Large-Scale Matrix Factorization with Distributed Stochastic Gradient Descent

Rainer Gemulla

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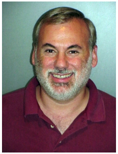
Peter J. Haas Yannis Sismanis Erik Nijkamp



Outline

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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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 & \begin{array}{ccc} \textit{Avatar} & \textit{The Matrix} & \textit{Up} \end{array} \\
\begin{array}{l} \textit{Alice} \\ \textit{Bob} \\ \textit{Charlie} \end{array} &
\begin{pmatrix} & 4 & 2 \\ 3 & 2 & \\ 5 & & 3 \end{pmatrix}
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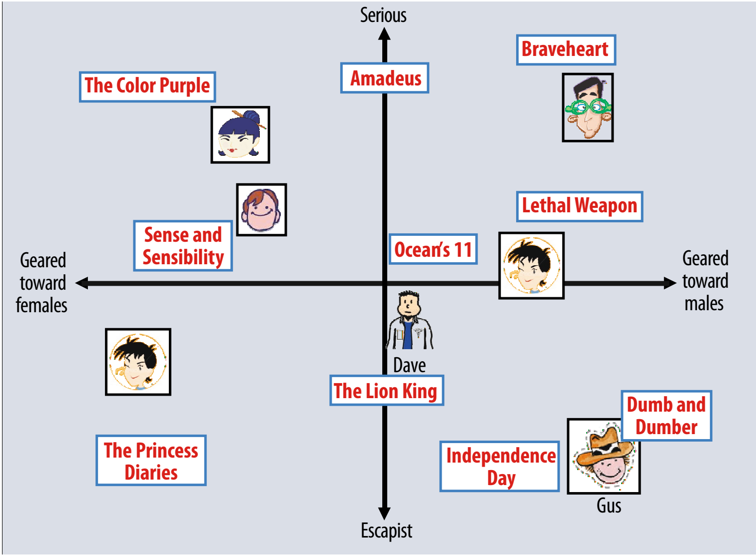
- Netflix competition: 500k users, 20k movies, 100M movie ratings, 3M question marks

Semantic Factors (Koren et al., 2009)



Latent Factor Models

- Discover latent factors ($r = 1$)

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

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$$\min_{\mathbf{W},\mathbf{H},\mathbf{u},\mathbf{m}} \sum_{(i,j)\in Z} (\mathbf{V}_{ij} - \mu - \mathbf{u}_i - \mathbf{m}_j - [\mathbf{WH}]_{ij})^2$$

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

- Bias, regularization

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$$\min_{\mathbf{W},\mathbf{H},\mathbf{u},\mathbf{m}} \sum_{(i,j,t)\in Z_t} \left(\mathbf{V}_{ij} - \mu - \mathbf{u}_i(t) - \mathbf{m}_j(t) - [\mathbf{W}(t)\mathbf{H}]_{ij}\right)^2 + \lambda\left(\|\mathbf{W}(t)\| + \|\mathbf{H}\| + \|\mathbf{u}(t)\| + \|\mathbf{m}(t)\|\right)$$

- Bias, regularization, time

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- A general machine learning problem
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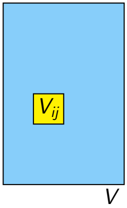

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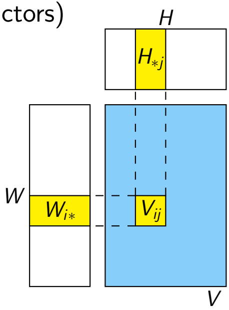

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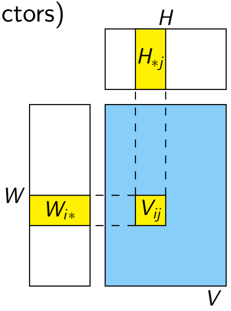

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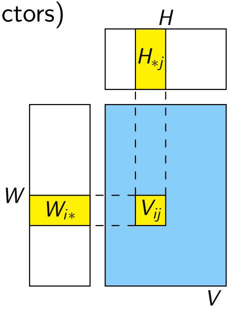
- Find best model

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



Successful Applications

- Movie recommendation (Netflix, competition papers)
  - $>$12M users, $>$20k movies, 2.4B ratings (projected)
  - 36GB data, 9.2GB model (projected)
  - Latent factor model
- Website recommendation (Microsoft, WWW10)
  - 51M users, 15M URLs, 1.2B clicks
  - 17.8GB data, 161GB metadata, 49GB model
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Distributed processing is necessary!

- Big data
- Large models
- Expensive computations

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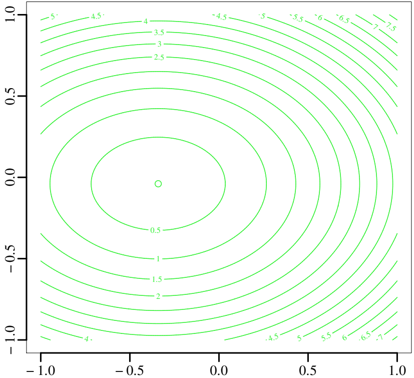
Stochastic Gradient Descent

- Find minimum θ^* of function L



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- Find minimum θ^* of function L
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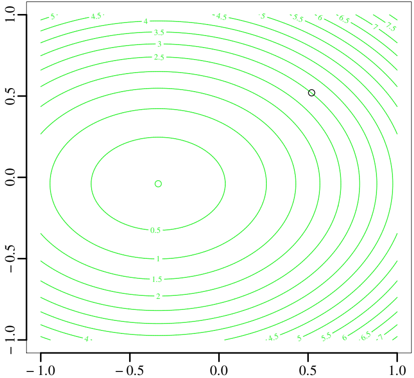

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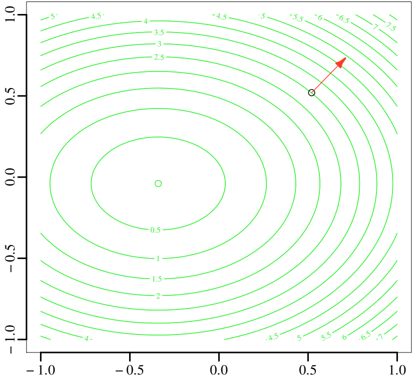

