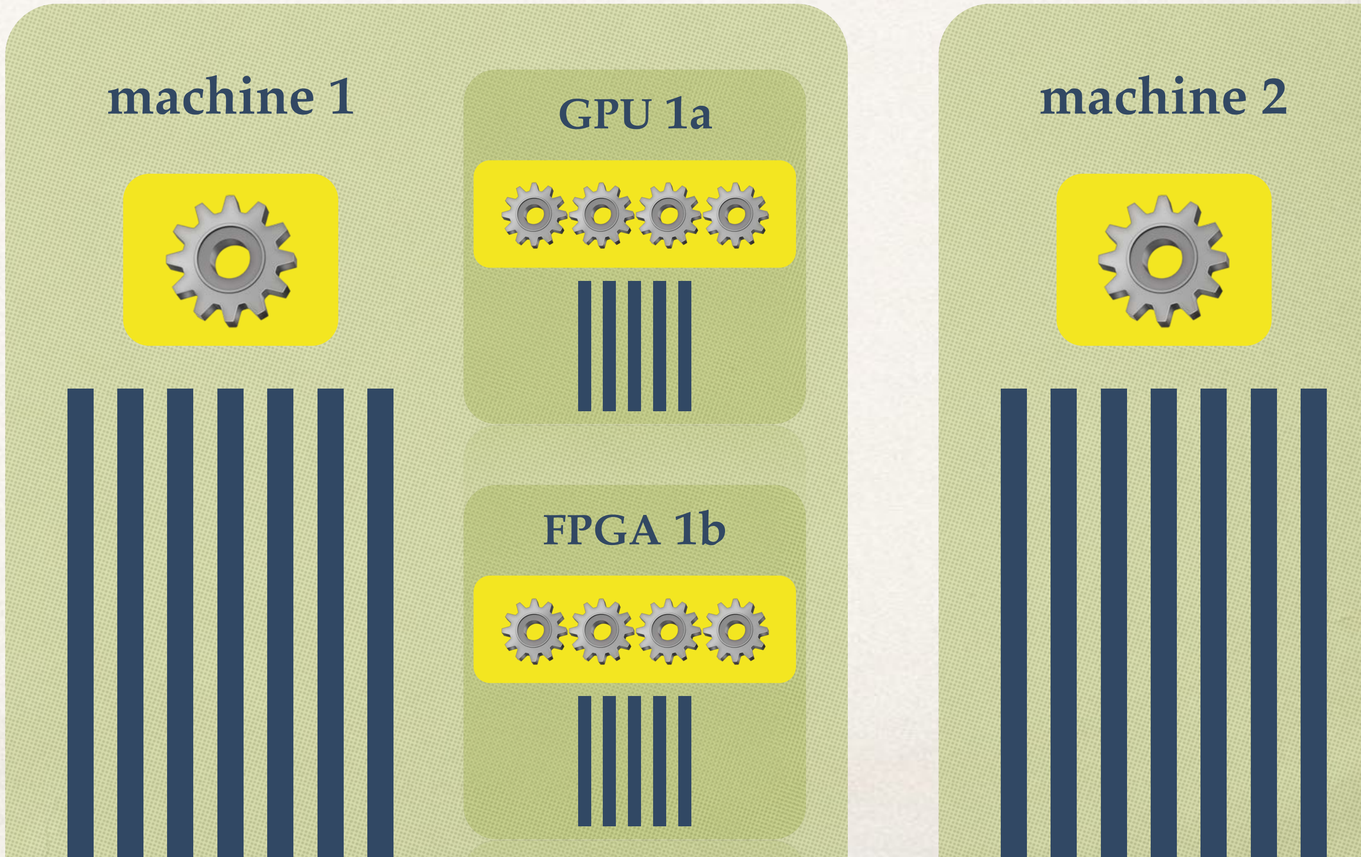
Spark Code:
github.com/gingsmith/proxcocoa

