# COCOA Communication-Efficient Coordinate Ascent

Virginia Smith

*Martin Jaggi, Martin Takáč, Jonathan Terhorst,*
*Sanjay Krishnan, Thomas Hofmann, & Michael I. Jordan*

# LARGE-SCALE OPTIMIZATION

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## COCOA

LARGE-SCALE OPTIMIZATION

COCOA

RESULTS

**LARGE-SCALE OPTIMIZATION**

COCOA

RESULTS

# Machine Learning with Large Datasets

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YouTube
IMAGENET
amazon.com
NETFLIX
illumina
facebook
twitter
Google
VISA

image/music/video tagging
document categorization
item recommendation
click-through rate prediction
sequence tagging
protein structure prediction
sensor data prediction
spam classification
fraud detection

# Machine Learning Workflow

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DATA & PROBLEM

*classification, regression, collaborative filtering, …*

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*logistic regression, lasso, support vector machines, …*

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OPTIMIZATION ALGORITHM

*gradient descent, coordinate descent, Newton's method, …*

# Example: SVM Classification

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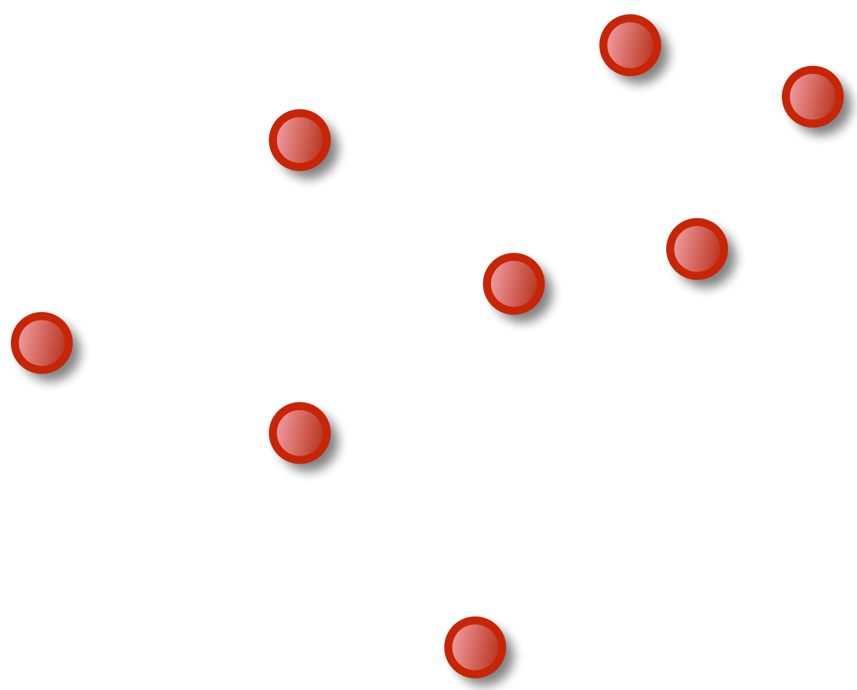

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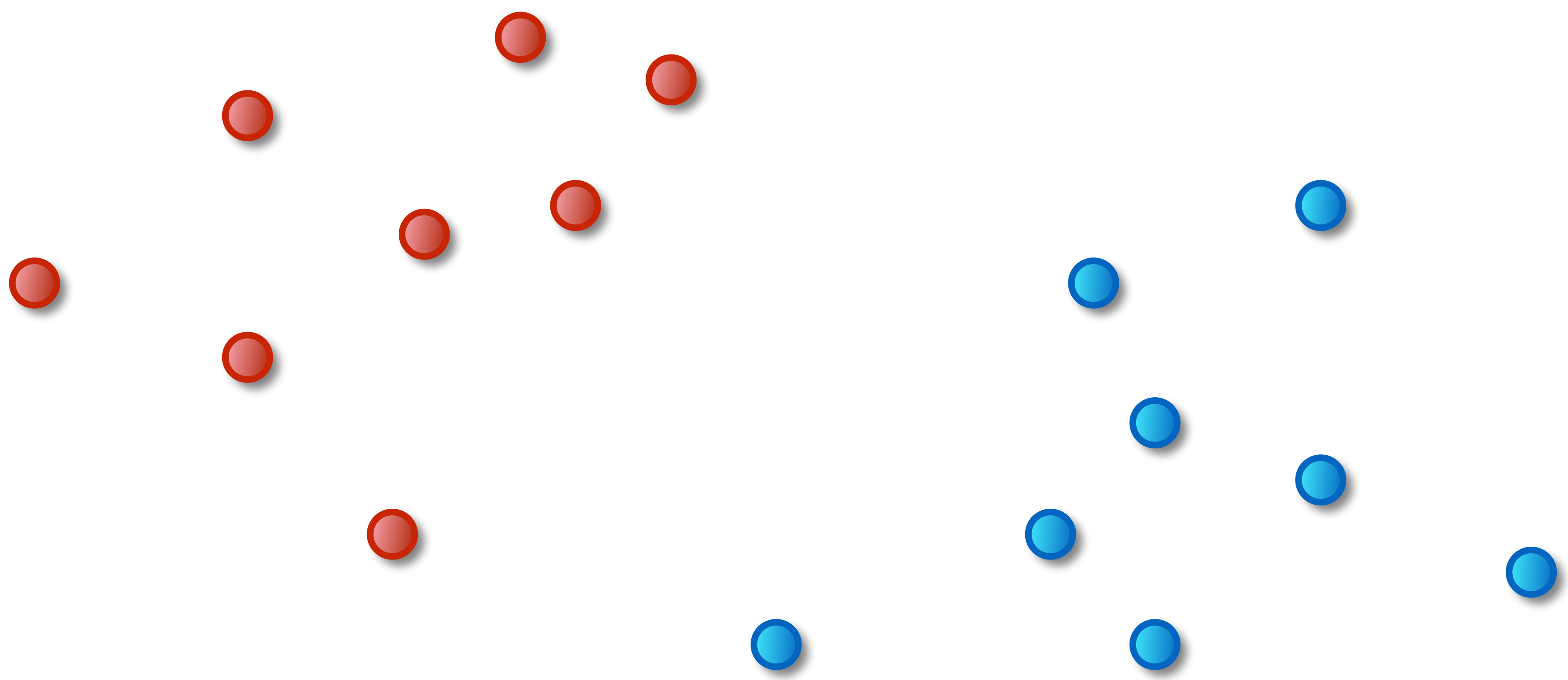

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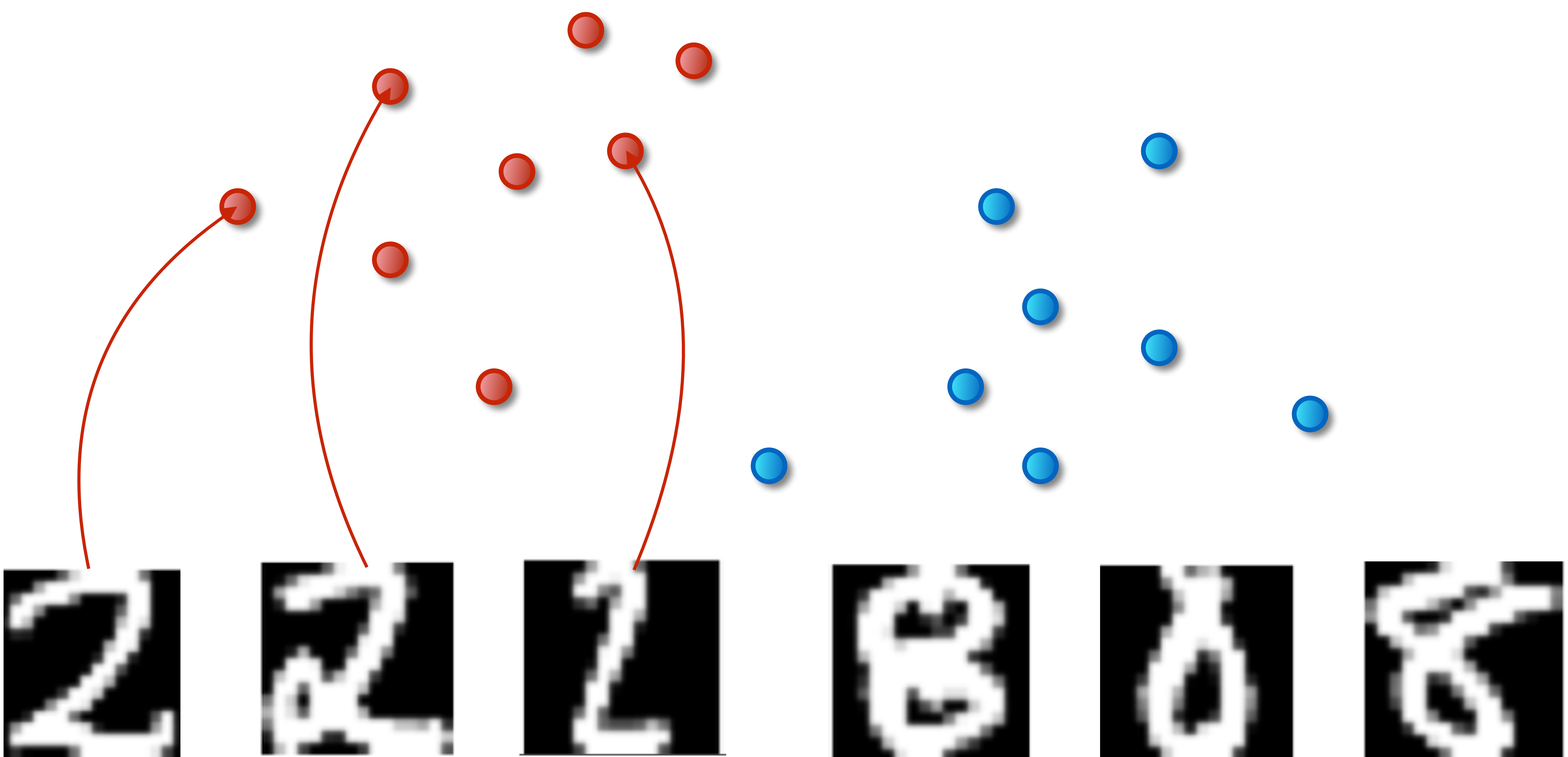

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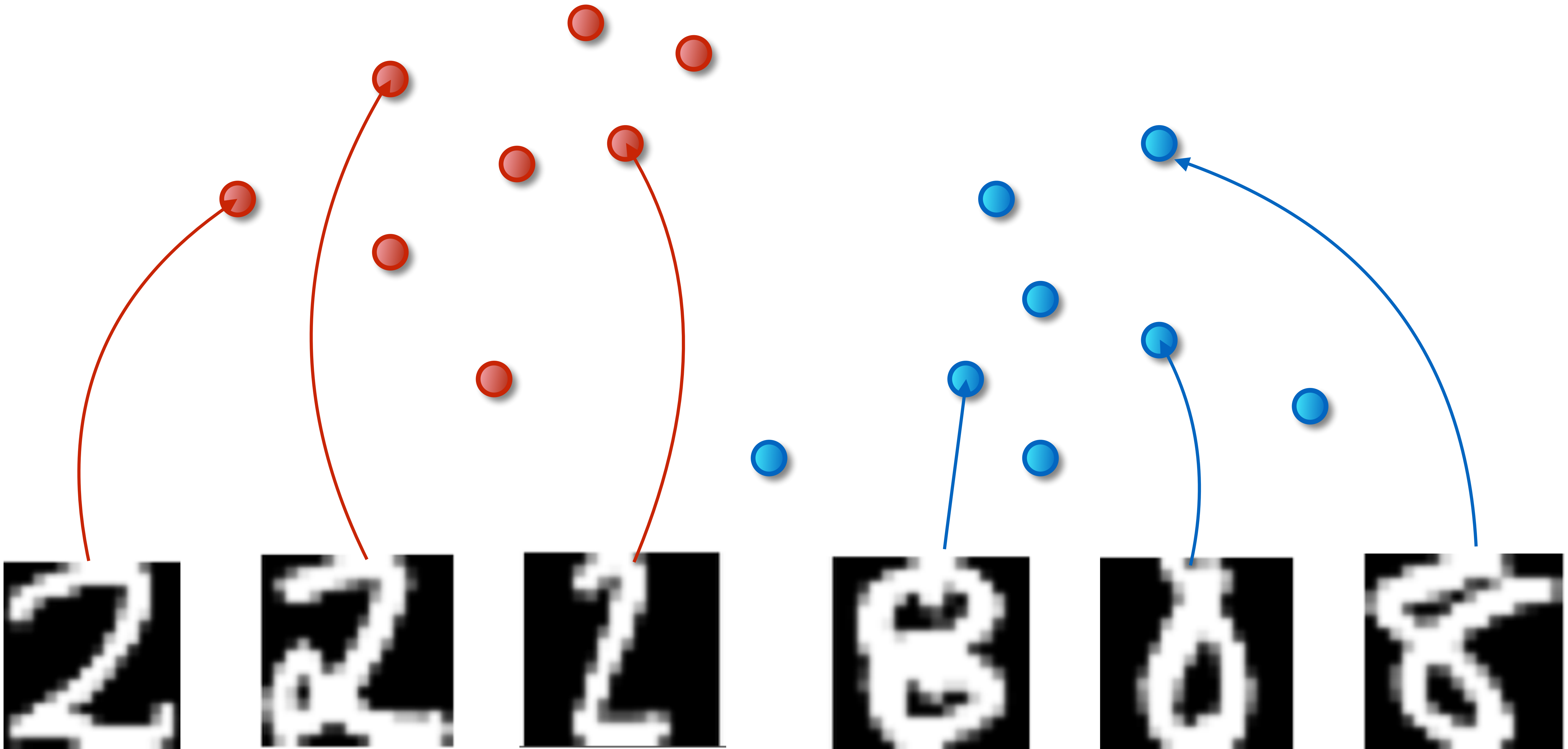