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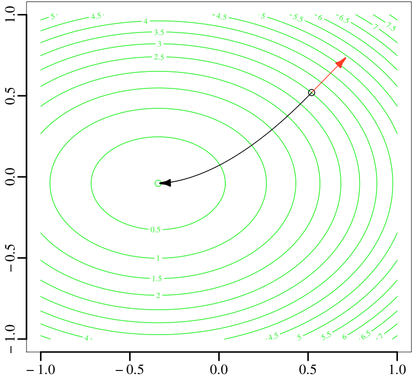

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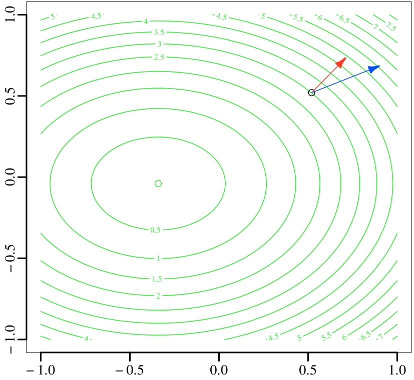

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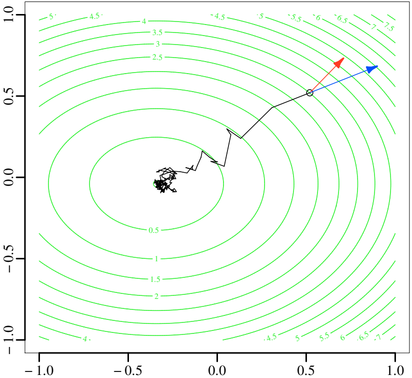

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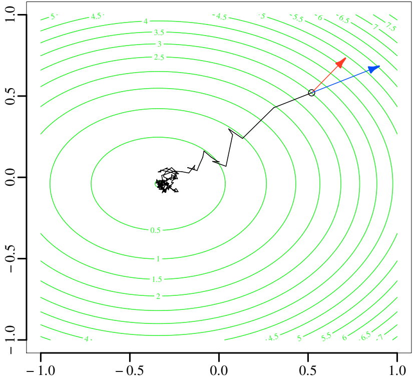
$$\theta_{n+1} = \theta_n - \epsilon_n \hat{L}'(\theta_n)$$



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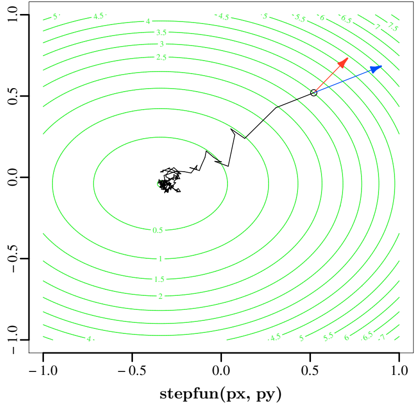
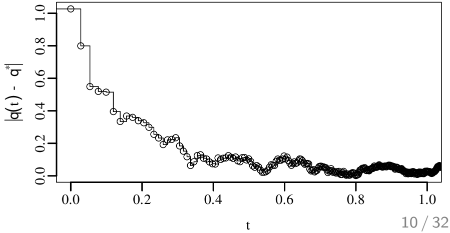
- Under certain conditions, asymptotically approximates (continuous) gradient descent

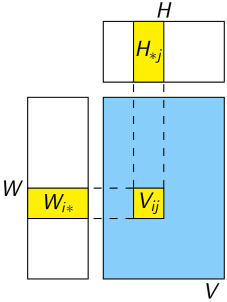




Stochastic Gradient Descent for Matrix Factorization

- 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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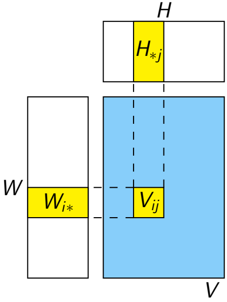

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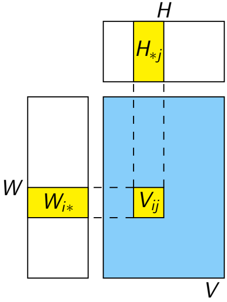
$$\hat{L}'(\theta, z) = NL'_{i_z j_z}(\mathbf{W}_{i_z *}, \mathbf{H}_{*j_z}),$$

where $N = |Z|$



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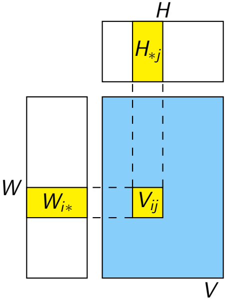
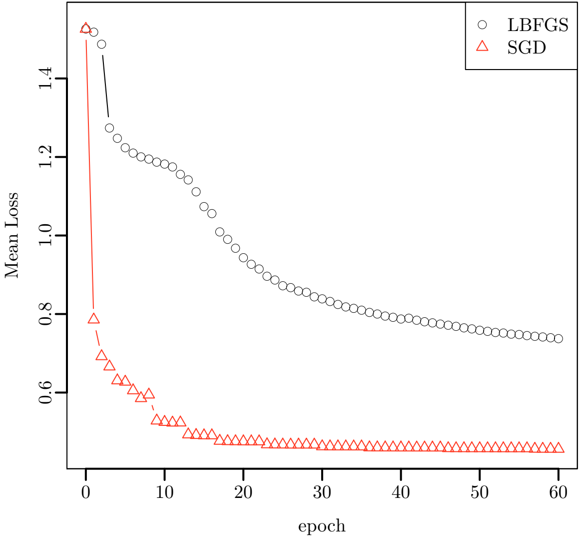


- SGD epoch
  1. Pick a random entry $z \in Z$
  2. Compute approximate gradient $\hat{L}'(\theta, z)$
  3. Update parameters

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

  4. Repeat N times

Stochastic Gradient Descent on Netflix Data



Comparison

- Per epoch, assuming $O(r)$ gradient computation per element

	GD	**SGD**
Algorithm	Deterministic	Randomized
Gradient computations	1	N
Gradient types	Exact	Approximate
Parameter updates	1	N
Time	$O(rN)$	$O(rN)$
Space	$O((m+n)r)$	$O((m+n)r)$

- Why stochastic?
  - *Fast convergence* to vicinity of optimum
  - Randomization may help escape local minima
  - Exploitation of "repeated structure"

Outline

Averaging Techniques

- SGD steps depend on each other

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

How to distribute?

