Large-Scale Matrix Factorization

Rainer Gemulla

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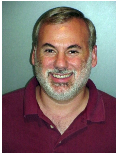
P. J. Haas Y. Sismanis E. Nijkamp C. Teflioudi F. Makari

Outline

Outline

Matrix Factorization

Stochastic Gradient Descent

Distributed SGD with MapReduce

Experiments

Summary

Collaborative Filtering

- Problem
  - Set of users
  - Set of items (movies, books, jokes, products, stories, ...)
  - Feedback (ratings, purchase, click-through, tags, ...)

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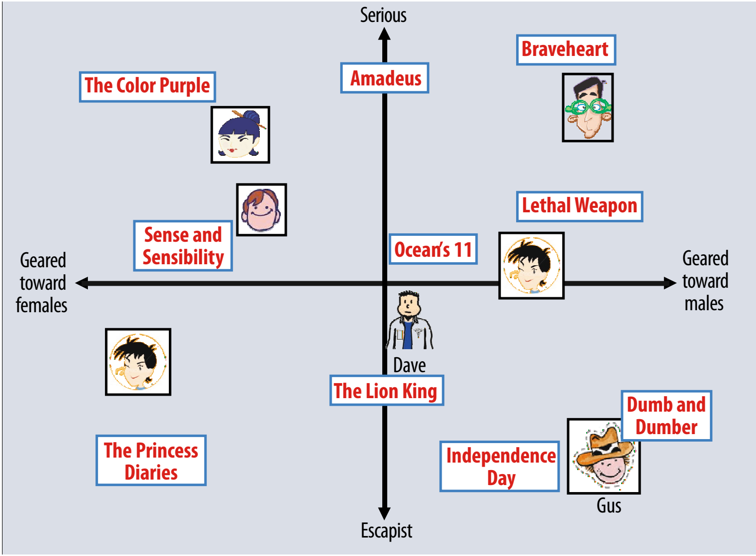
- Netflix competition: 500k users, 20k movies, 100M movie ratings, 3M question marks

Semantic Factors (Koren et al., 2009)



Latent Factor Models

- Discover latent factors ($r = 1$)

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Alice		**4**	**2**
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$$\min_{\mathbf{W},\mathbf{H}} \sum_{(i,j)\in Z} (\mathbf{V}_{ij} - [\mathbf{WH}]_{ij})^2$$

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$$+ \lambda \left(\|\mathbf{W}\| + \|\mathbf{H}\| + \|\mathbf{u}\| + \|\mathbf{m}\| \right)$$

- Bias, regularization

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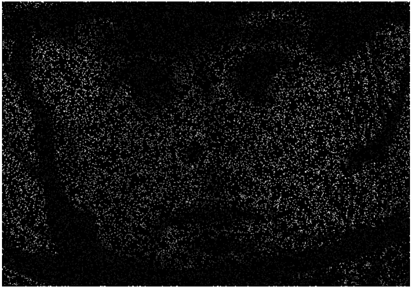
- Bias, regularization, time

Another Matrix

Matrix Reconstruction (unregularized)



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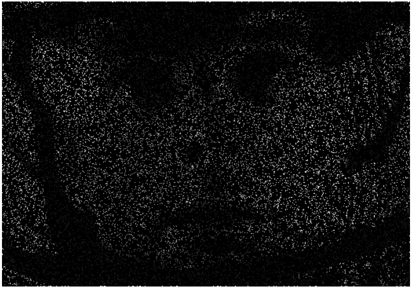

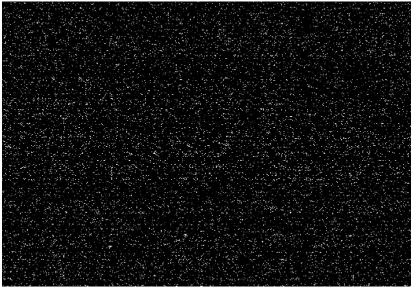

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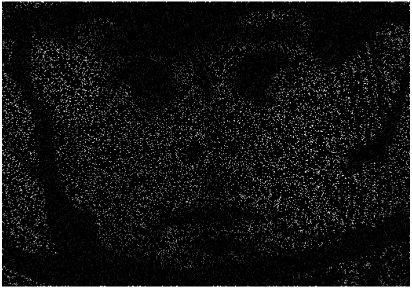

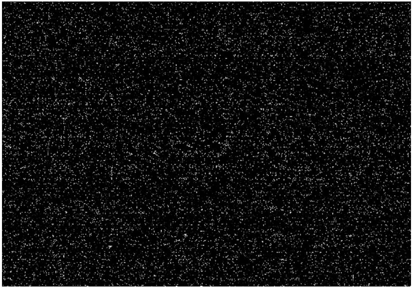

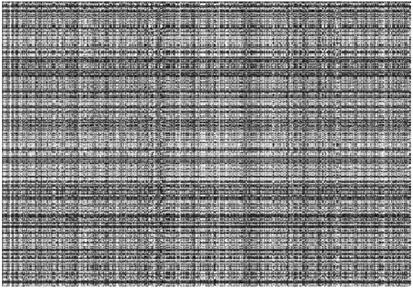

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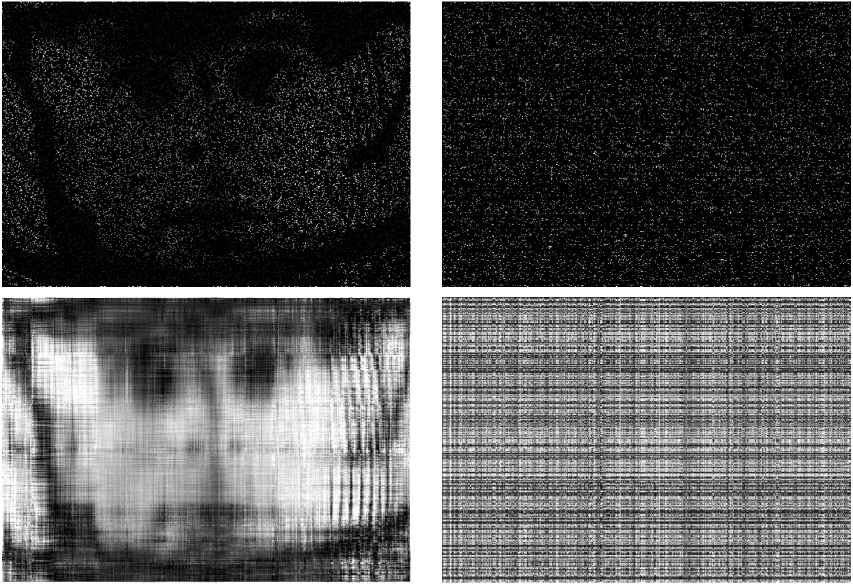
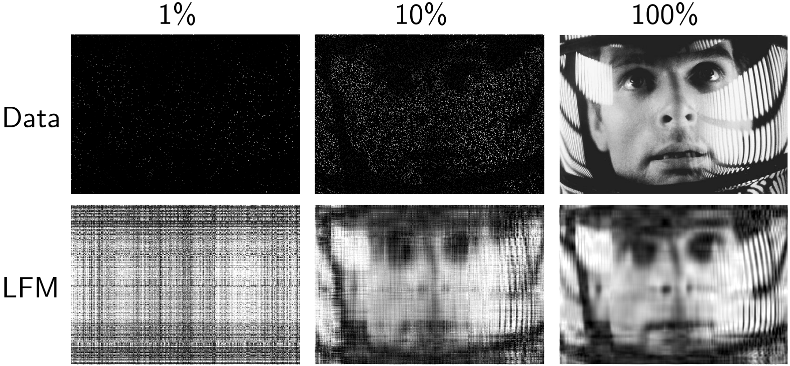