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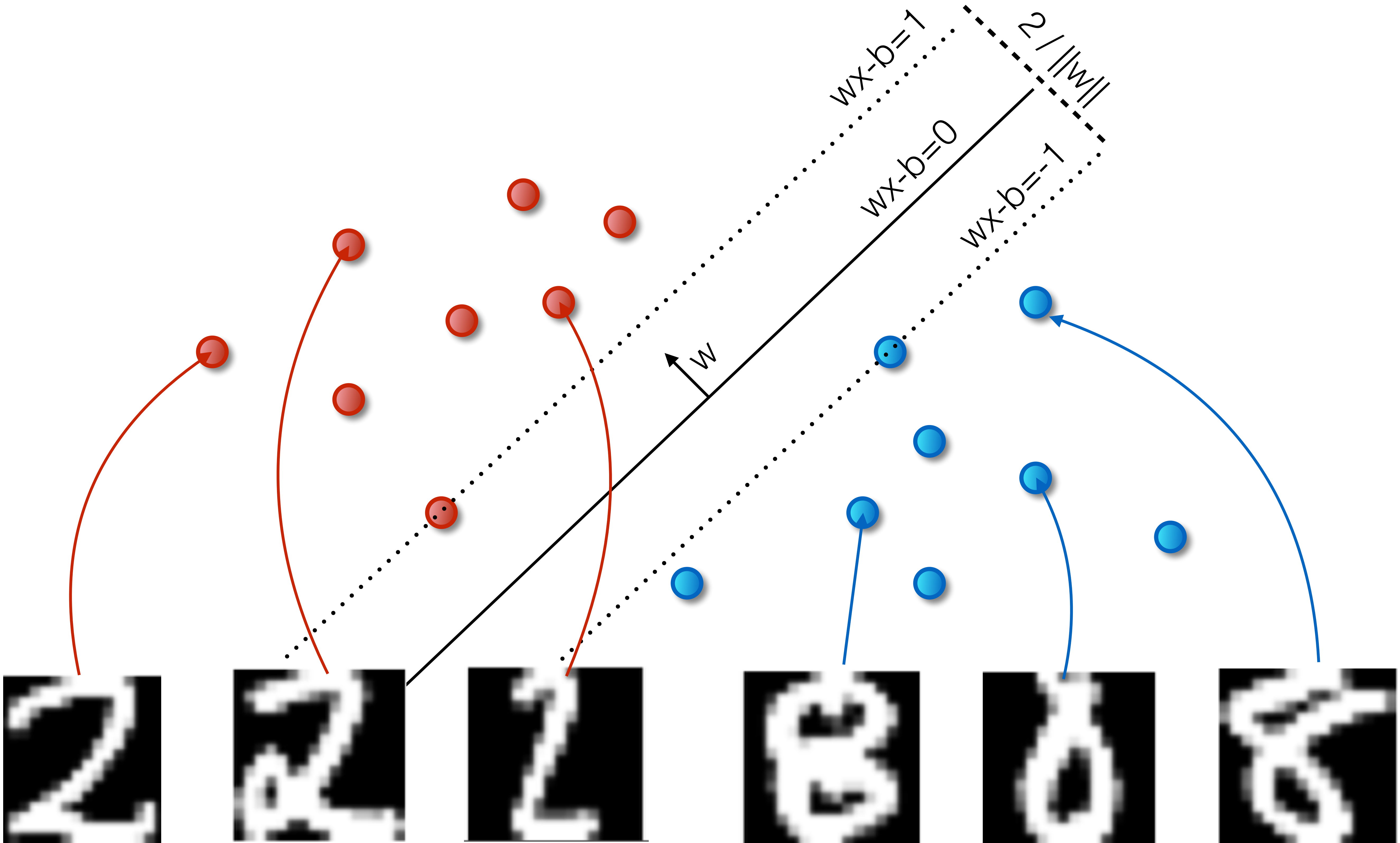

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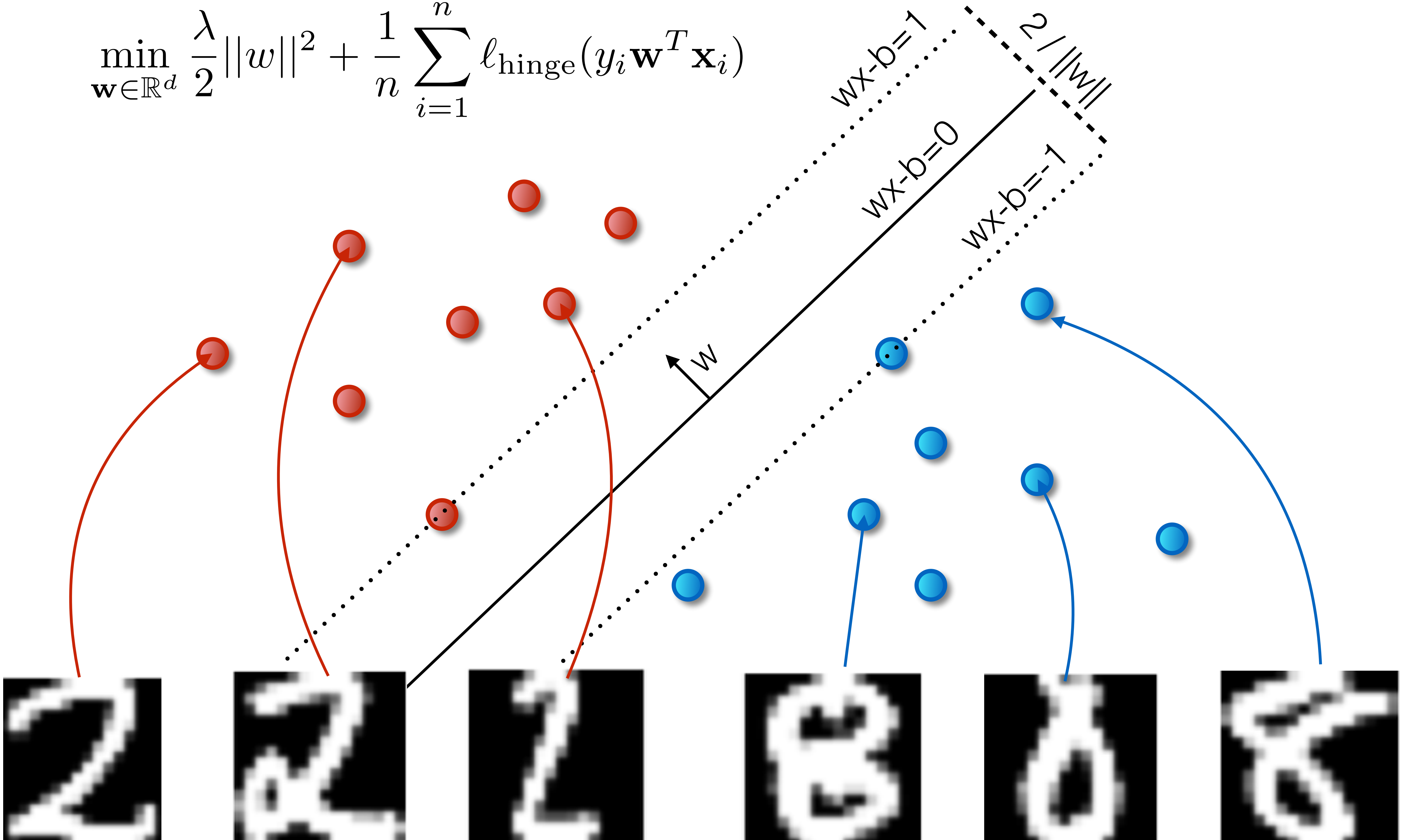

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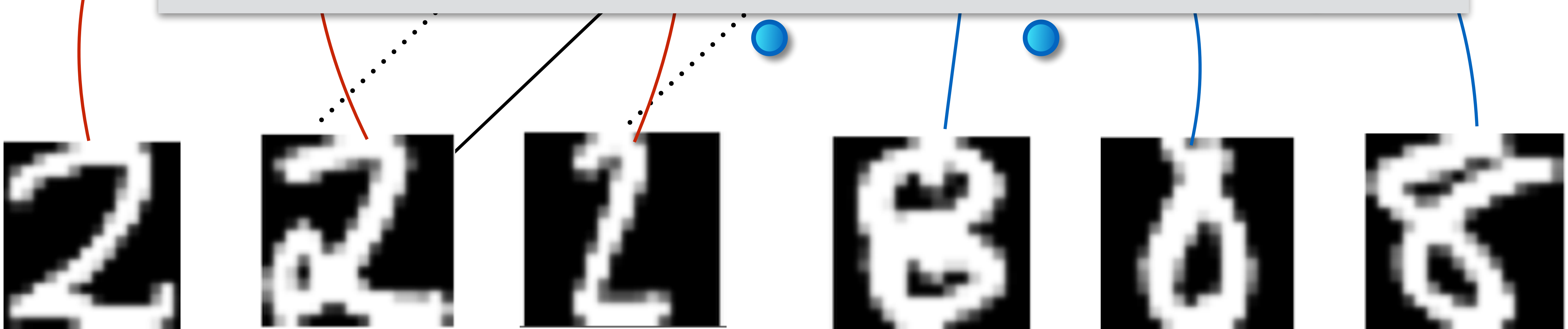
Descent algorithms and line search methods
Acceleration, momentum, and conjugate gradients
Newton and Quasi-Newton methods
Coordinate descent
Stochastic and incremental gradient methods
*SMO*
*SVM$^{light}$*
*LIBLINEAR*



# Linear Regularized Loss Minimization

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- logistic regression

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- ridge regression

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| | |
|---|---|
| DATA & PROBLEM | *classification, regression, collaborative filtering, …* |
| MACHINE LEARNING MODEL | *logistic regression, lasso, support vector machines, …* |
| SYSTEMS SETTING | *multi-core, cluster, cloud, supercomputer, …* |
| OPTIMIZATION ALGORITHM | *gradient descent, coordinate descent, Newton’s method, …* |

# Machine Learning Workflow

classification, regression

*Open Problem:*

efficiently solving objective when data is distributed

OPTIMIZATION ALGORITHM

*gradient descent, coordinate descent, Newton's method, …*

# Distributed Optimization

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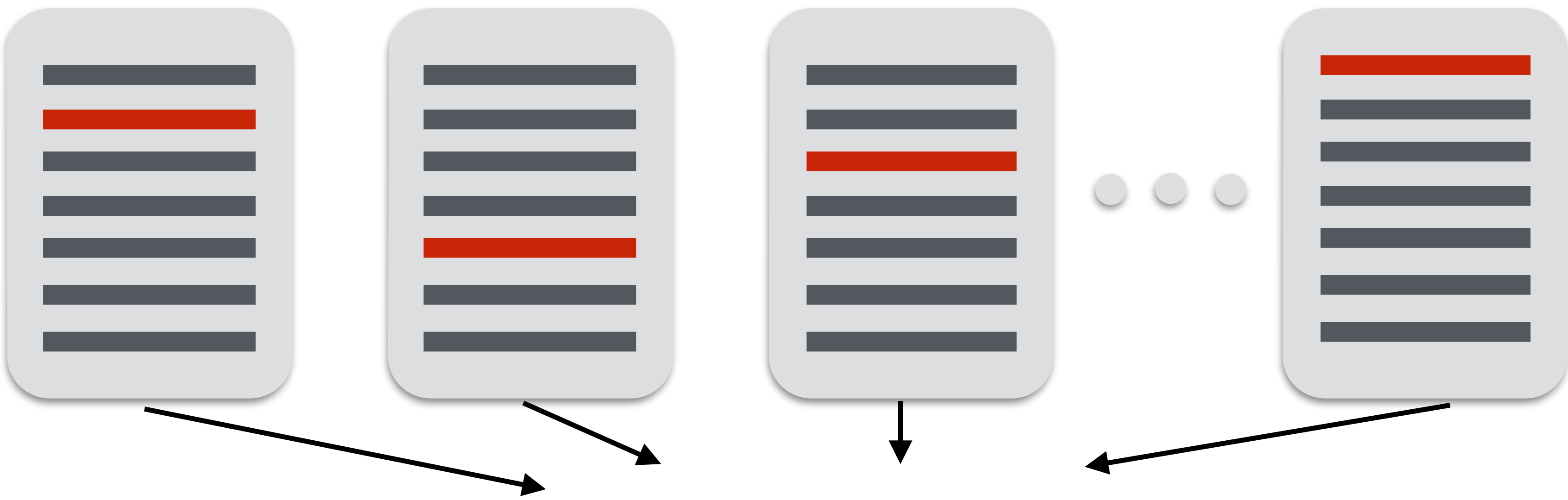