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  - *Map*: Run independent instances of SGD on subsets of the data (until convergence)
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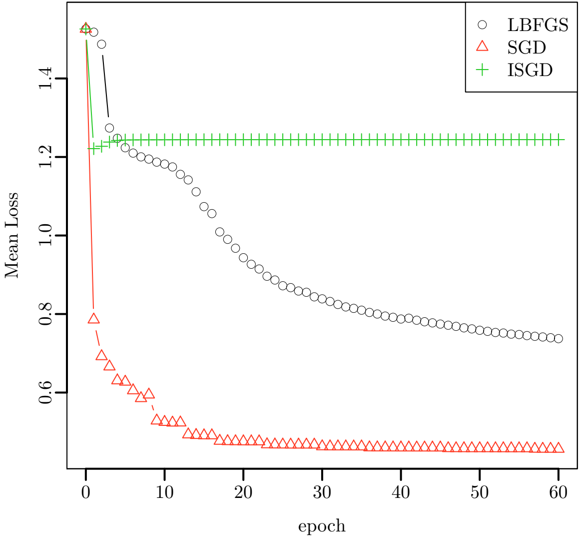

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- Iterative Parameter mixing (PSGD)
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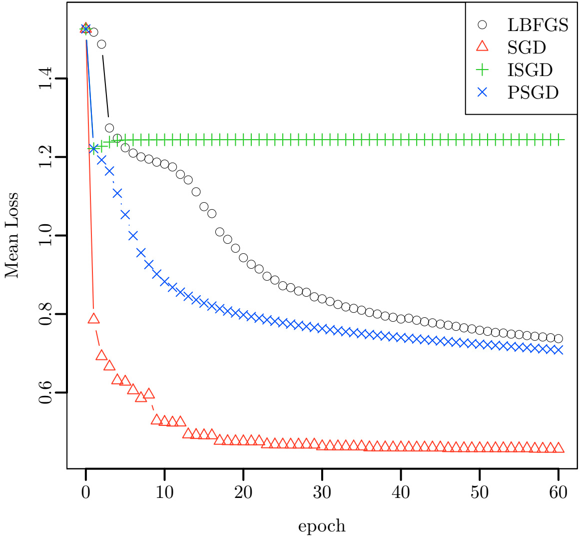
  - *Reduce*: Average results
  - Repeat

Averaging Techniques



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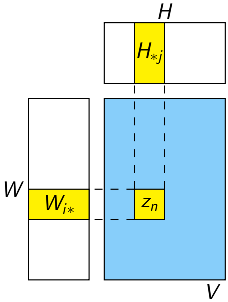
  - Repeat
  - Converges slowly!

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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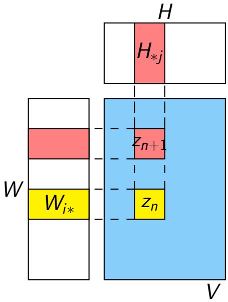

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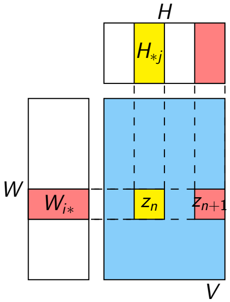

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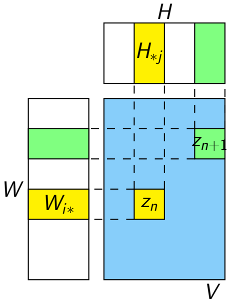
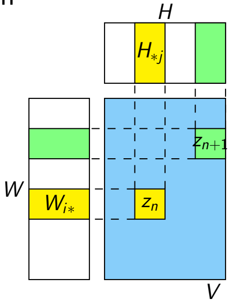
  3. Updates $W_{i_z *}$ and $H_{* j_z}$
- Not all steps are dependent



Interchangeability

- Two elements $z_1, z_2 \in Z$ are *interchangeable* if they share neither row nor column



- When z_n and z_{n+1} are interchangeable, the SGD steps

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

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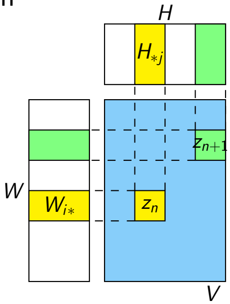

- When z_n and z_{n+1} are interchangeable, the SGD steps

$$\theta_{n+2} = \theta_n - \epsilon \hat{L}'(\theta_n, z_n) - \epsilon \hat{L}'(\theta_{n+1}, z_{n+1})$$

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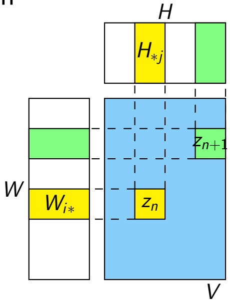

- When z_n and z_{n+1} are interchangeable, the SGD steps

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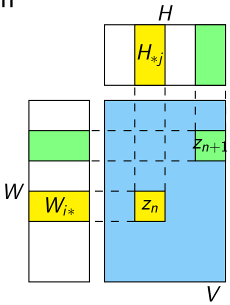

- When z_n and z_{n+1} are interchangeable, the SGD steps

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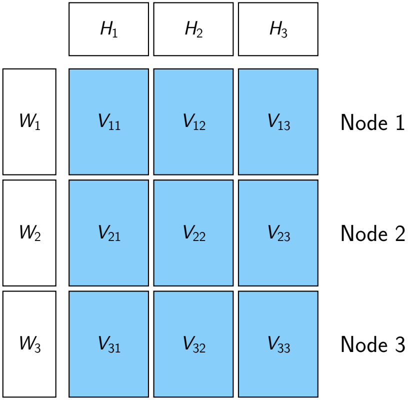
become parallelizable!