Latent Factor Models (unregularized)



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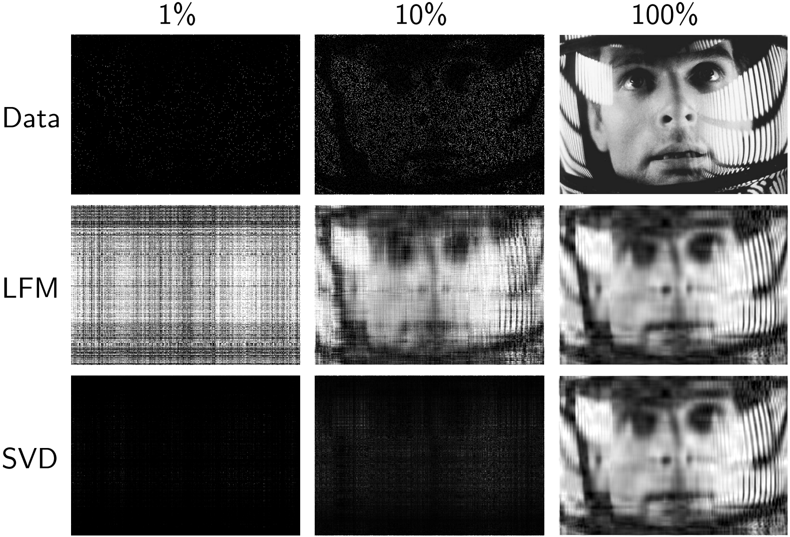

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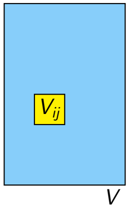

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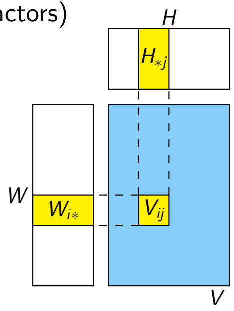
  - **H**: column factors (e.g., $r \times n$ latent movie factors)



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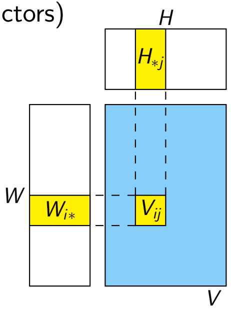
- Model
  - $L_{ij}(\mathbf{W}_{i*}, \mathbf{H}_{*j})$: loss at element (i, j)
  - Includes prediction error, regularization, auxiliary information, ...
  - Constraints (e.g., non-negativity)



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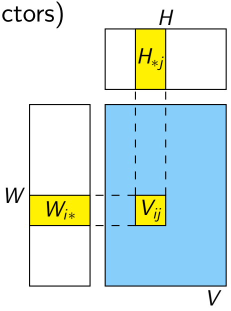
- Find best model

$$\underset{\mathbf{W},\mathbf{H}}{\operatorname{argmin}} \sum_{(i,j)\in Z} L_{ij}(\mathbf{W}_{i*}, \mathbf{H}_{*j})$$



Successful Applications

- Movie recommendation (Netflix)
  - $>$20M users, $>$20k movies, 4B ratings (projected)
  - 60GB data, 15GB model (projected)
  - Collaborative filtering
- Website recommendation (Microsoft, WWW10)
  - 51M users, 15M URLs, 1.2B clicks
  - 17.8GB data, 161GB metadata, 49GB model
  - Gaussian non-negative matrix factorization
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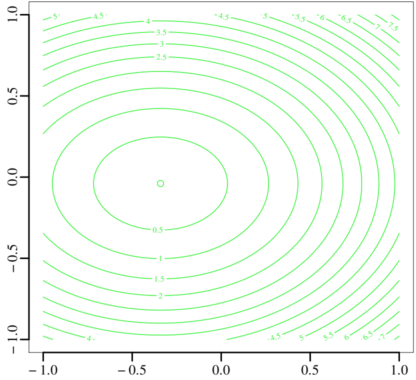
How to handle such massive scale?

- Big data
- Large models
- Expensive, iterative computations

Outline

Stochastic Gradient Descent

- Find minimum θ^* of function L



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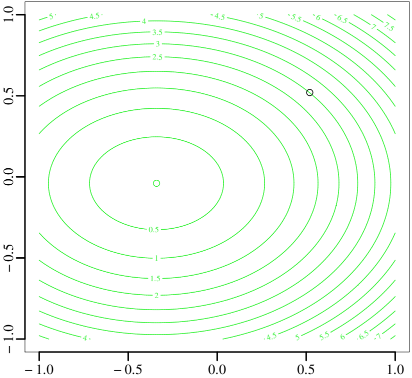

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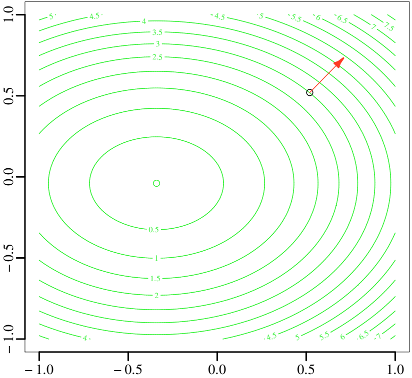

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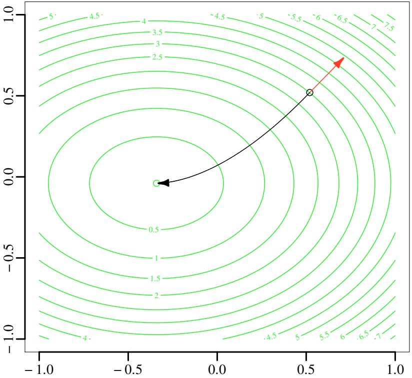
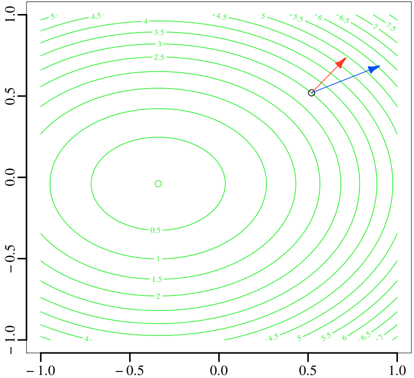


Stochastic Gradient Descent

- Find minimum θ^* of function L
- Pick a starting point θ_0
- Approximate gradient $\hat{L}'(\theta_0)$



Stochastic Gradient Descent

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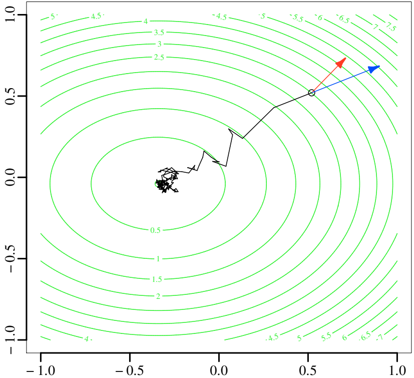
- Approximate gradient $\hat{L}'(\theta_0)$
- Jump "approximately" downhill