+ TensorFlow
+ Apache Flink

Challenge

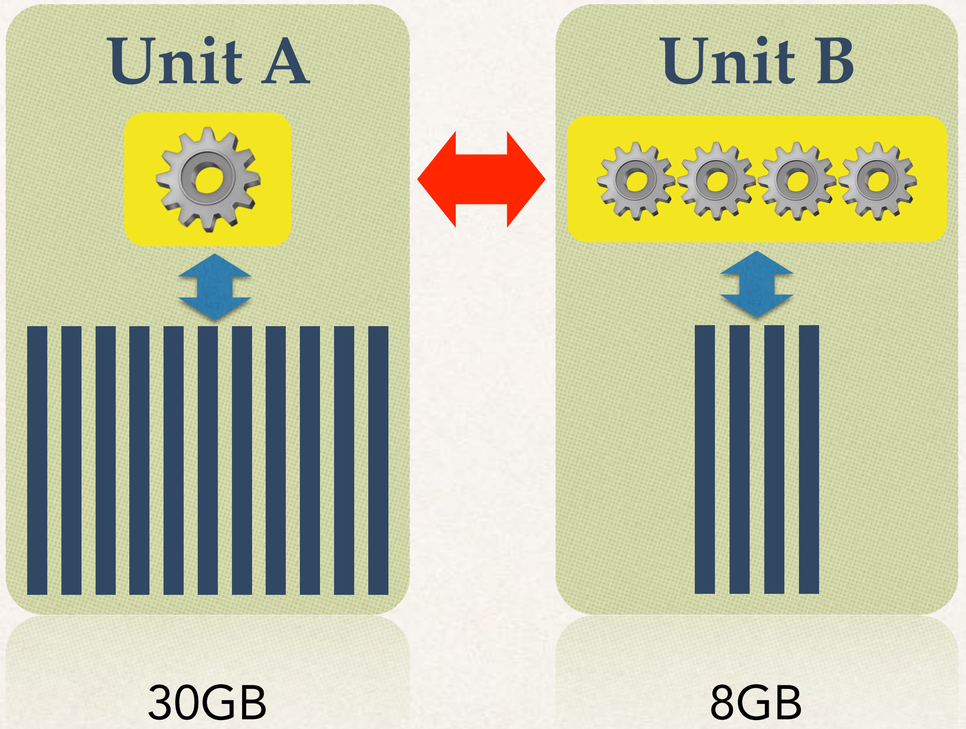
Leveraging Memory Hierarchy

Which data to put in which memory?