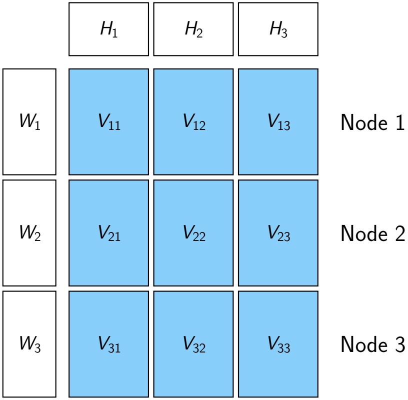
Exploitation

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



Exploitation

- Block and distribute the input matrix **V**
- High-level approach (Map only)
  1. Pick a "diagonal"
  2. Run SGD on the diagonal (in parallel)
  3. Merge the results
  4. Move on to next "diagonal"
  - Steps 1–3 form a *cycle*



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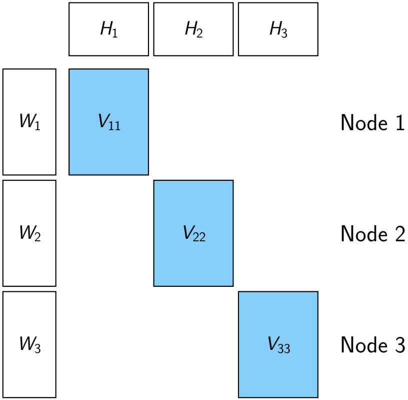

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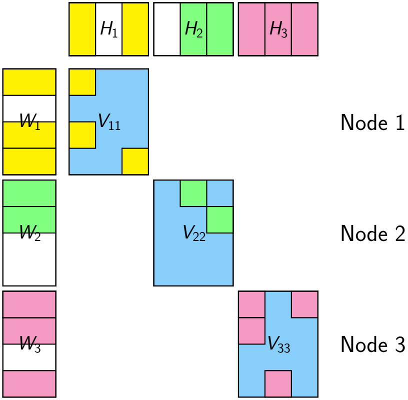
- Step 2:
  Simulate sequential SGD
  - Interchangeable blocks
  - Throw dice of how many iterations per block
  - Throw dice of which step sizes per block



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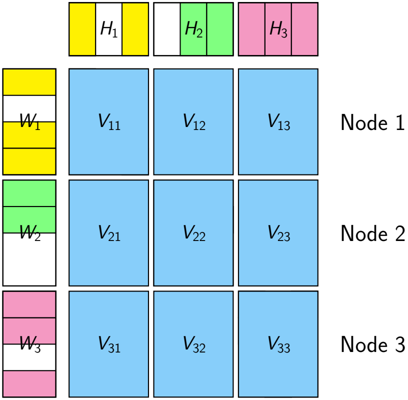

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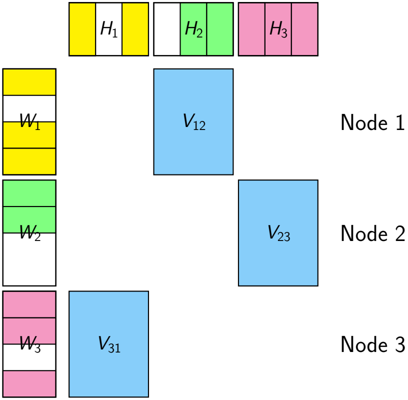

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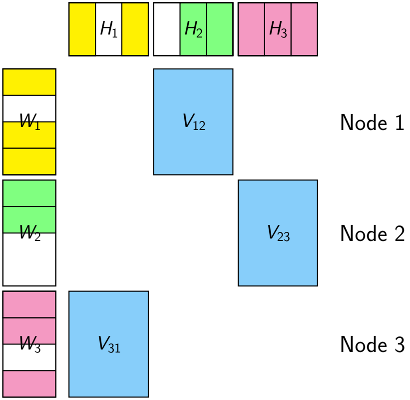
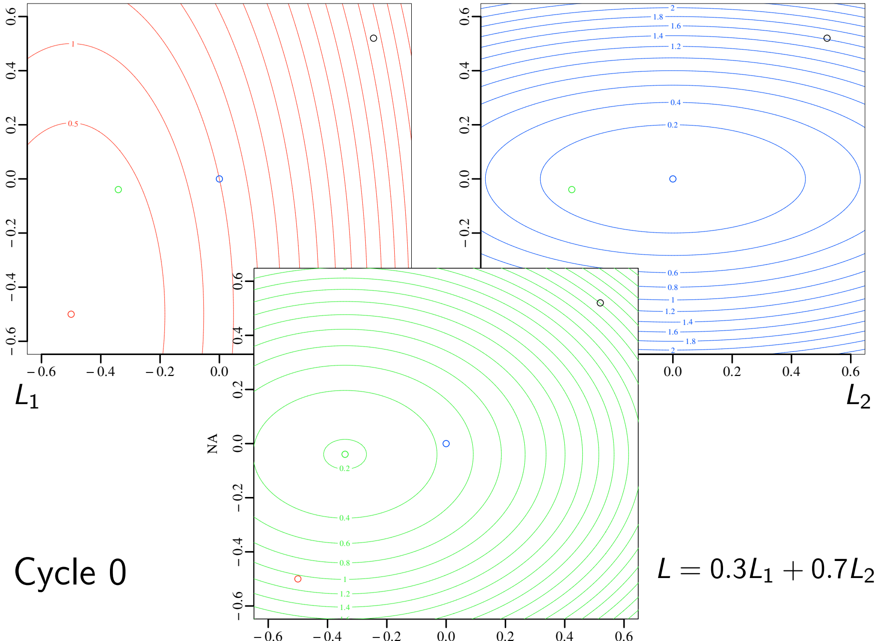
  - Throw dice of how many iterations per block
  - Throw dice of which step sizes per block
- Instance of "stratified SGD"
- Provably correct



How does it work?