Stochastic Gradient Descent

- Find minimum θ^* of function L
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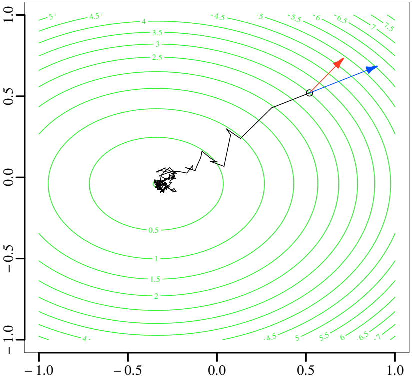
- Stochastic difference equation

$$\theta_{n+1} = \theta_n - \epsilon_n \hat{L}'(\theta_n)$$



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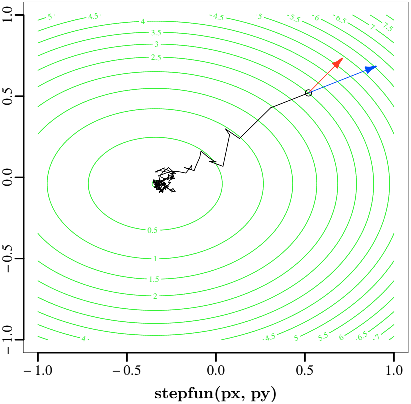
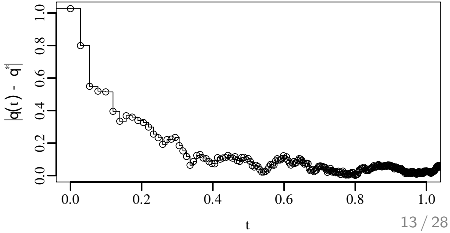
- Under certain conditions, asymptotically approximates (continuous) gradient descent

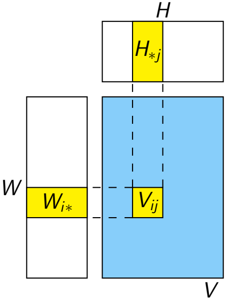




Stochastic Gradient Descent for Matrix Factorization

- Set $\theta = (\mathbf{W}, \mathbf{H})$ and use

$$L(\theta) = \sum_{(i,j) \in Z} L_{ij}(\mathbf{W}_{i*}, \mathbf{H}_{*j})$$



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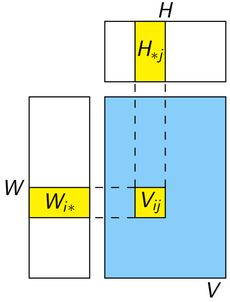

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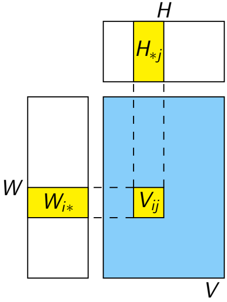
$$\hat{L}'(\theta, z) = N L'_{i_z j_z}(\mathbf{W}_{i_z *}, \mathbf{H}_{* j_z}),$$

where $N = |Z|$



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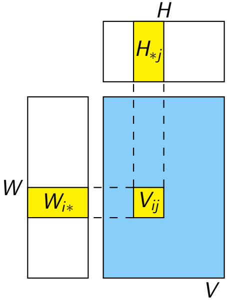

- SGD epoch
  1. Pick a random entry $z \in Z$
  2. Compute approximate gradient $\hat{L}'(\theta, z)$
  3. Update parameters
  $$\theta_{n+1} = \theta_n - \epsilon_n \hat{L}'(\theta_n, z)$$
  4. Repeat N times

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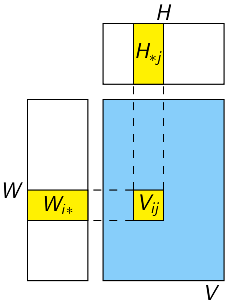

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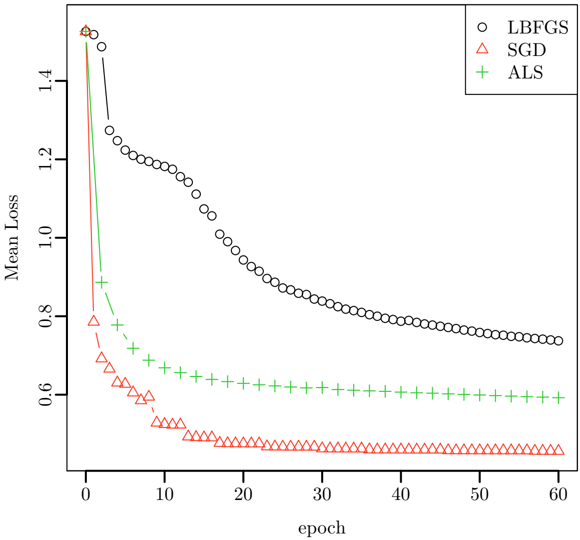
Random data access patterns.

Stochastic Gradient Descent on Netflix Data



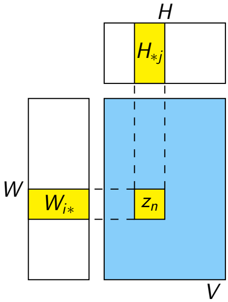
Outline

Problem Structure

- SGD steps depend on each other

$$\theta_{n+1} = \theta_n - \epsilon_n \hat{L}'(\theta_n)$$

- An SGD step on example $z \in Z$ ...
  1. Reads $W_{i_z *}$ and $H_{* j_z}$
  2. Performs gradient computation $L'_{ij}(W_{i_z *}, H_{* j_z})$
  3. Updates $W_{i_z *}$ and $H_{* j_z}$



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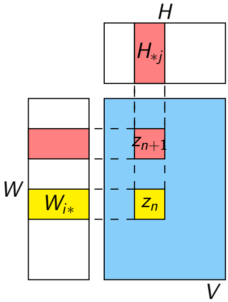

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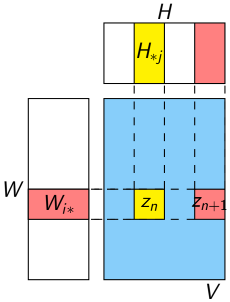

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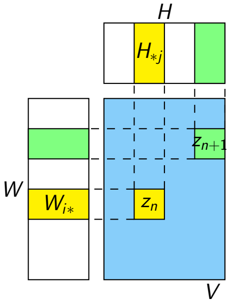

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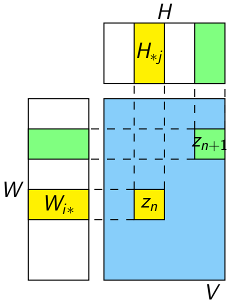
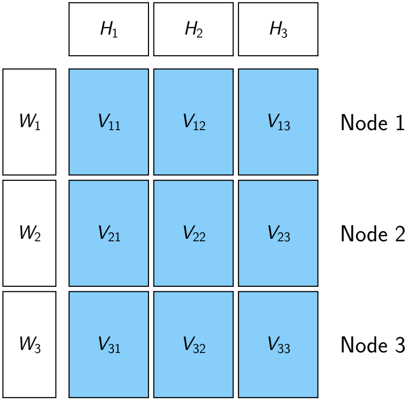


Synchronization provides an efficient shared-memory parallel SGD algorithm.