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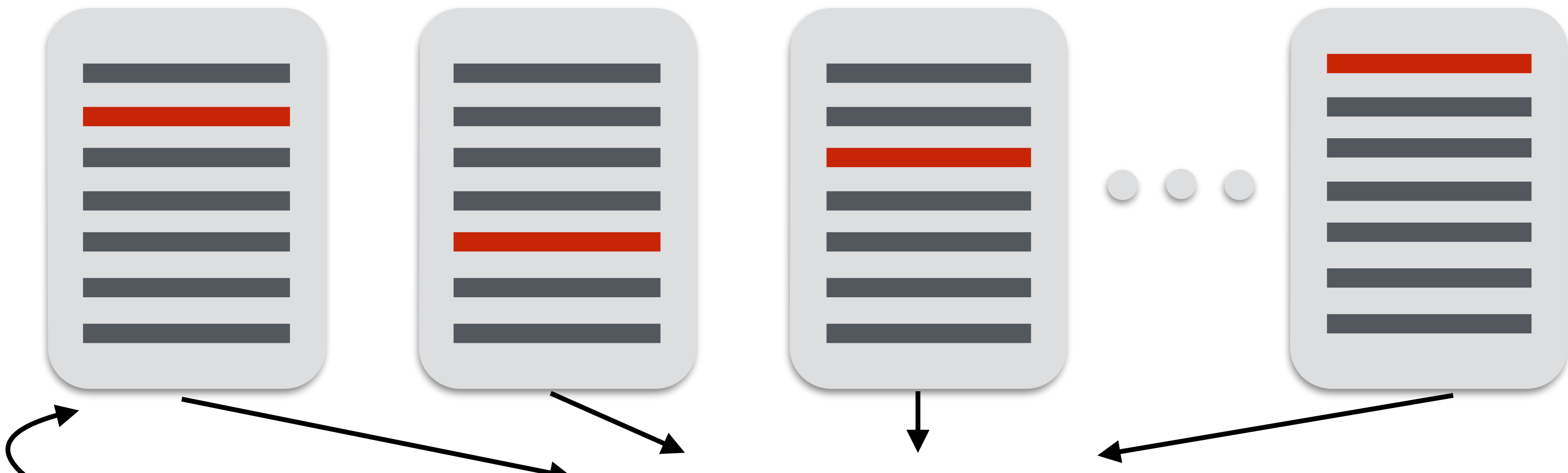

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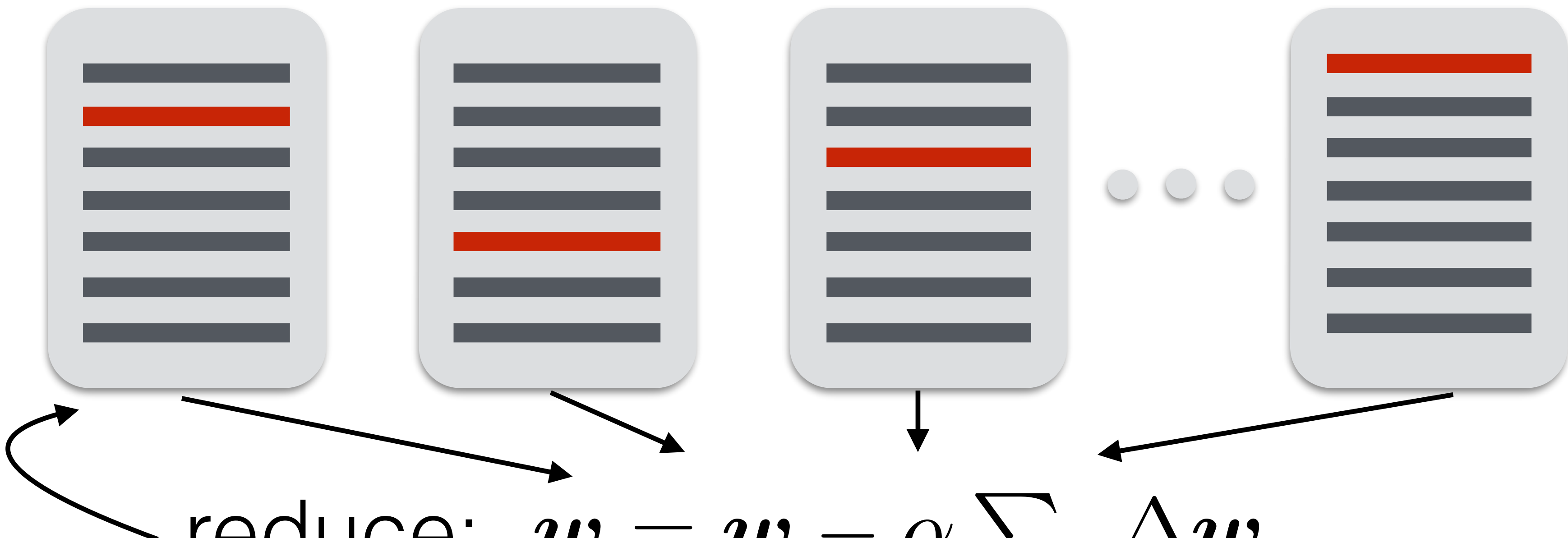

*"always communicate"*

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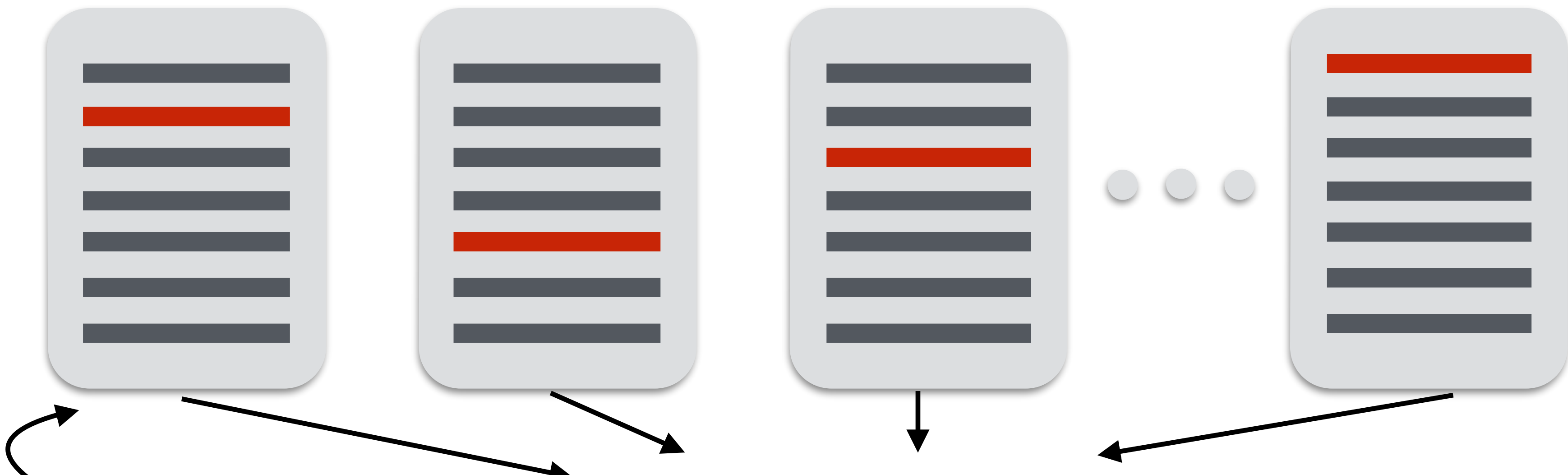

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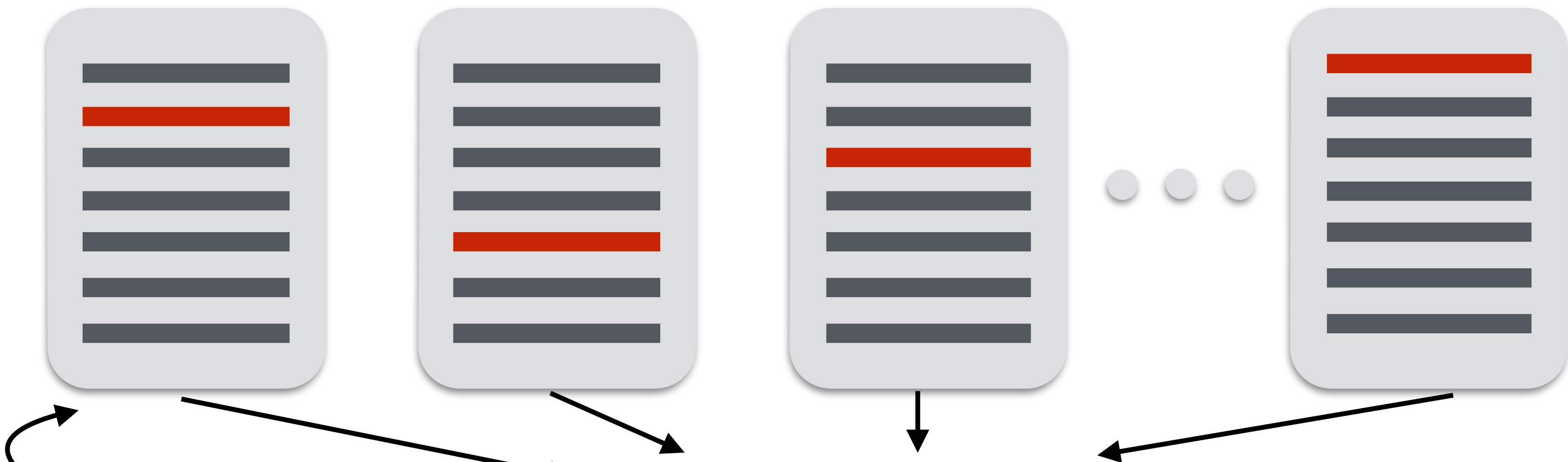

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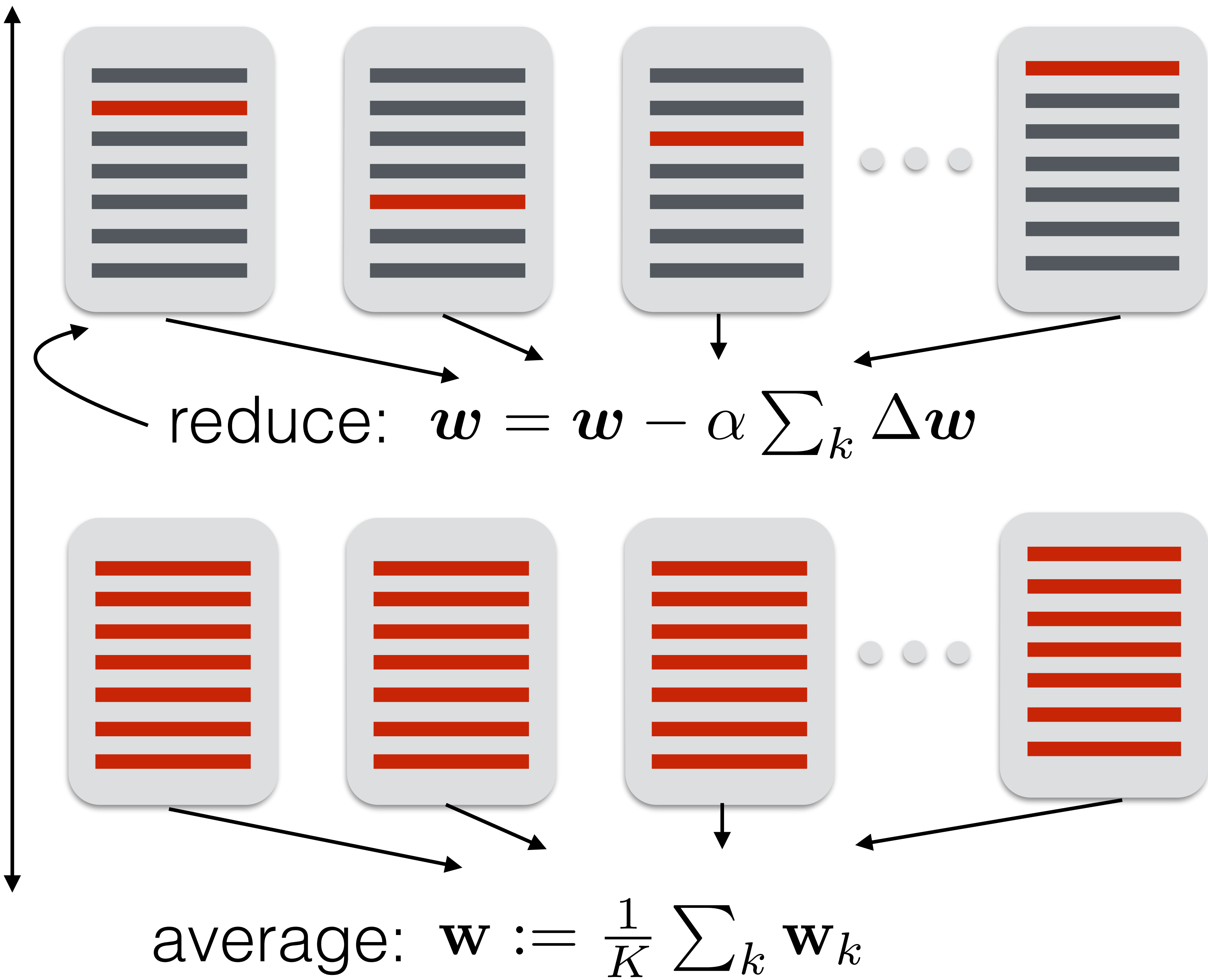