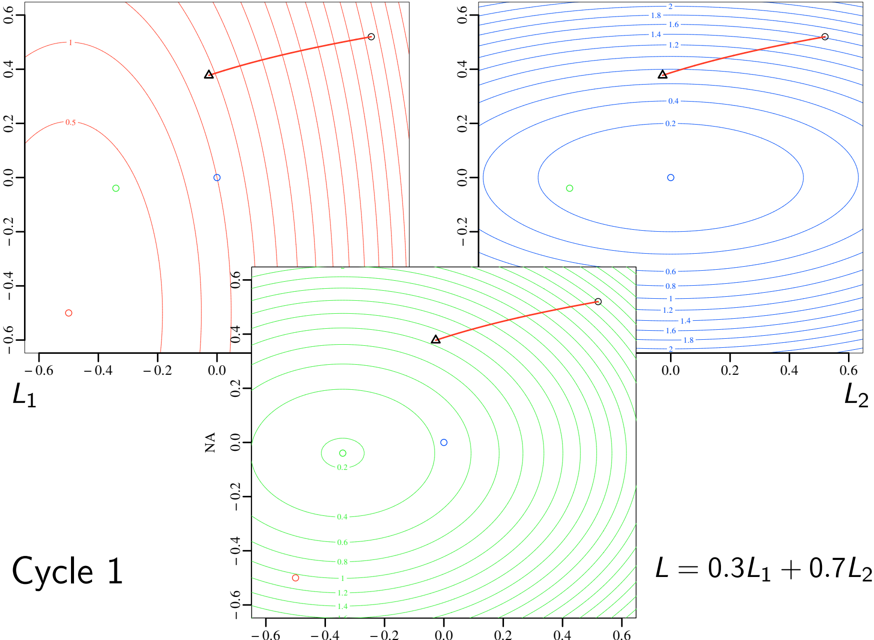
L_1

L_2

Cycle 0

$L = 0.3 L_1 + 0.7 L_2$

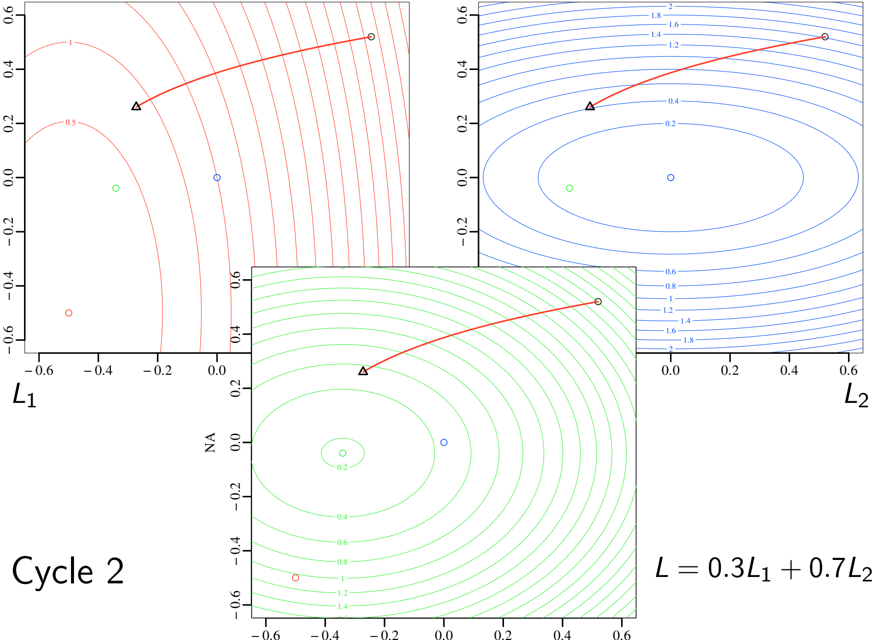
How does it work?



Cycle 1

$L = 0.3L_1 + 0.7L_2$

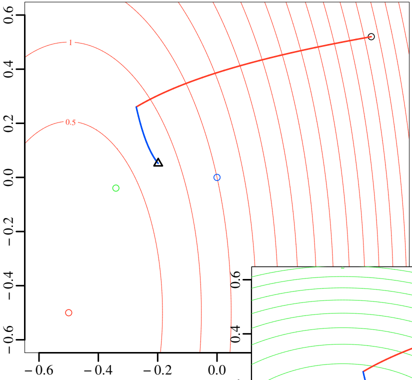
How does it work?



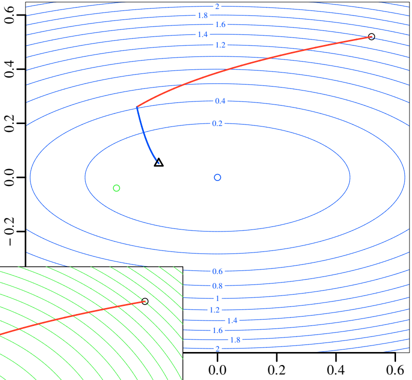
Cycle 2

$L = 0.3L_1 + 0.7L_2$

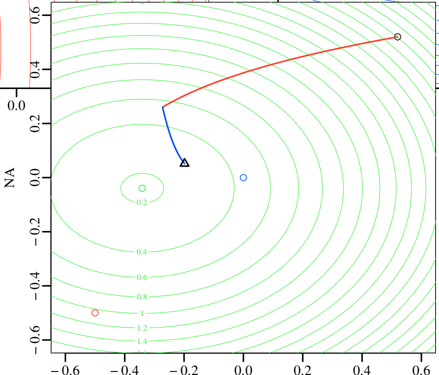
How does it work?