Exploitation in MapReduce (DSGD: WWW11, Biglearn11)

- Block and distribute the input matrix **V**



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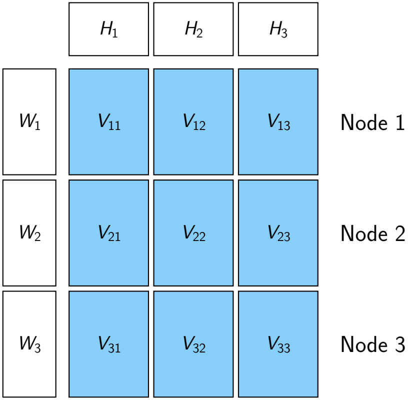

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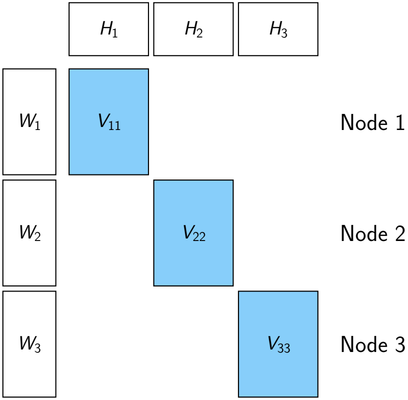

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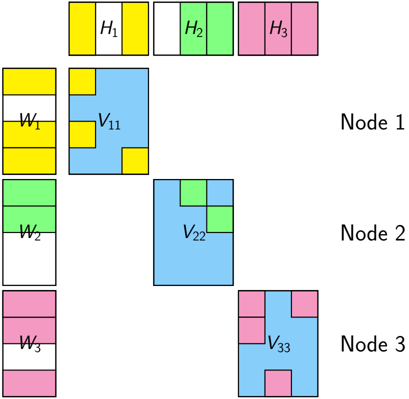

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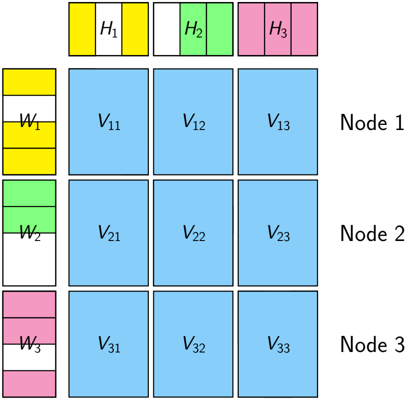

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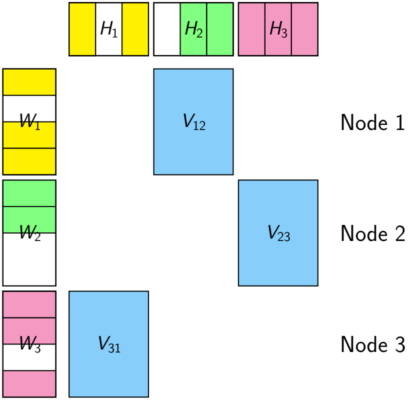

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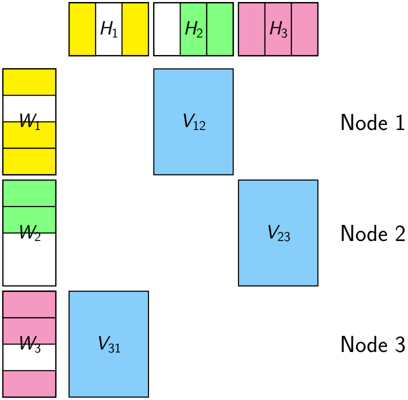
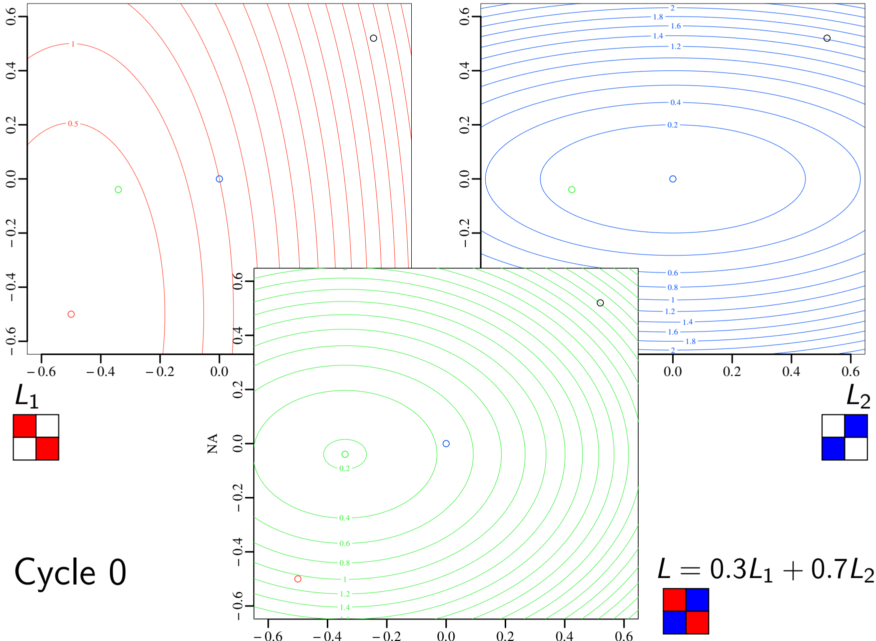


How does it work?



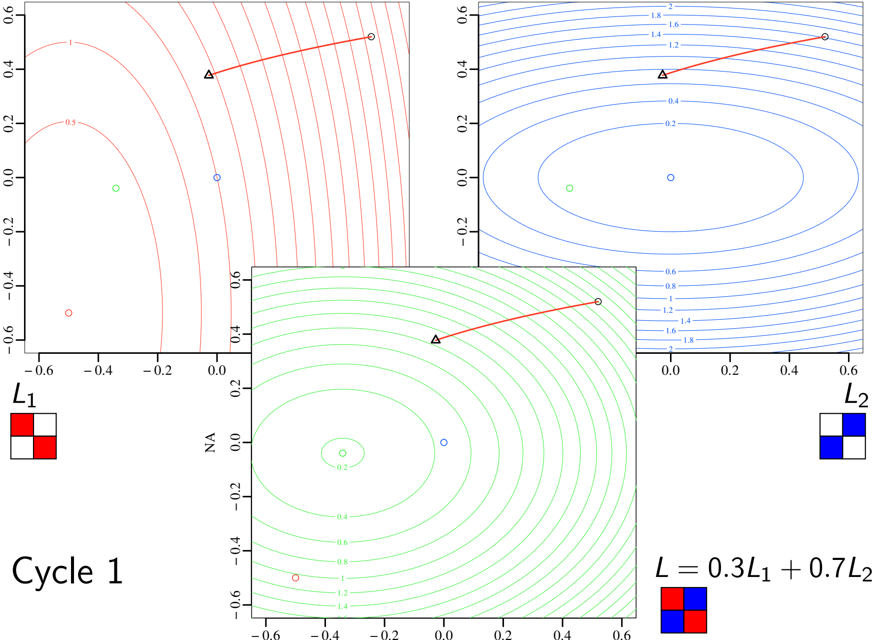
L_1

L_2

Cycle 0

$L = 0.3L_1 + 0.7L_2$

How does it work?