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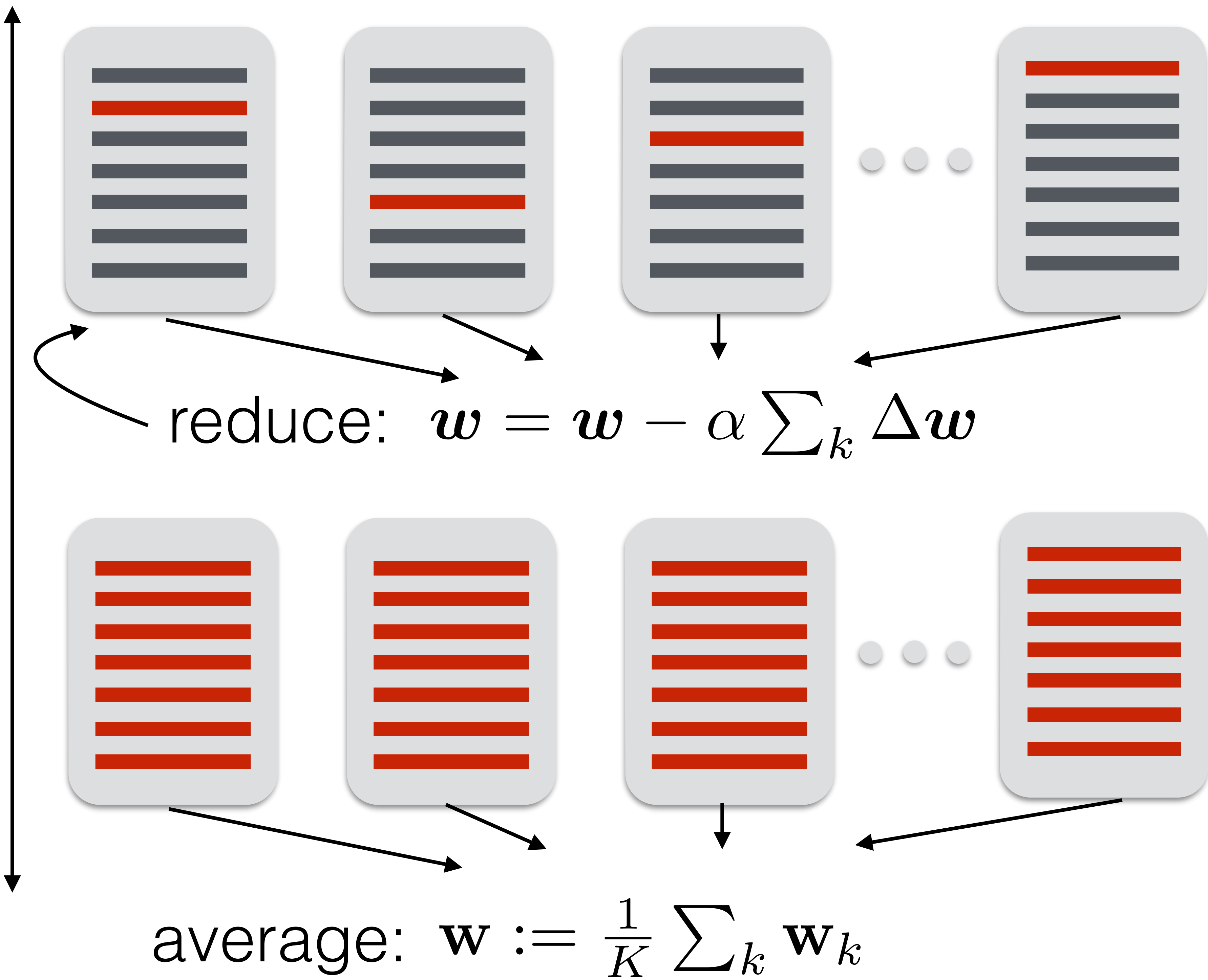


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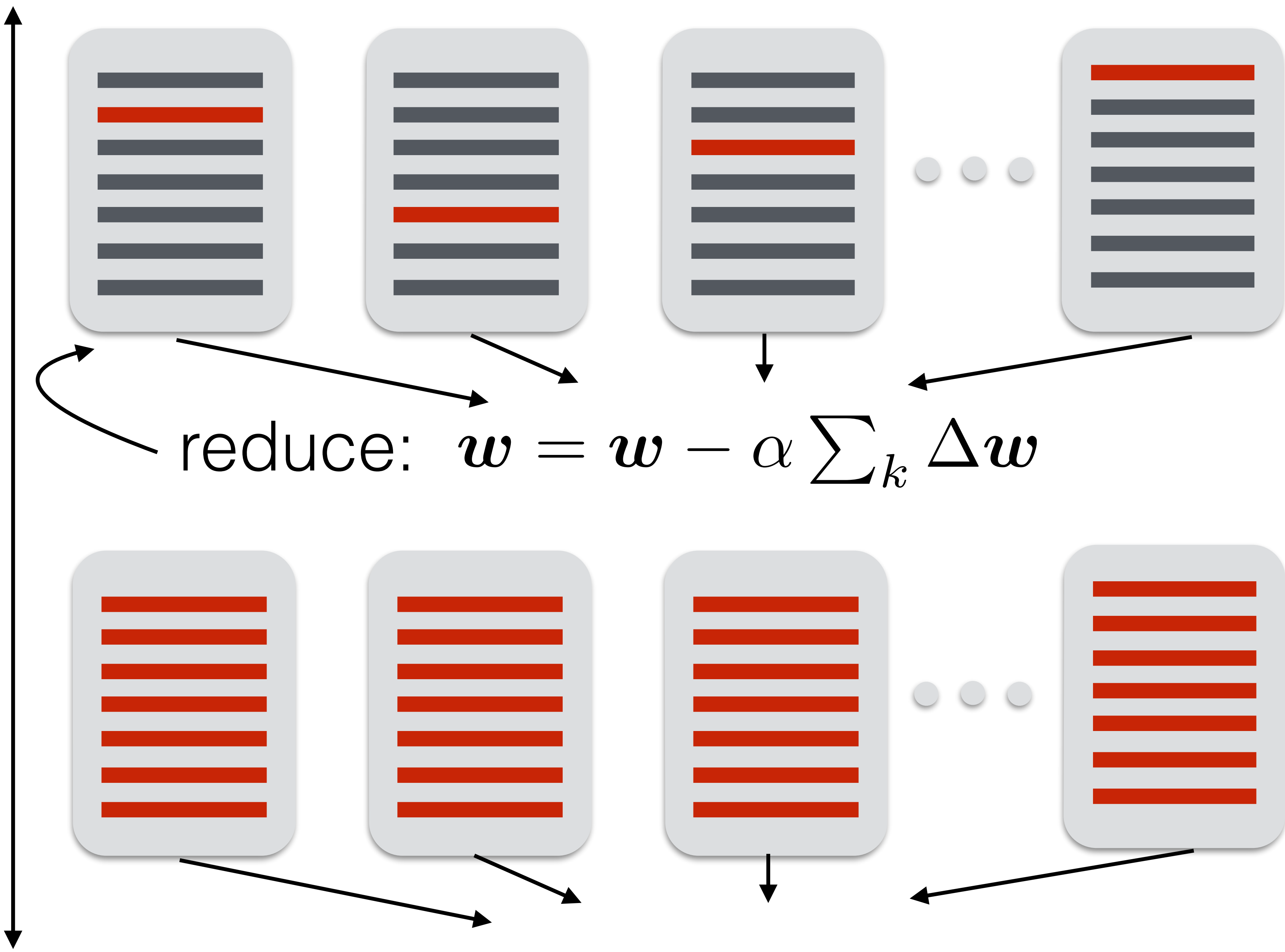


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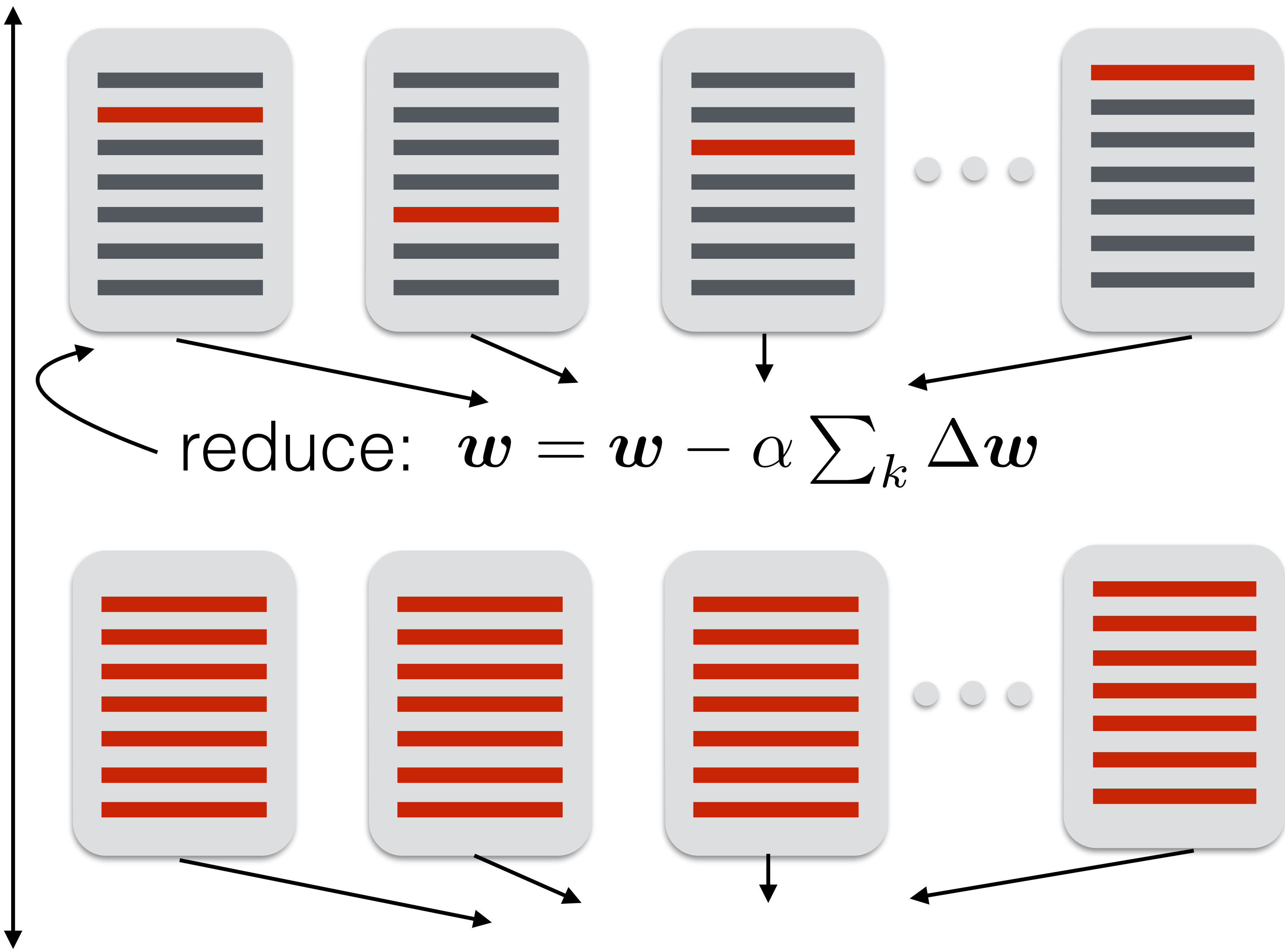