L_1



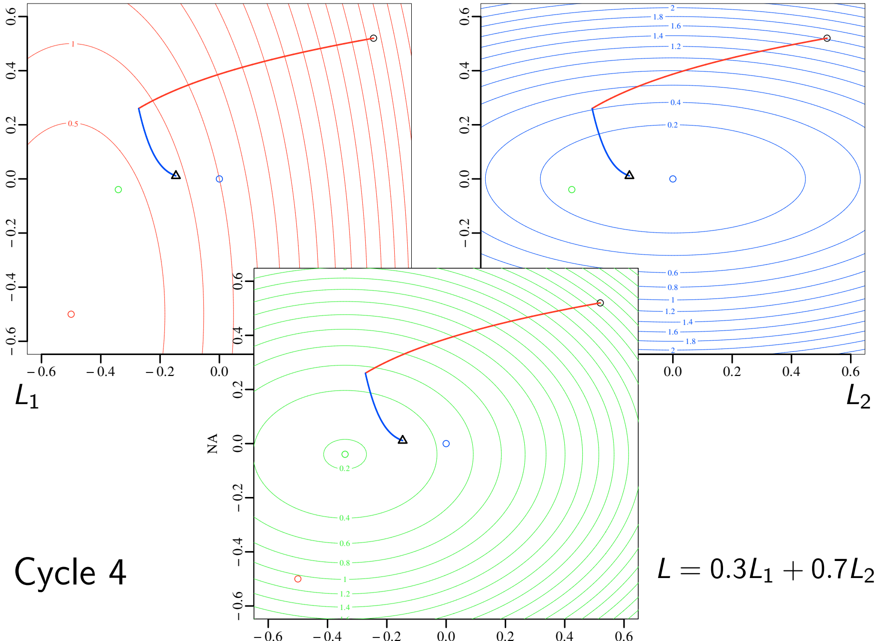
L_2



Cycle 3

$L = 0.3L_1 + 0.7L_2$

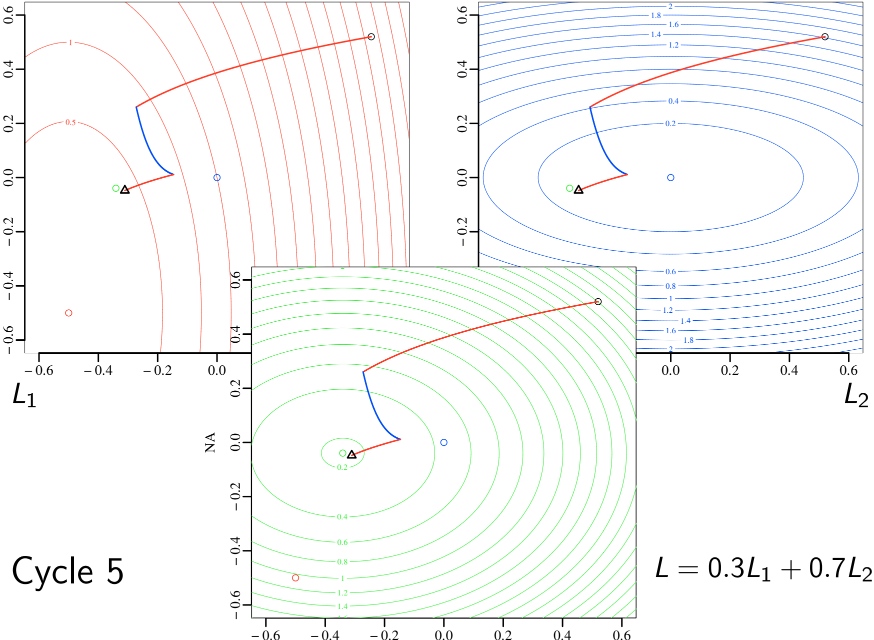
How does it work?



Cycle 4

$L = 0.3L_1 + 0.7L_2$

How does it work?



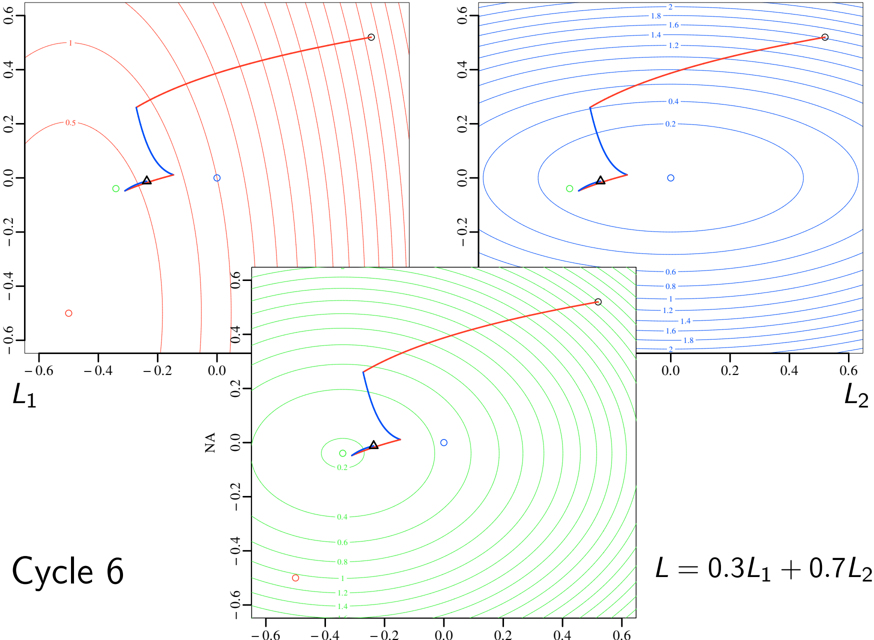
L_1

L_2

Cycle 5

$L = 0.3L_1 + 0.7L_2$

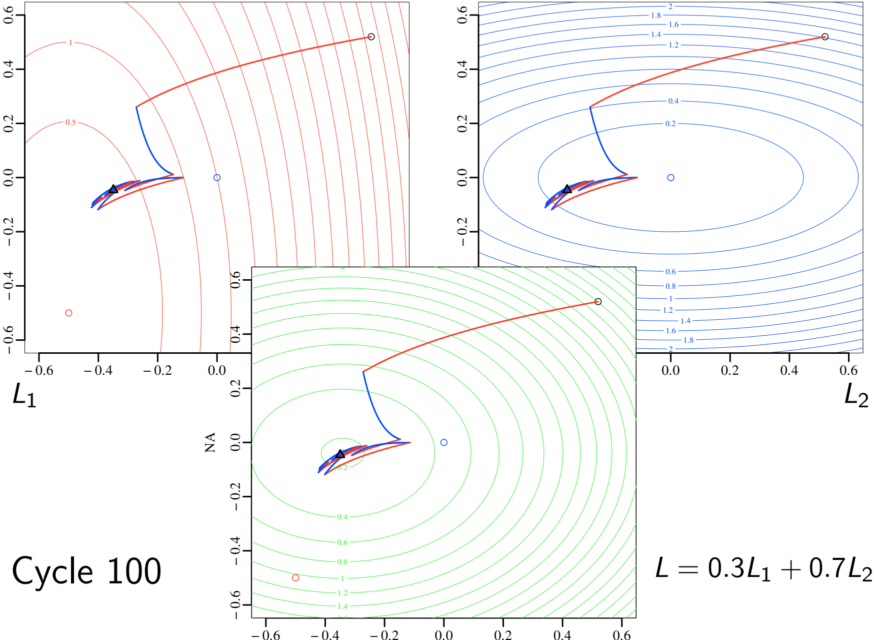
How does it work?