L_1

L_2

Cycle 1

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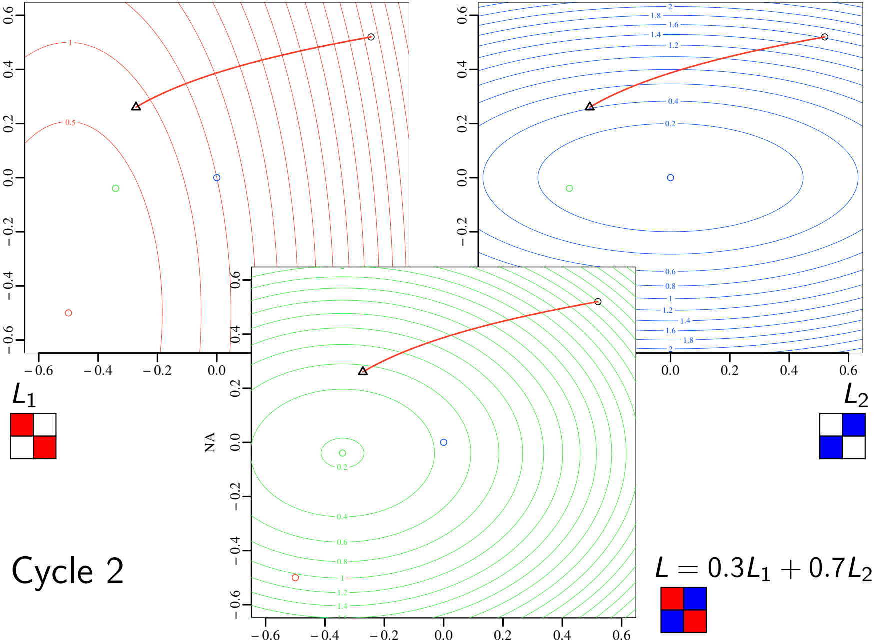
How does it work?



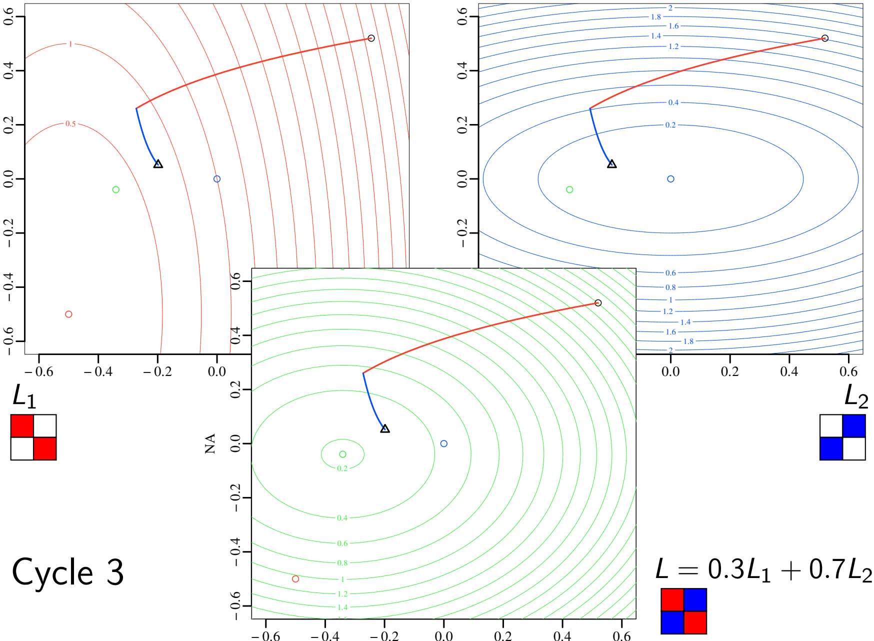
L_1

L_2

Cycle 2

$L = 0.3L_1 + 0.7L_2$

How does it work?



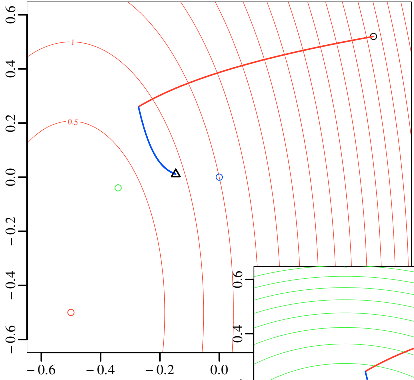
L_1

L_2

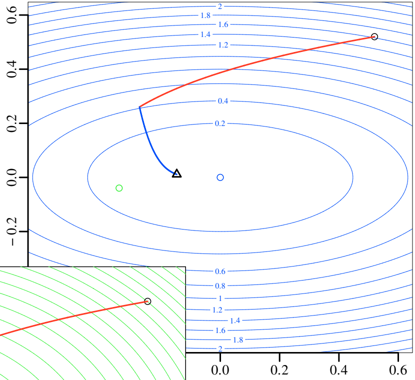
Cycle 3

$L = 0.3L_1 + 0.7L_2$

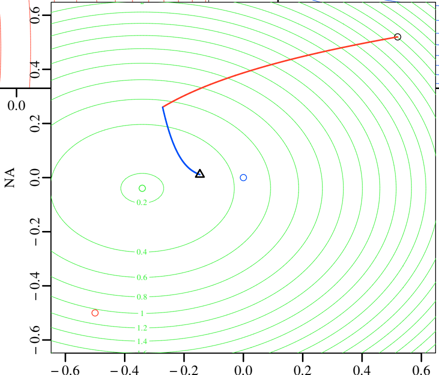
How does it work?



L_1



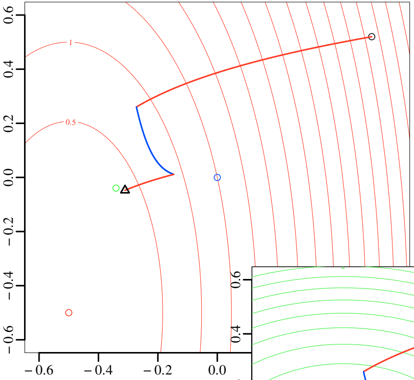
L_2

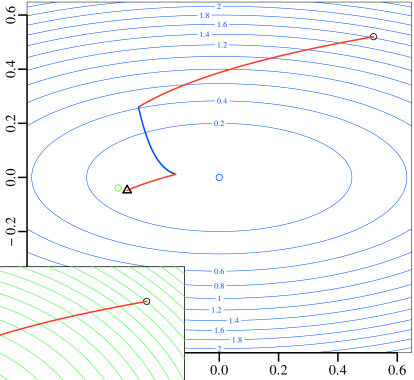


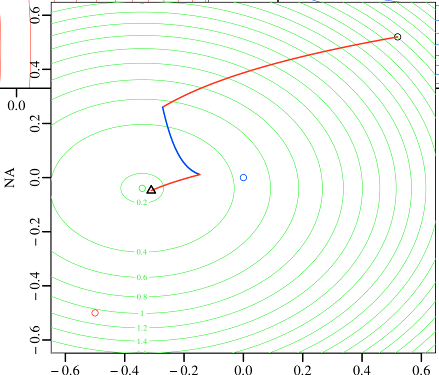
Cycle 4

$L = 0.3L_1 + 0.7L_2$

How does it work?