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ZDWJ, 2012

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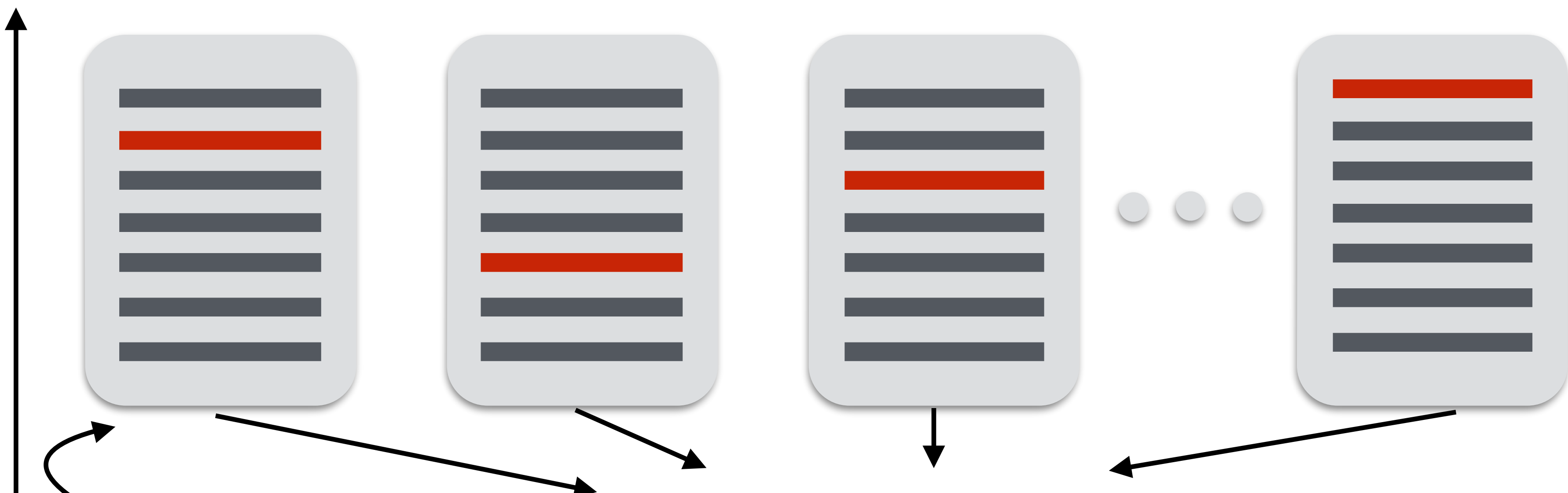

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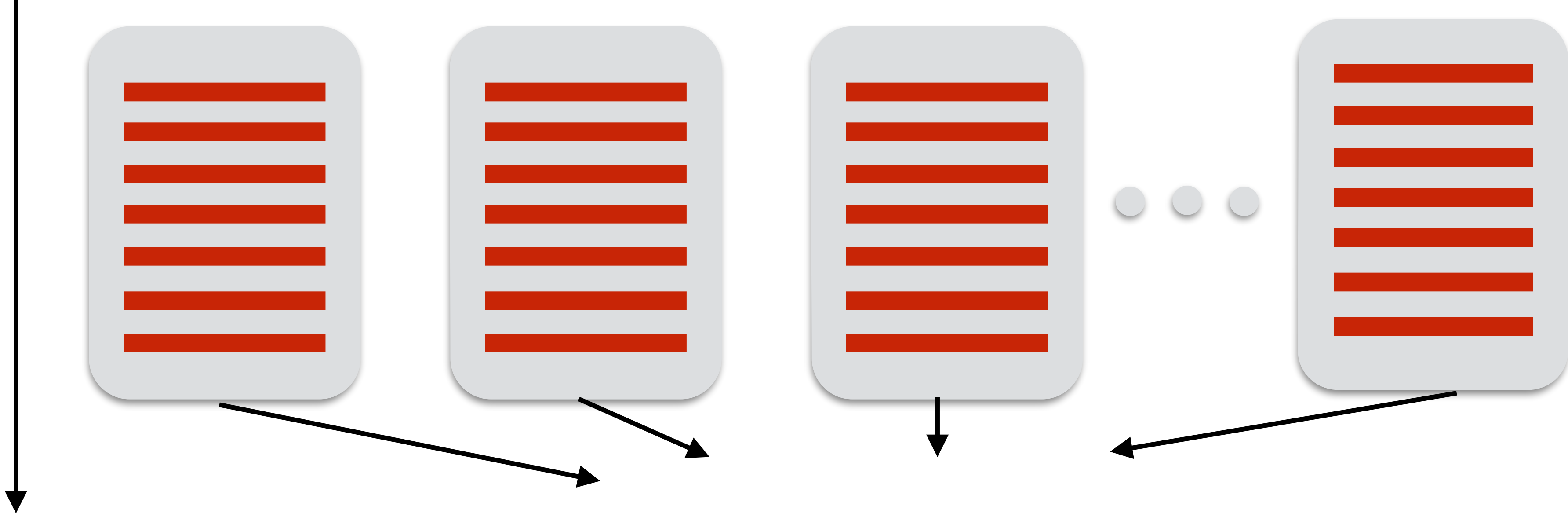

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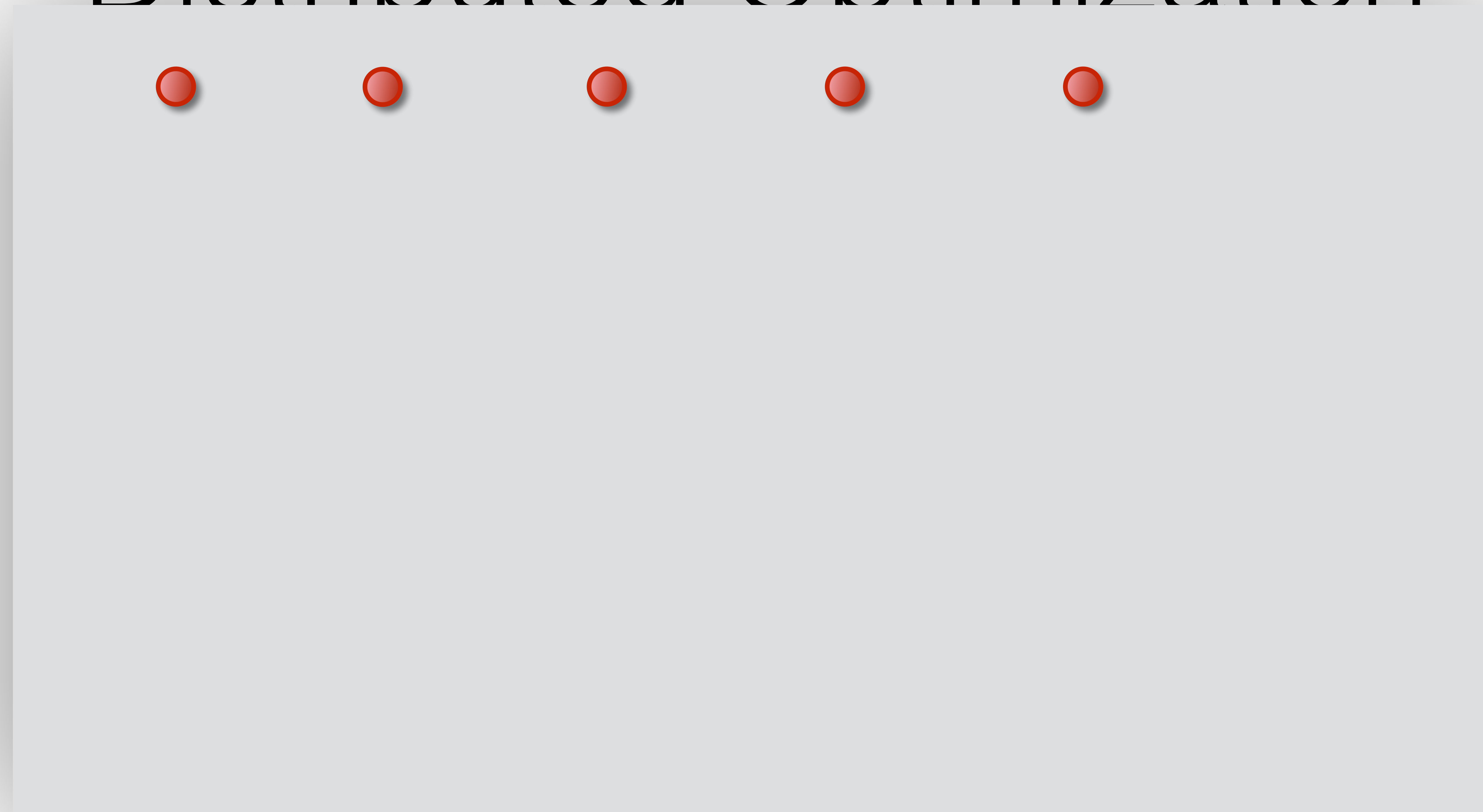

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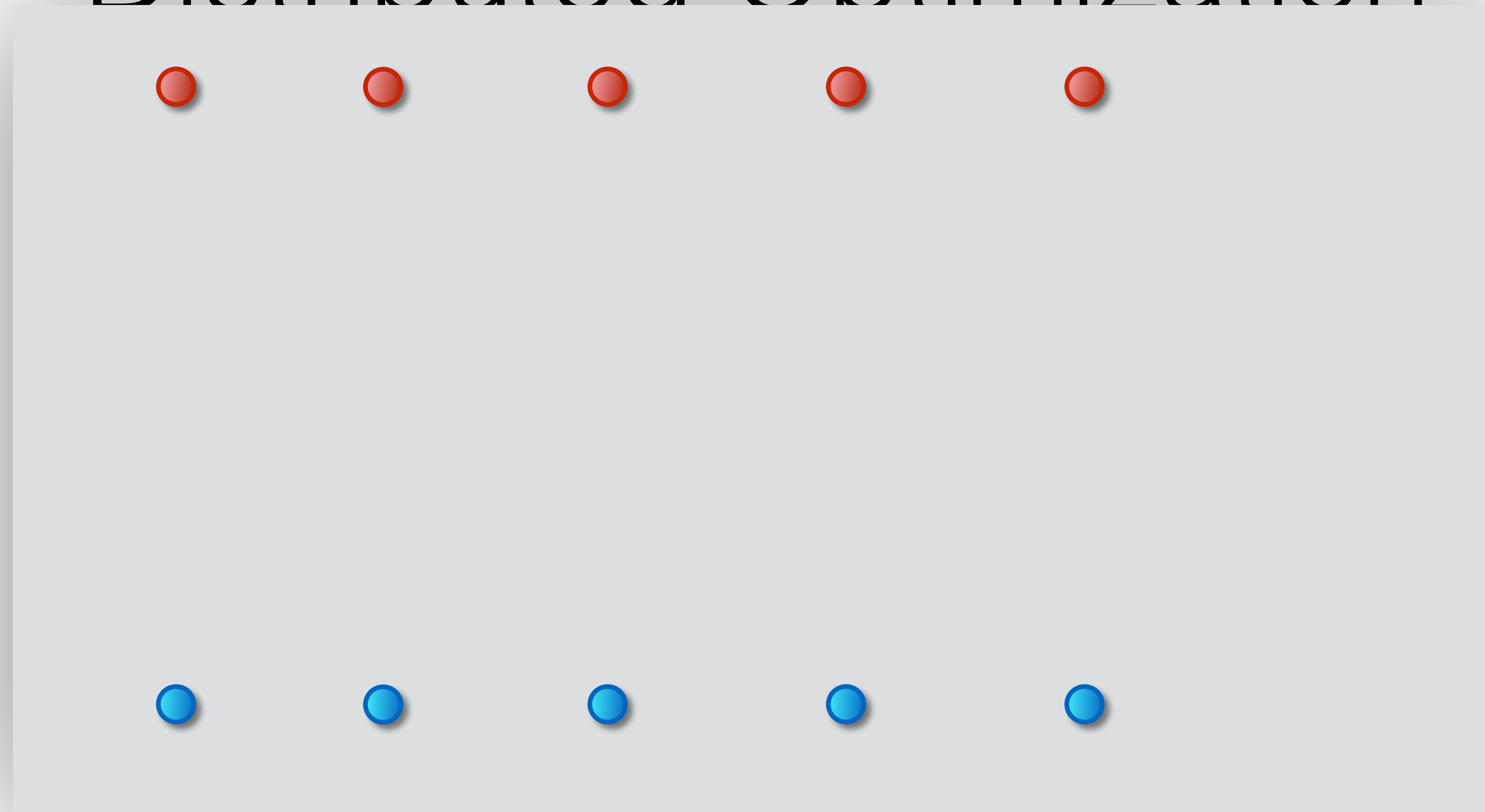