Cycle 6

$L = 0.3L_1 + 0.7L_2$

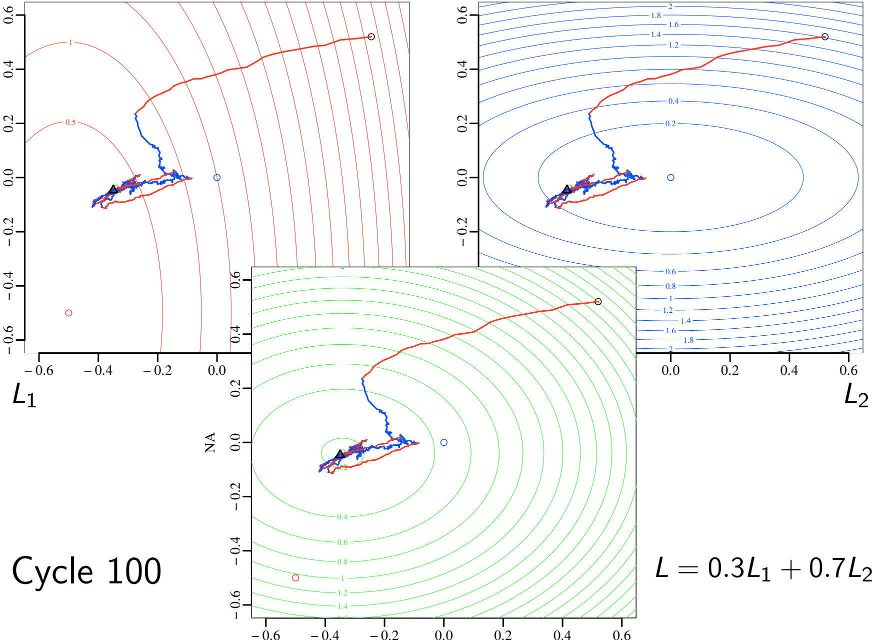
How does it work?



Cycle 100

$L = 0.3L_1 + 0.7L_2$

How does it work?



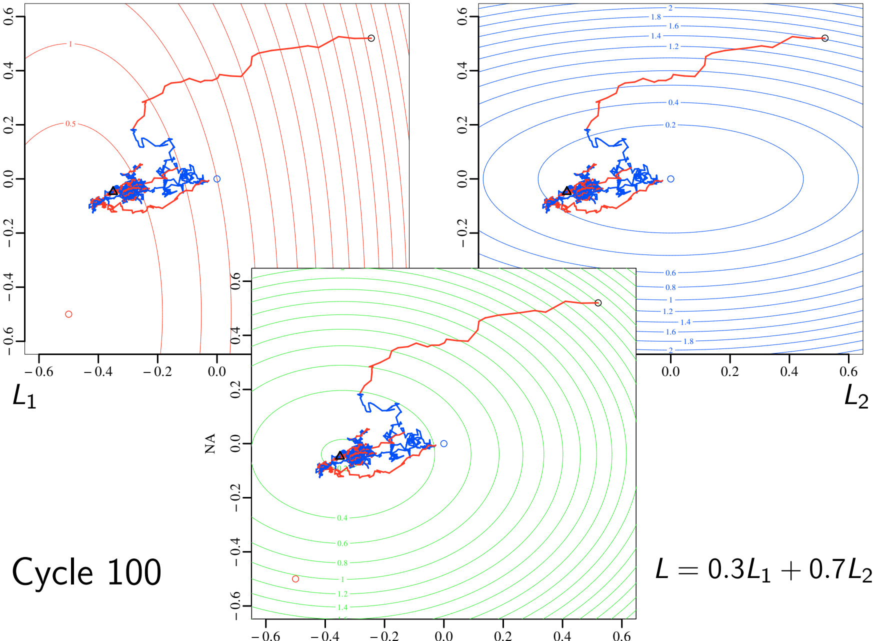
L_1

L_2

Cycle 100

$L = 0.3L_1 + 0.7L_2$

How does it work?

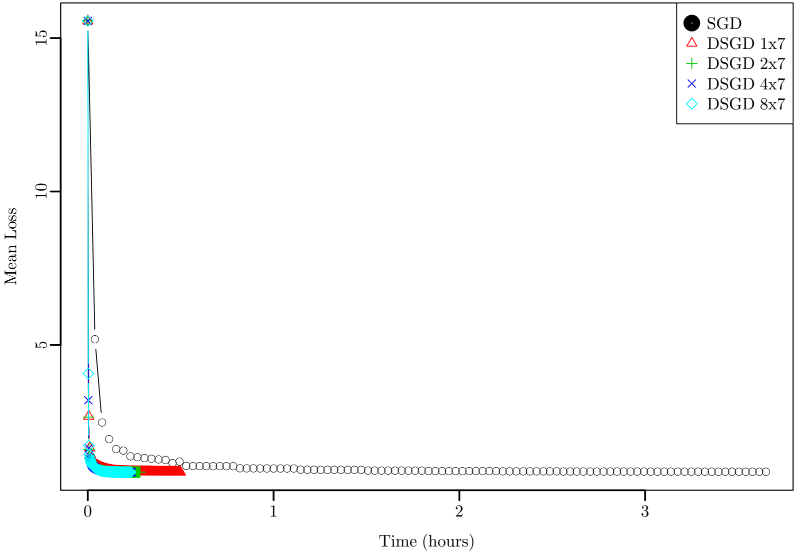


Cycle 100

$L = 0.3L_1 + 0.7L_2$

Outline

DSGD scales well (Netflix, NZSL+L2)