Leveraging Memory Hierarchy

duality gap as selection criterion

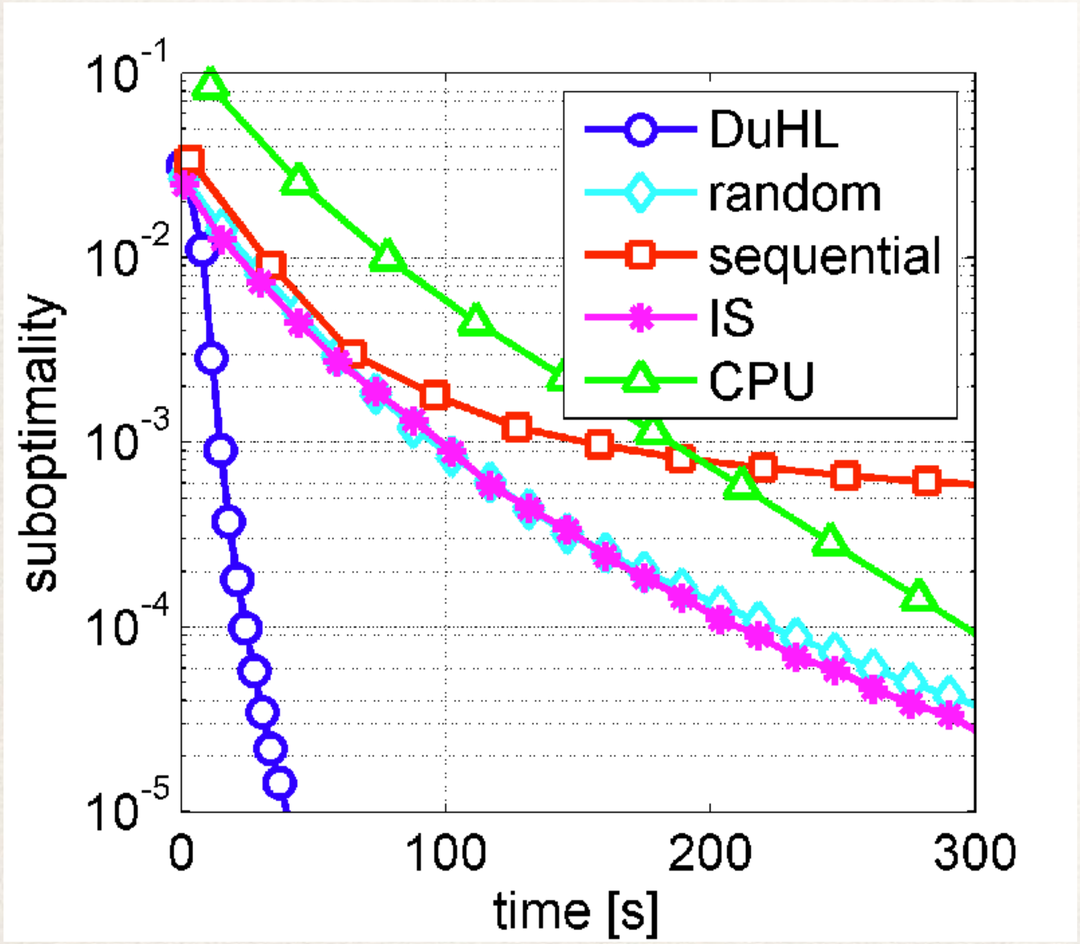


adaptive importance sampling

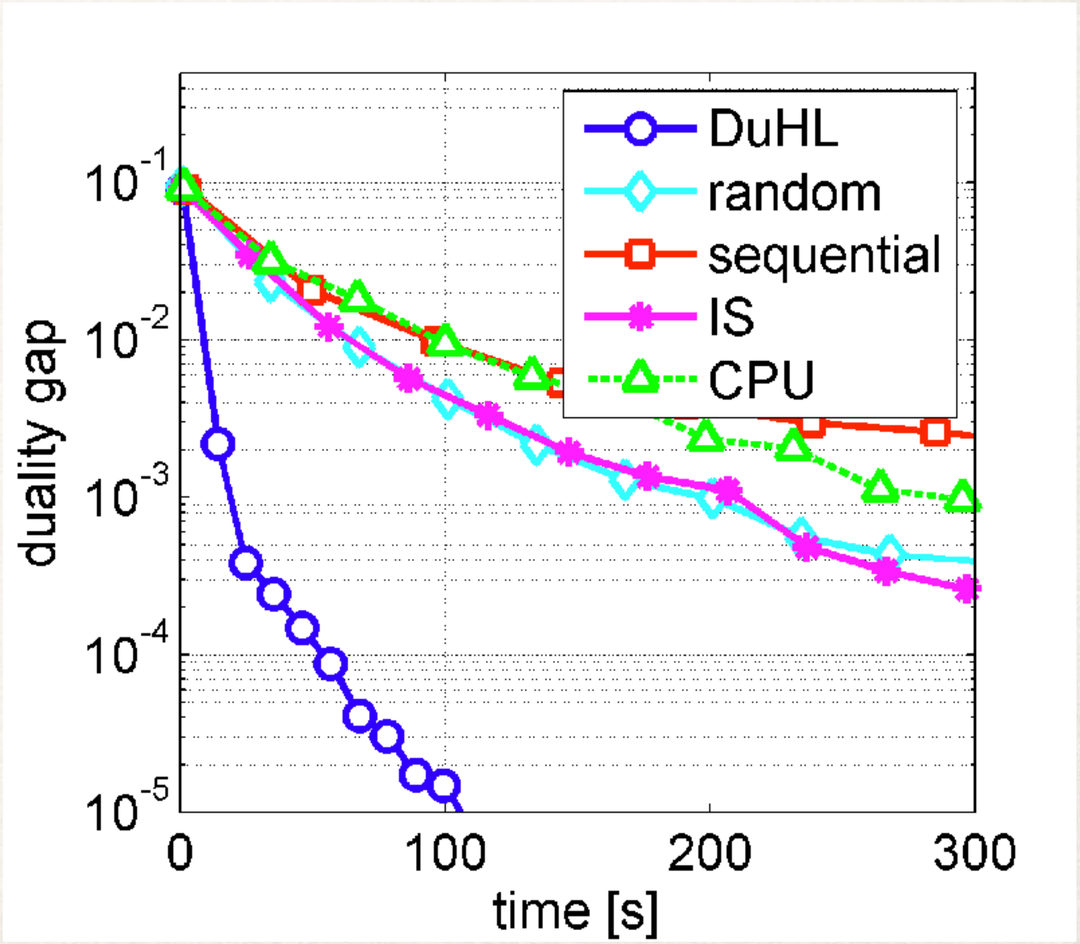
AISTATS 2017

Experiments

RAM ⟷ GPU, 30GB dataset



Lasso



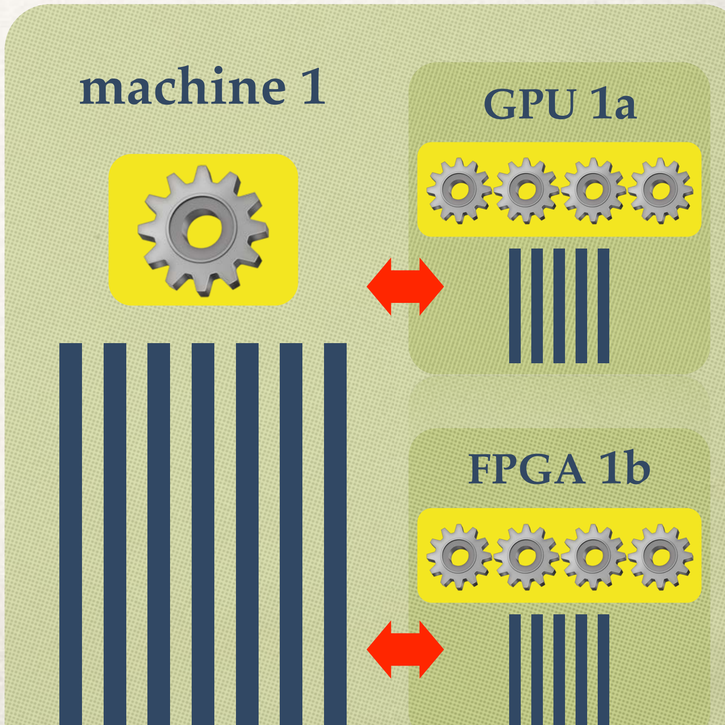
SVM

Conclusion

- try to improve **usability** of large-scale ML
- full **adaptivity** to the communication cost, memory hierarchy and bandwidth
- **re-usability** of good single machine solvers
- **accuracy** certificates

Open Research

- **limited precision operations** for efficiency of communication and computation
- **asynchronous** and **fault tolerant** algorithms
- **multi-level approach** on heterogenous systems
- more **re-usable** algorithmic building blocks
  - for more systems and problems



Project:

Distributed Machine Learning Benchmark

Goal:

Public and Reproducible

Comparison of Distributed Solvers

github.com/mlbench/mlbench

Apache

Google

Apache

HPC

Thanks!

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