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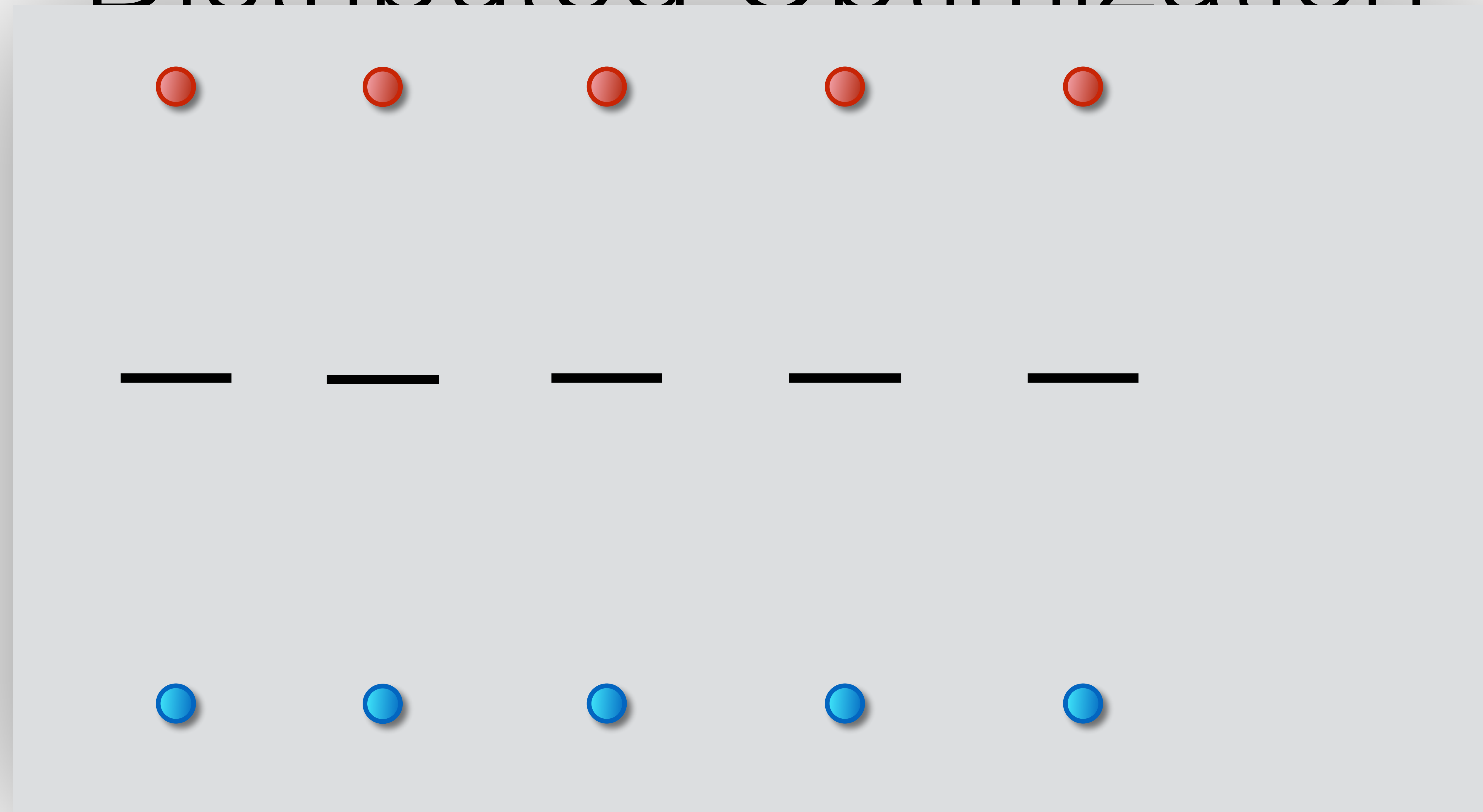

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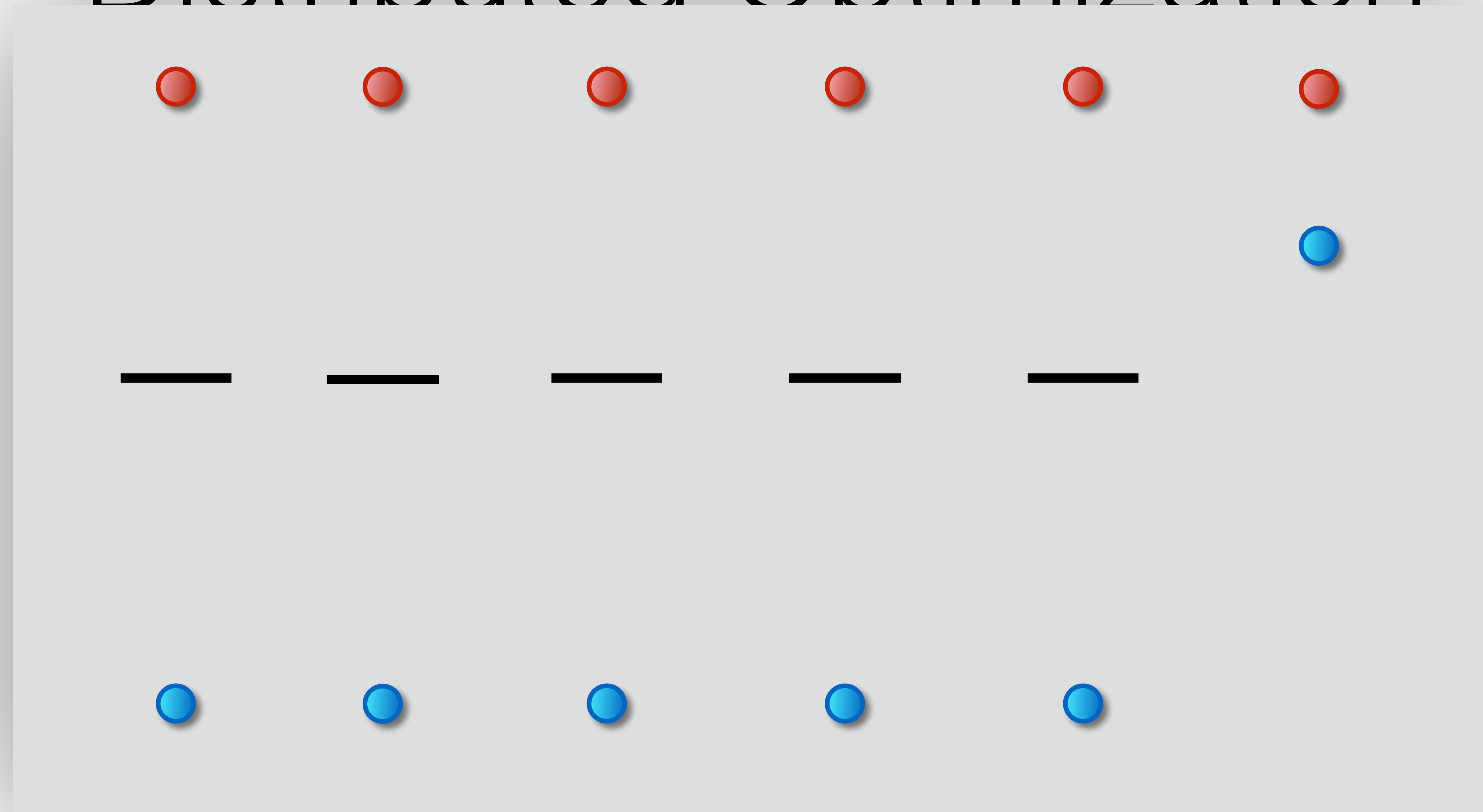

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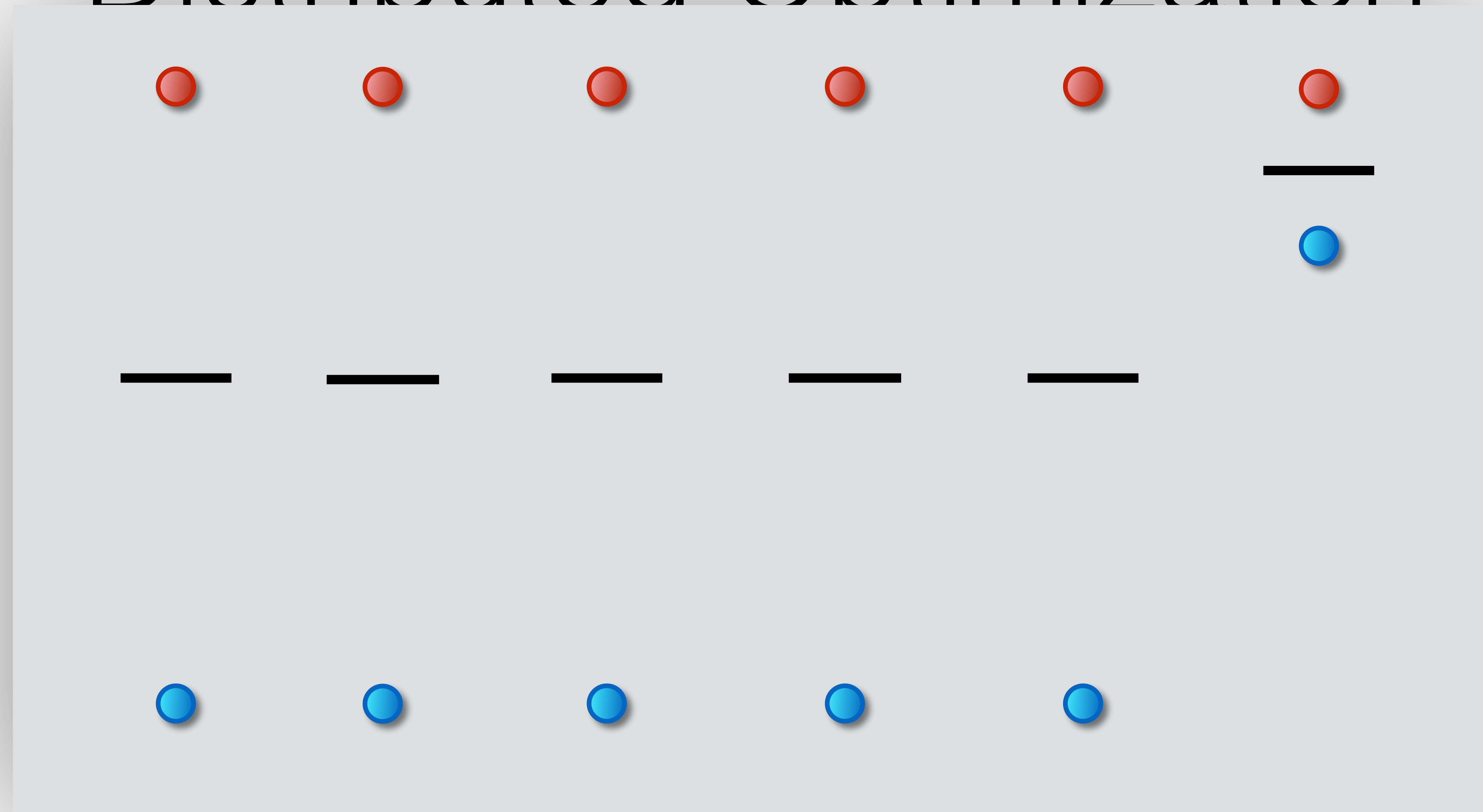

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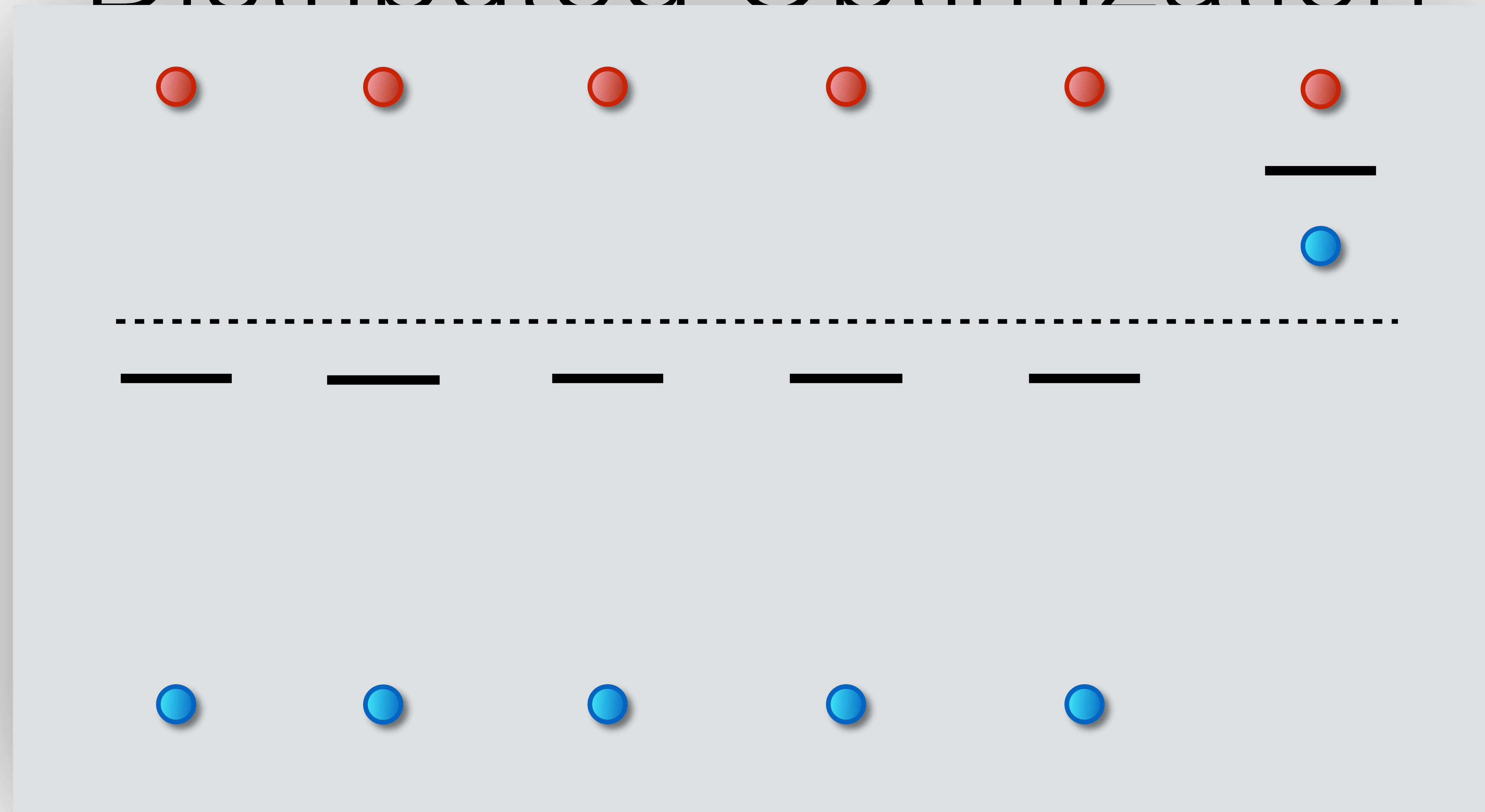