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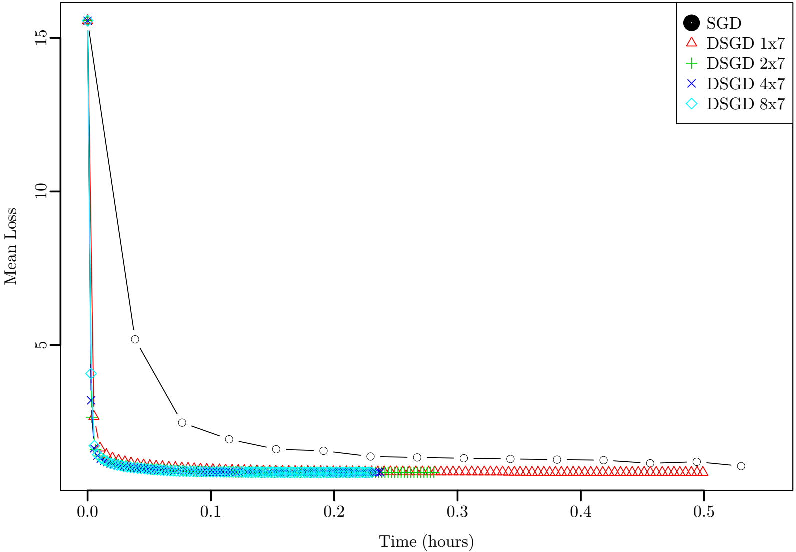
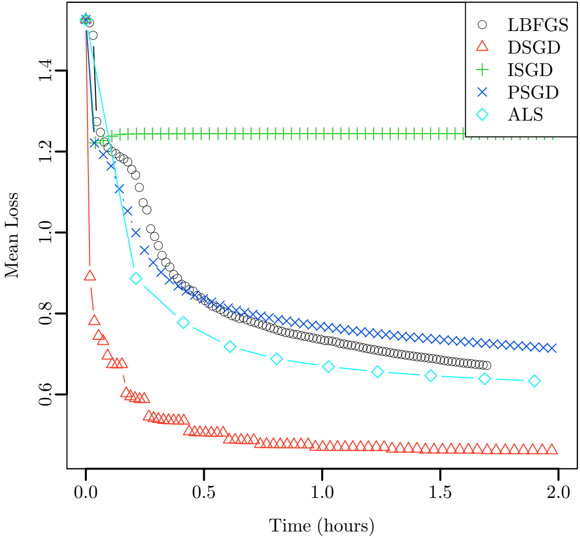


DSGD is fast (8x8, Netflix, NZSL)



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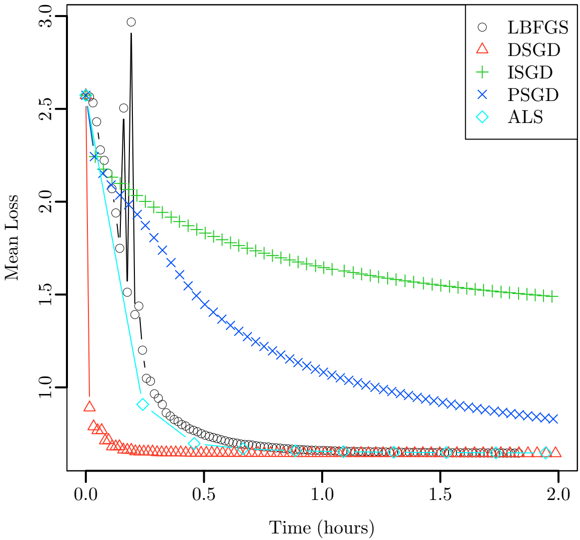
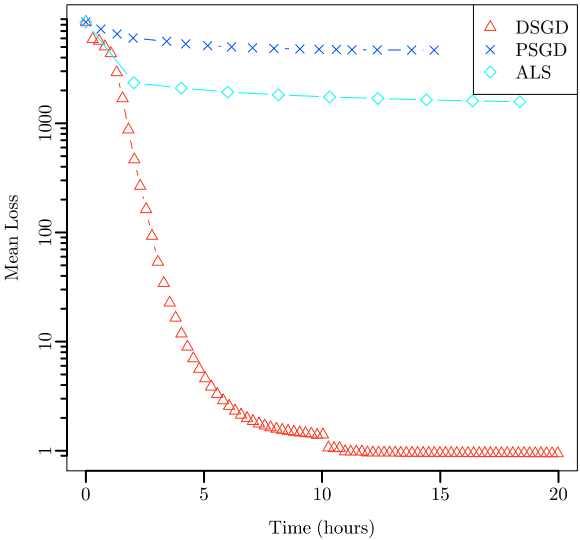
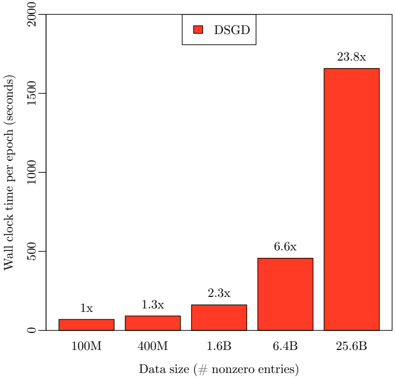


DSGD is fast (8x8, synth., NZSL+L2)

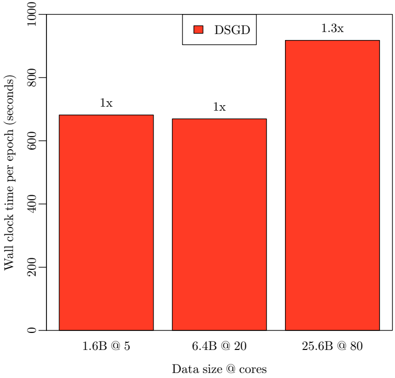


DSGD runs on Hadoop

Fixed CPU (@24)



Scaled CPU



(25.6B entries $>$ 1/2TB of data)

Outline

Summary

- Matrix factorization
  - Widely applicable via customized loss functions
  - Large instances (millions $\times$ millions with billions of entries)
- Distributed Stochastic Gradient Descent
  - Simple and versatile
  - Avoids averaging via novel "stratified SGD" variant
  - Achieves
    - Fully distributed data/model
    - Fully distributed processing
    - Same or better loss
    - Faster
    - Good scalability
- Future Directions
  - More decompositions (e.g., losses at 0)
  - Tensors
  - Stratified SGD for other models
  - ...

Thank you!