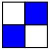






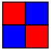
L_1

L_2



Cycle 5

$L = 0.3L_1 + 0.7L_2$



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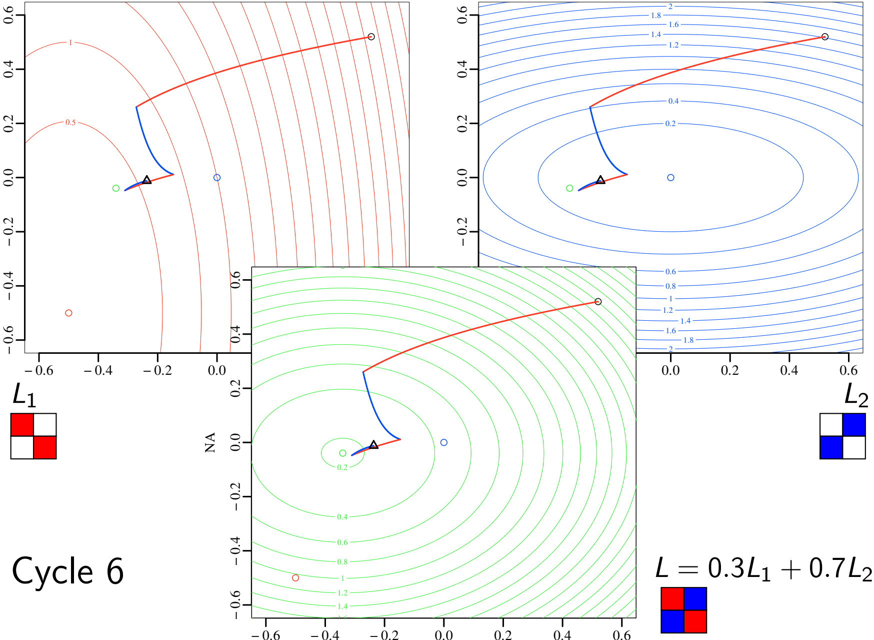


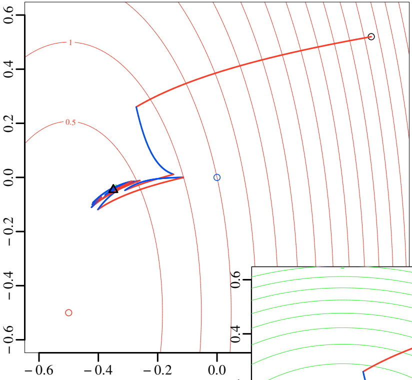
L_1

L_2

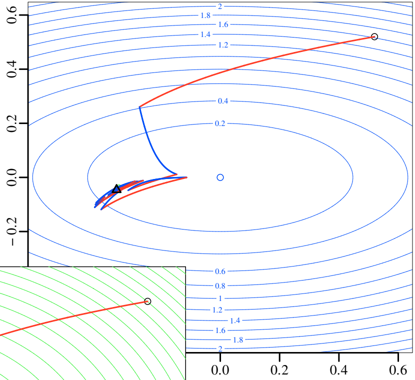
Cycle 6

$L = 0.3L_1 + 0.7L_2$

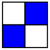
How does it work?

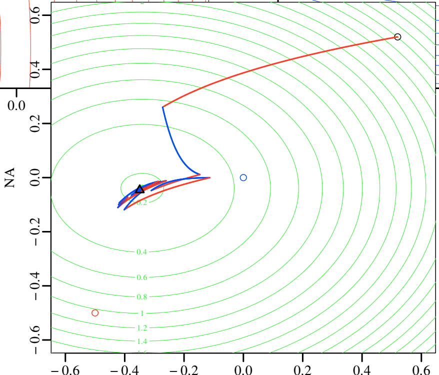


L_1



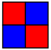
L_2





Cycle 100

$L = 0.3L_1 + 0.7L_2$



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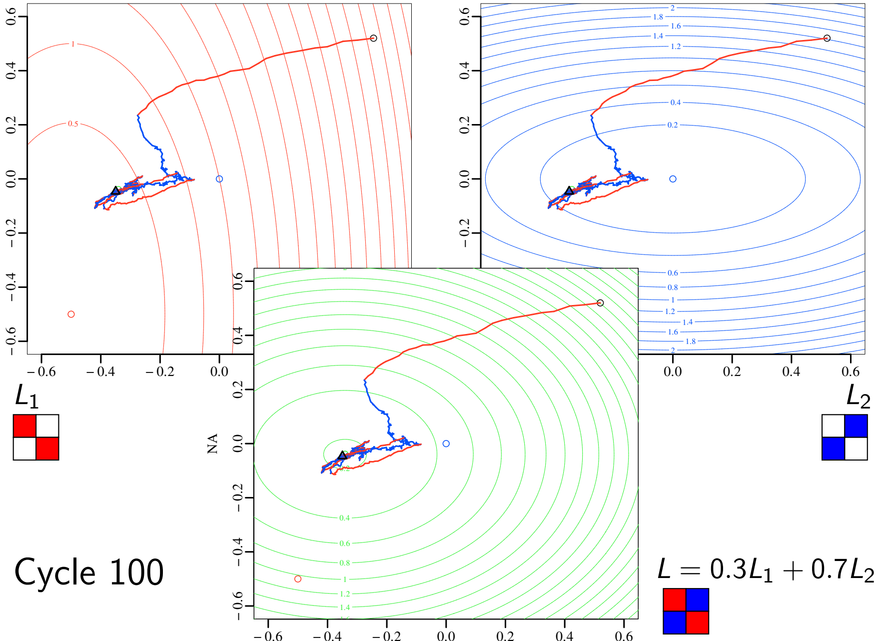

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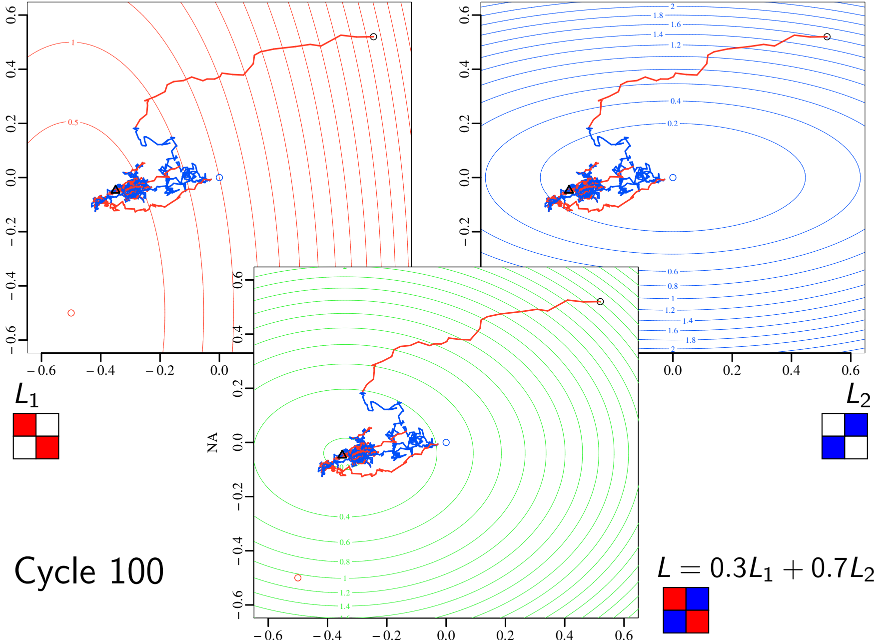