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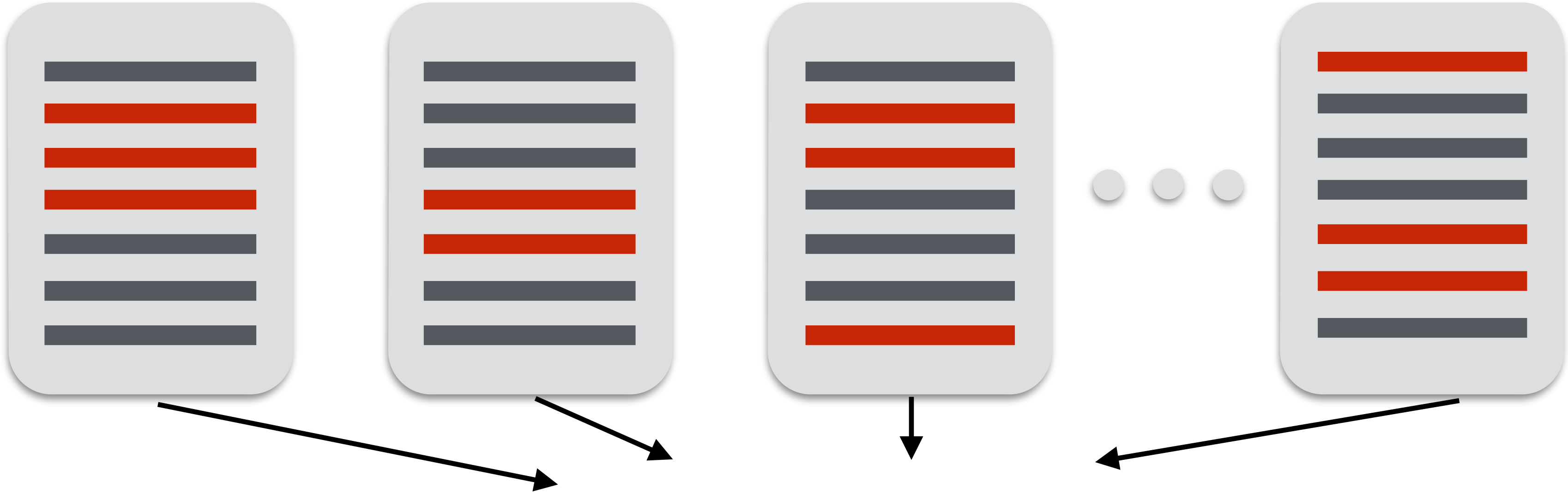

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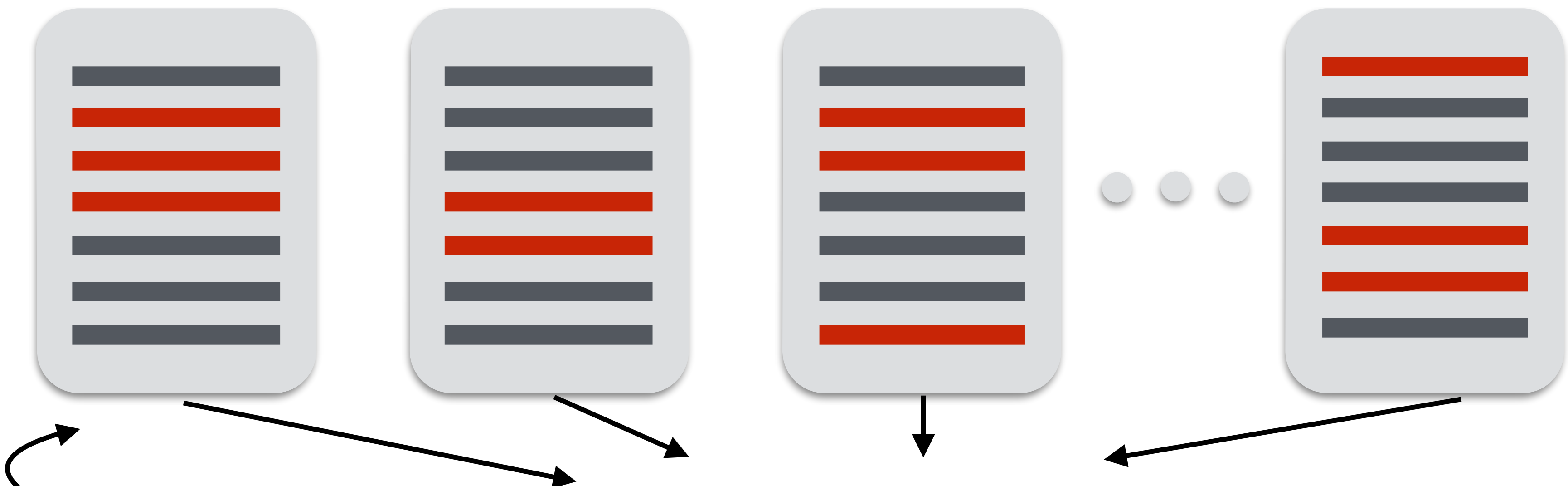

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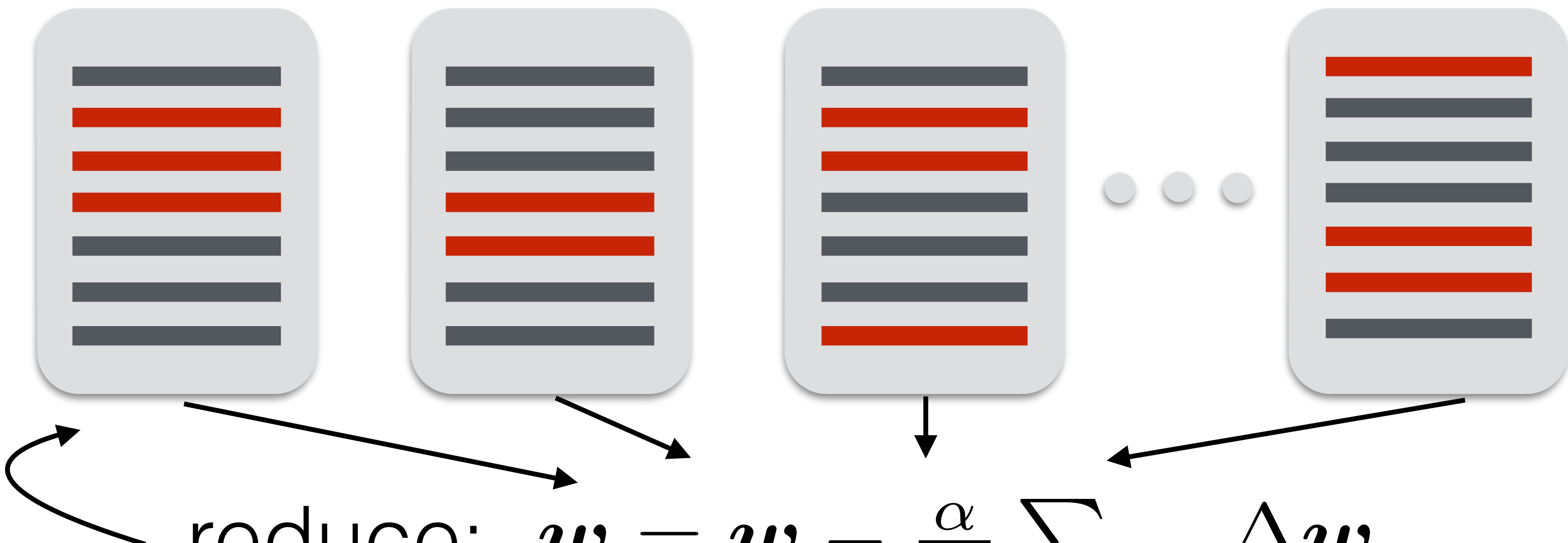

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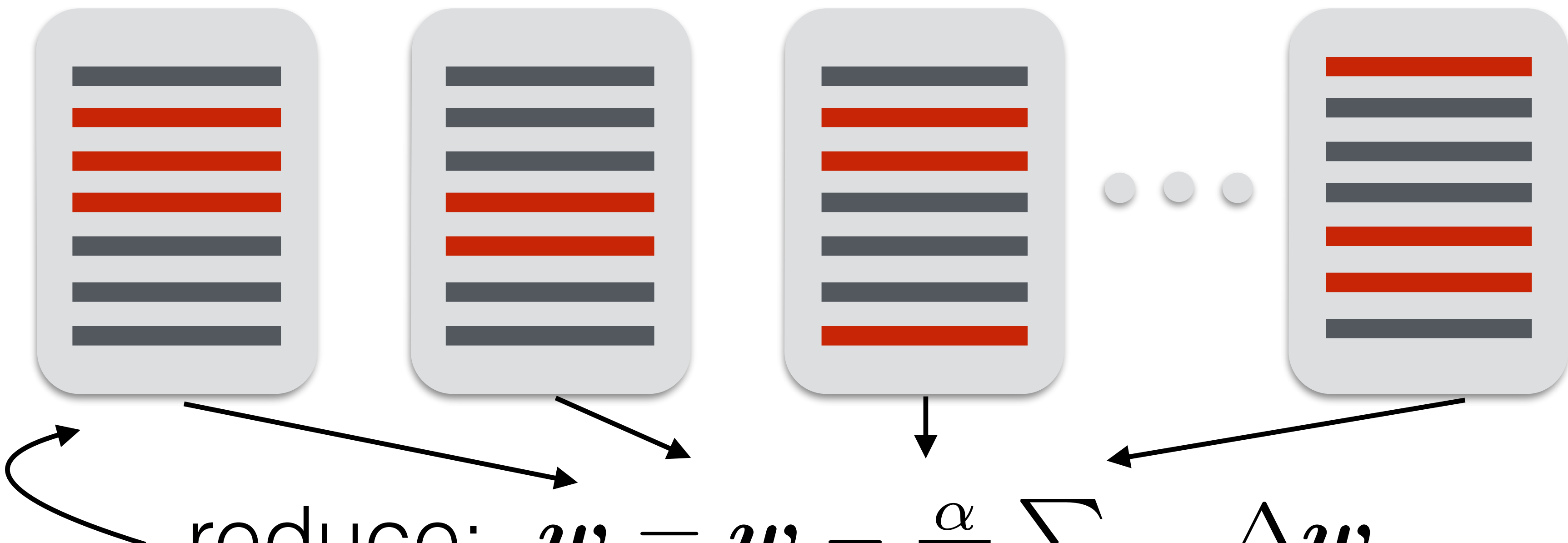

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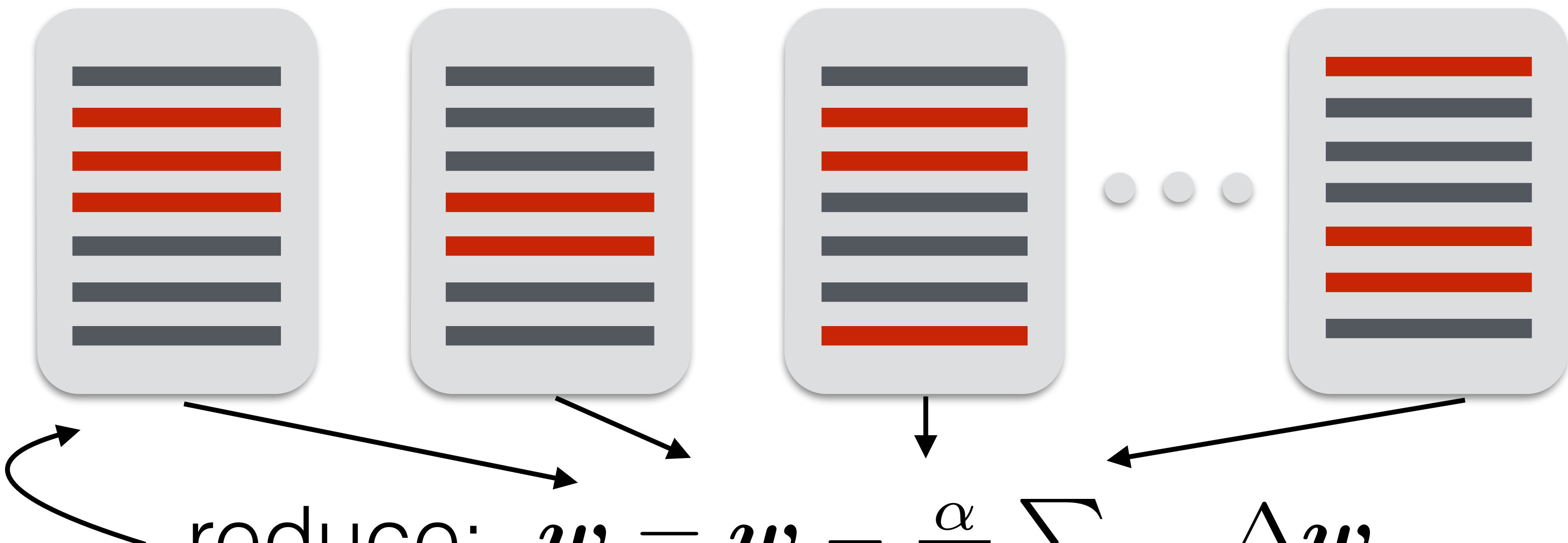