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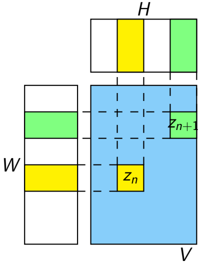

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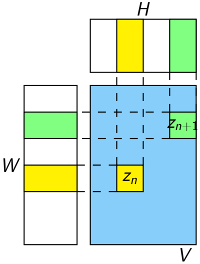

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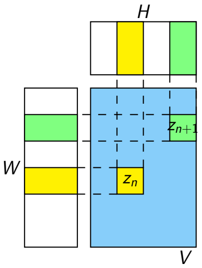

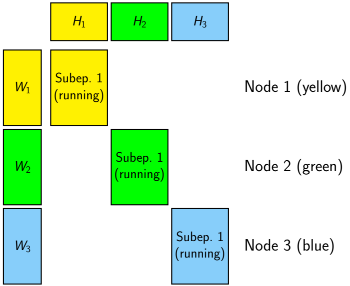

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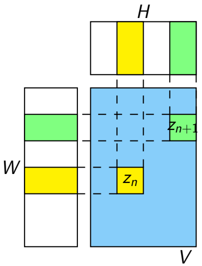

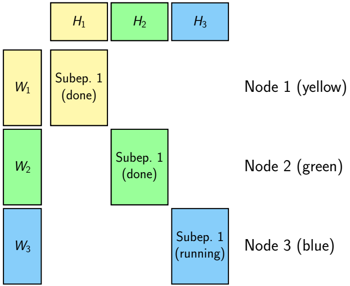

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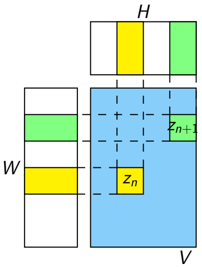

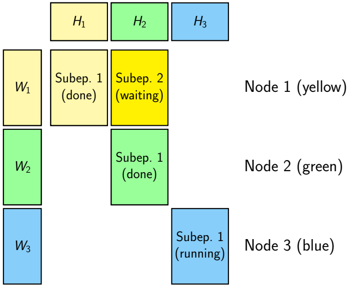

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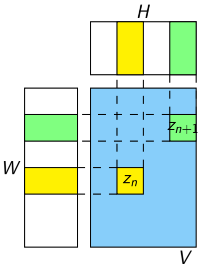

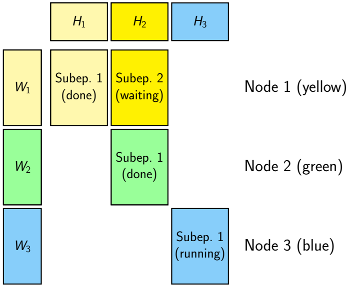

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- Prefetch data/parameters for next SGD step(s)
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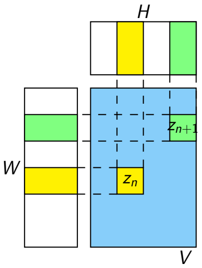
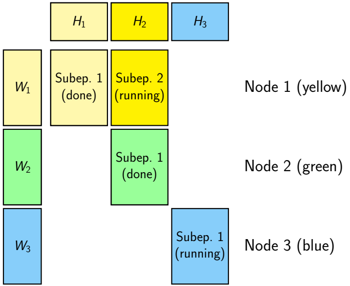
- Directly communicate parameters between nodes
- Overlay subepochs





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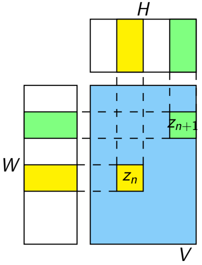
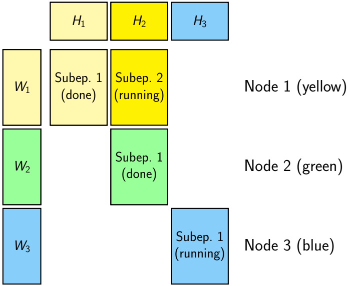


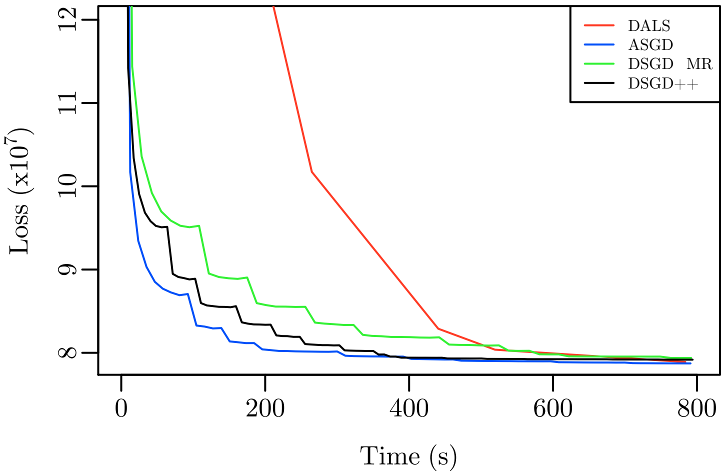


Outline

Setup

- Small blade cluster
  - 16 compute nodes
  - Intel Xeon E5530, 8 cores, 2.4GHz
  - 48GB memory
- All algorithms implemented in C++ and MPI
  - Alternating least squares (ALS)
  - Stochastic gradient descent (SGD)
  - Parallel ALS (PALS)
  - Parallel SGD (PSGD)
  - Distributed ALS (DALS)
  - Asynchronous SGD (ASGD)
  - Distributed SGD (DSGD-MR)
  - Distributed SGD++ (DSGD++)
- Datasets
  - Netflix (480k $\times$ 18k, 99M entries)
  - KDD (1M $\times$ 625k, 253M entries)
  - Synthetic (varying size, 1B–10B entries)

Example: Netflix data, 4x8 (relatively small, few items)



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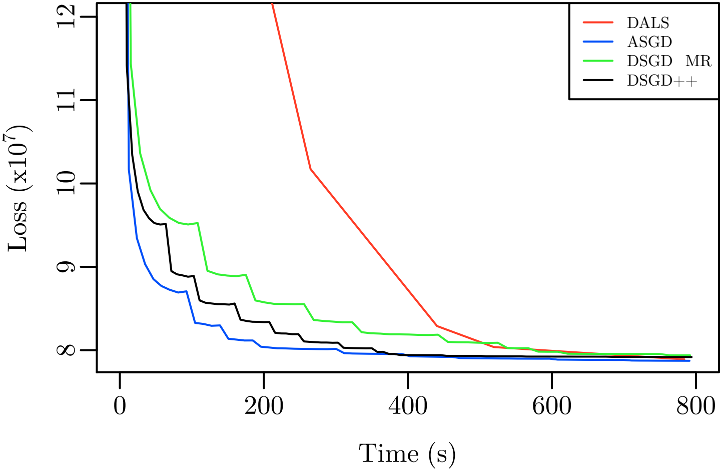
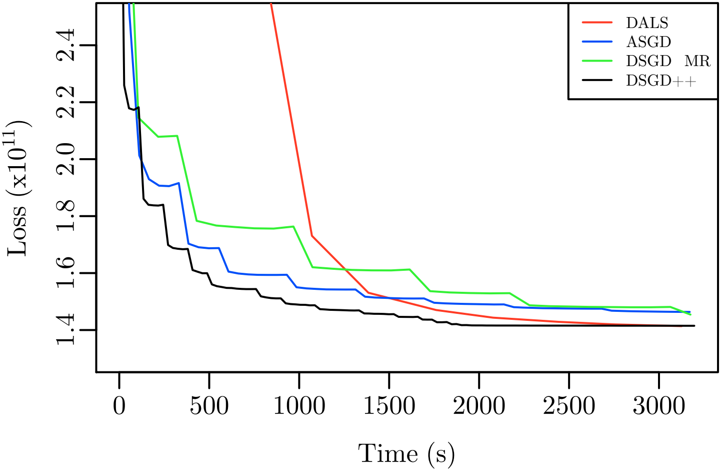


MapReduce algorithms slow; ASGD best, DSGD++ close.

Example: KDD data, 4x8 (moderatly large, many items)



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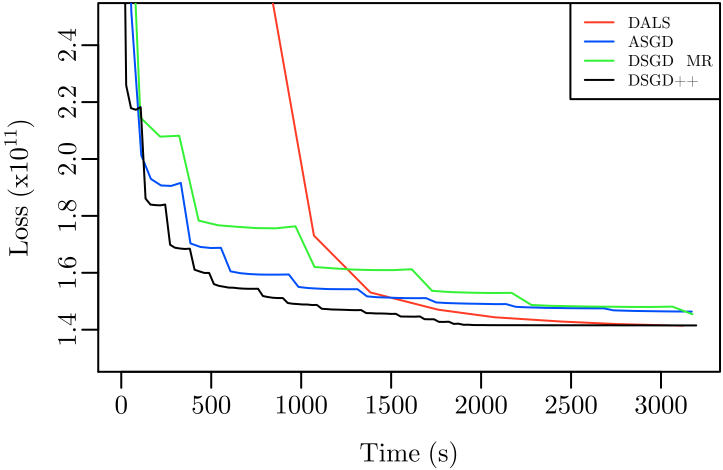
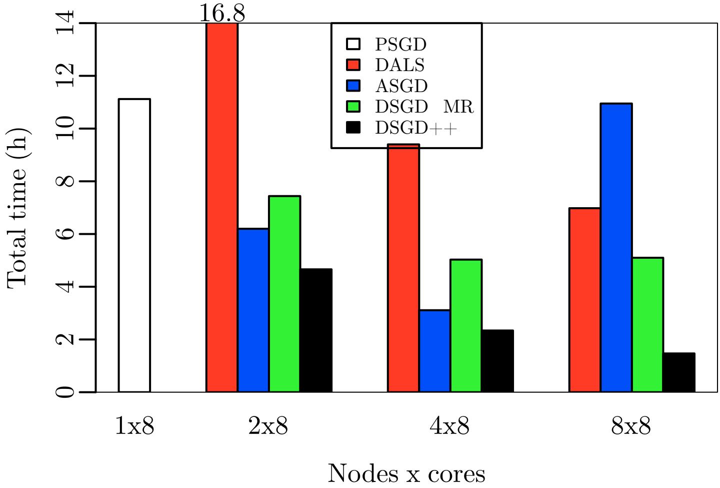


DSGD++ best, ALS competitive.

Strong scalability: Large syn. data (10M × 1M, 1B entries)



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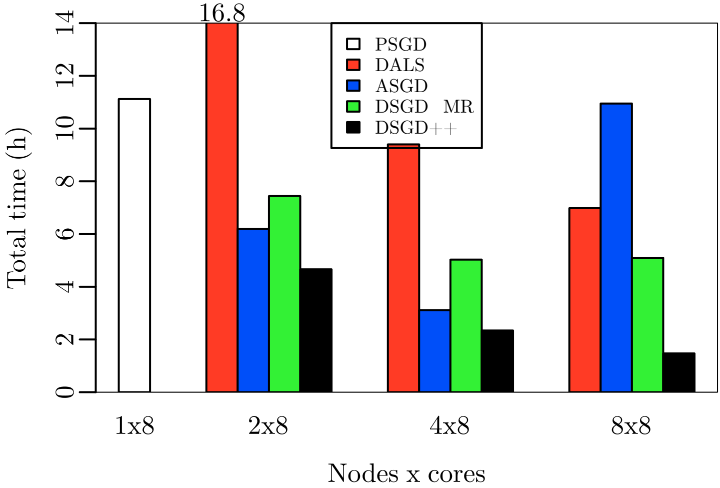
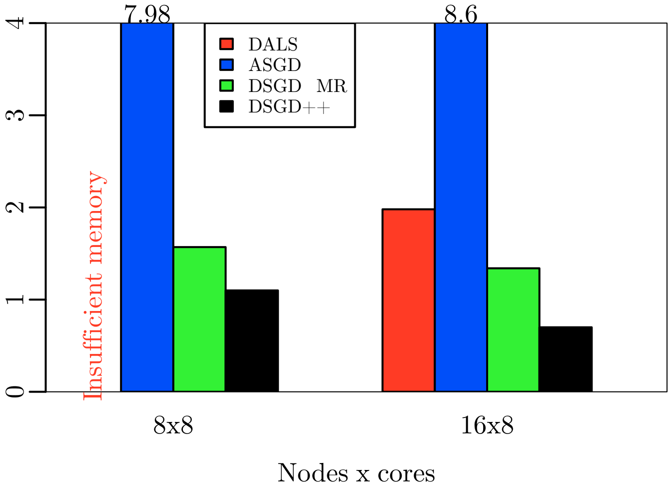


DSGD++ fastest, best scalability.

(DALS converged to bad solution.)

Strong scalability: Huge syn. data (10M $\times$ 1M, 10B)



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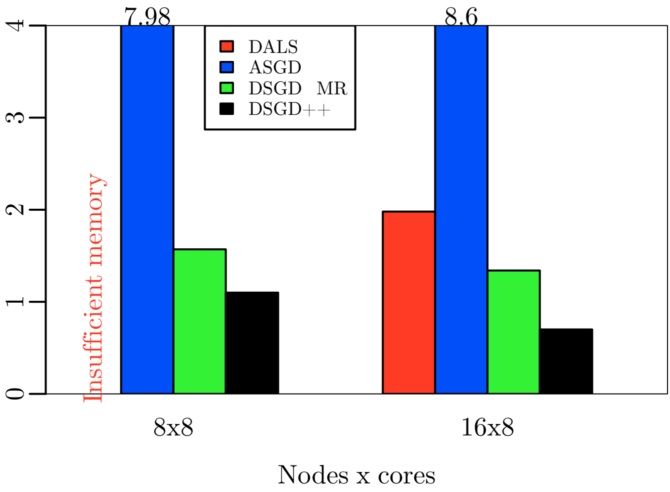

DSGD++ faster on 4 nodes than any other technique on 8 nodes.

(ASGD converged to bad solution.)

Outline

Summary

- Matrix factorization
  - Currently best single approach for collaborative filtering
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Thank you!