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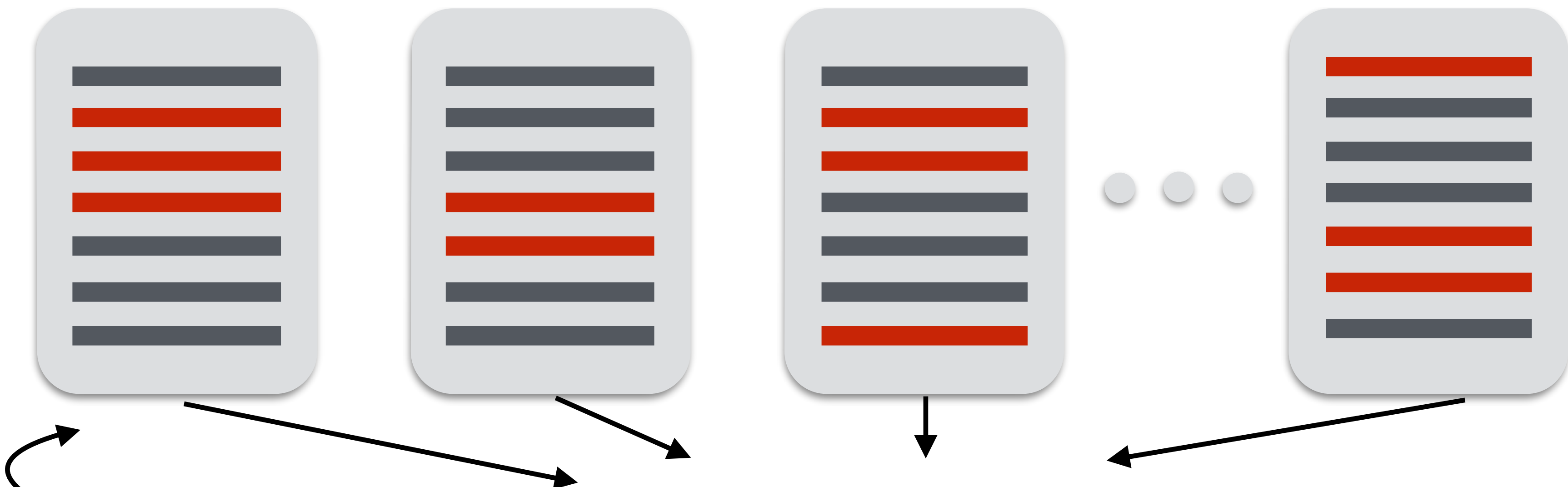

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LARGE-SCALE OPTIMIZATION

COCOA

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LARGE-SCALE OPTIMIZATION

**COCOA**

RESULTS

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1. METHODS BEYOND SGD
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1. ~~METHODS BEYOND SGD~~

   *Use Primal-Dual Framework*

2. ~~STALE UPDATES~~

   *Immediately apply local updates*

3. ~~AVERAGE OVER BATCH SIZE~~

   *Average over K << batch size*

# *Co*mmunication-Efficient Distributed Dual *Co*ordinate *A*scent (CoCoA)

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$$\max_{\alpha\in\mathbb{R}^n}\left[D(\alpha) := -||A\alpha||^2 - \frac{1}{n}\sum_{i=1}^{n}\ell_i^*(-\alpha_i)\right]$$

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- Stopping criteria given by duality gap
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- Default in software packages e.g. liblinear

# 2. Immediately Apply Updates

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STALE

$$
\begin{aligned}
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&\quad | \quad \Delta \boldsymbol{w} \leftarrow \Delta \boldsymbol{w} - \alpha \nabla_i P(\boldsymbol{w}) \\
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FRESH

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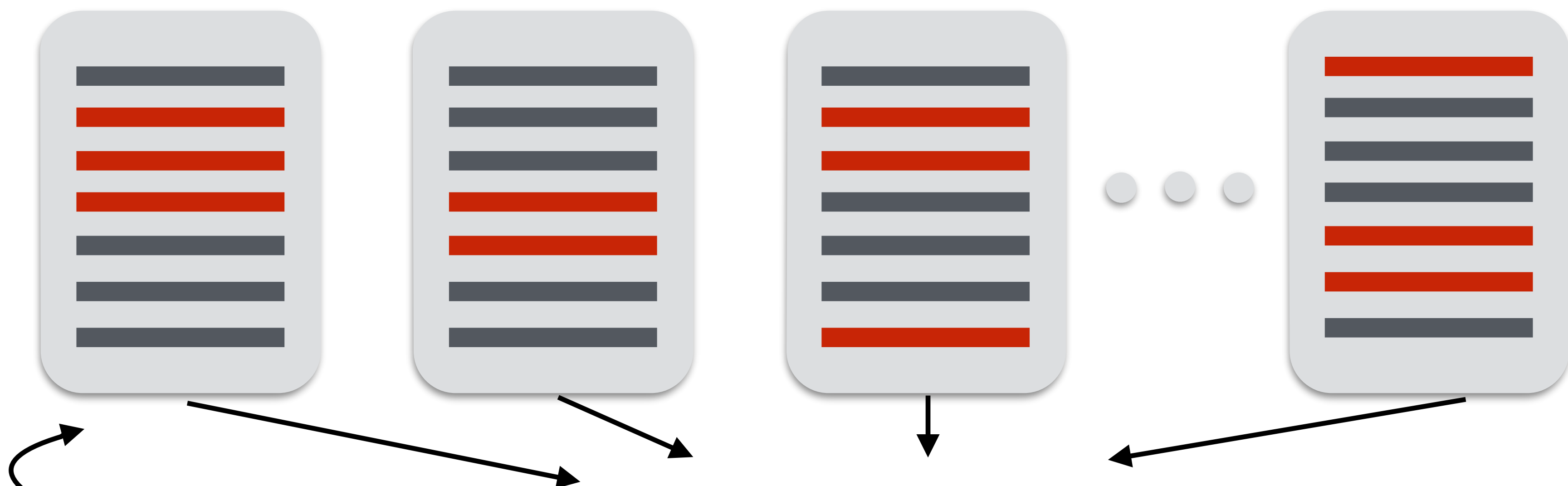

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# CoCoA

**Algorithm 1:** CoCoA

**Input**: $T \geq 1$, scaling parameter $1 \leq \beta_K \leq K$ (default: $\beta_K := 1$).
**Data**: $\{(\boldsymbol{x}_i, y_i)\}_{i=1}^n$ distributed over $K$ machines
**Initialize**: $\boldsymbol{\alpha}_{[k]}^{(0)} \leftarrow 0$ for all machines $k$, and $\boldsymbol{w}^{(0)} \leftarrow 0$
**for** $t = 1, 2, \dots, T$
  **for *all machines*** $k = 1, 2, \dots, K$ ***in parallel***
    $(\Delta\boldsymbol{\alpha}_{[k]}, \Delta\boldsymbol{w}_k) \leftarrow \textsc{LocalDualMethod}(\boldsymbol{\alpha}_{[k]}^{(t-1)}, \boldsymbol{w}^{(t-1)})$
    $\boldsymbol{\alpha}_{[k]}^{(t)} \leftarrow \boldsymbol{\alpha}_{[k]}^{(t-1)} + \frac{\beta_K}{K}\Delta\boldsymbol{\alpha}_{[k]}$
  **end**
  *reduce* $\boldsymbol{w}^{(t)} \leftarrow \boldsymbol{w}^{(t-1)} + \frac{\beta_K}{K}\sum_{k=1}^K \Delta\boldsymbol{w}_k$
**end**

**Procedure A:** LocalDualMethod: Dual algorithm on machine $k$

**Input**: Local $\boldsymbol{\alpha}_{[k]} \in \mathbb{R}^{n_k}$, and $\boldsymbol{w} \in \mathbb{R}^d$ consistent with other coordinate blocks of $\boldsymbol{\alpha}$ s.t. $\boldsymbol{w} = A\boldsymbol{\alpha}$
**Data**: Local $\{(\boldsymbol{x}_i, y_i)\}_{i=1}^{n_k}$
**Output**: $\Delta\boldsymbol{\alpha}_{[k]}$ and $\Delta\boldsymbol{w} := A_{[k]}\Delta\boldsymbol{\alpha}_{[k]}$

# CoCoA

✔ <10 lines of code in *Spark*

blocks of $\alpha$ s.t. $w = A\alpha$

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- $\ell_i$ are $1/\gamma$-smooth
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LARGE-SCALE OPTIMIZATION

COCOA

RESULTS!

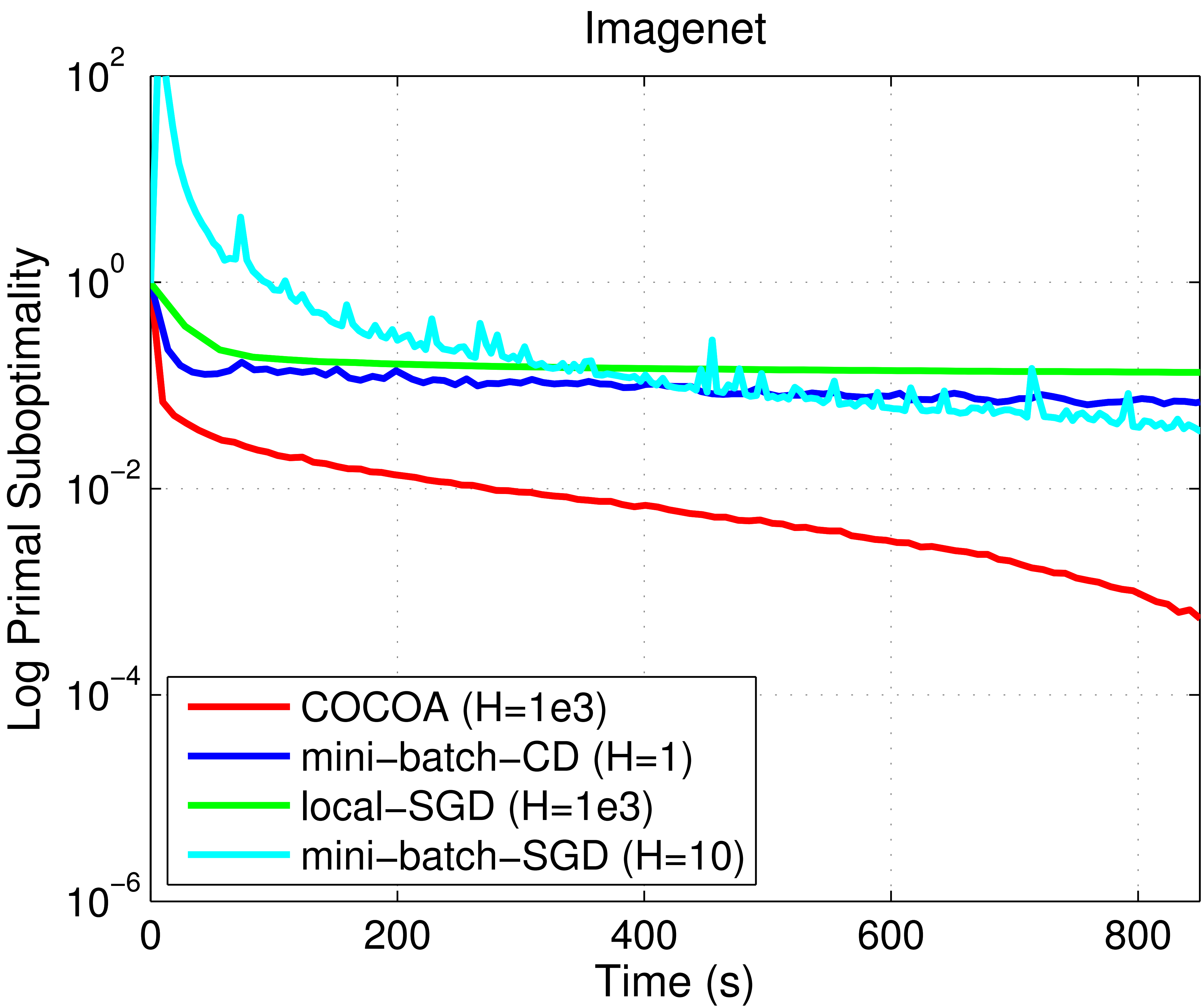
LARGE-SCALE OPTIMIZATION

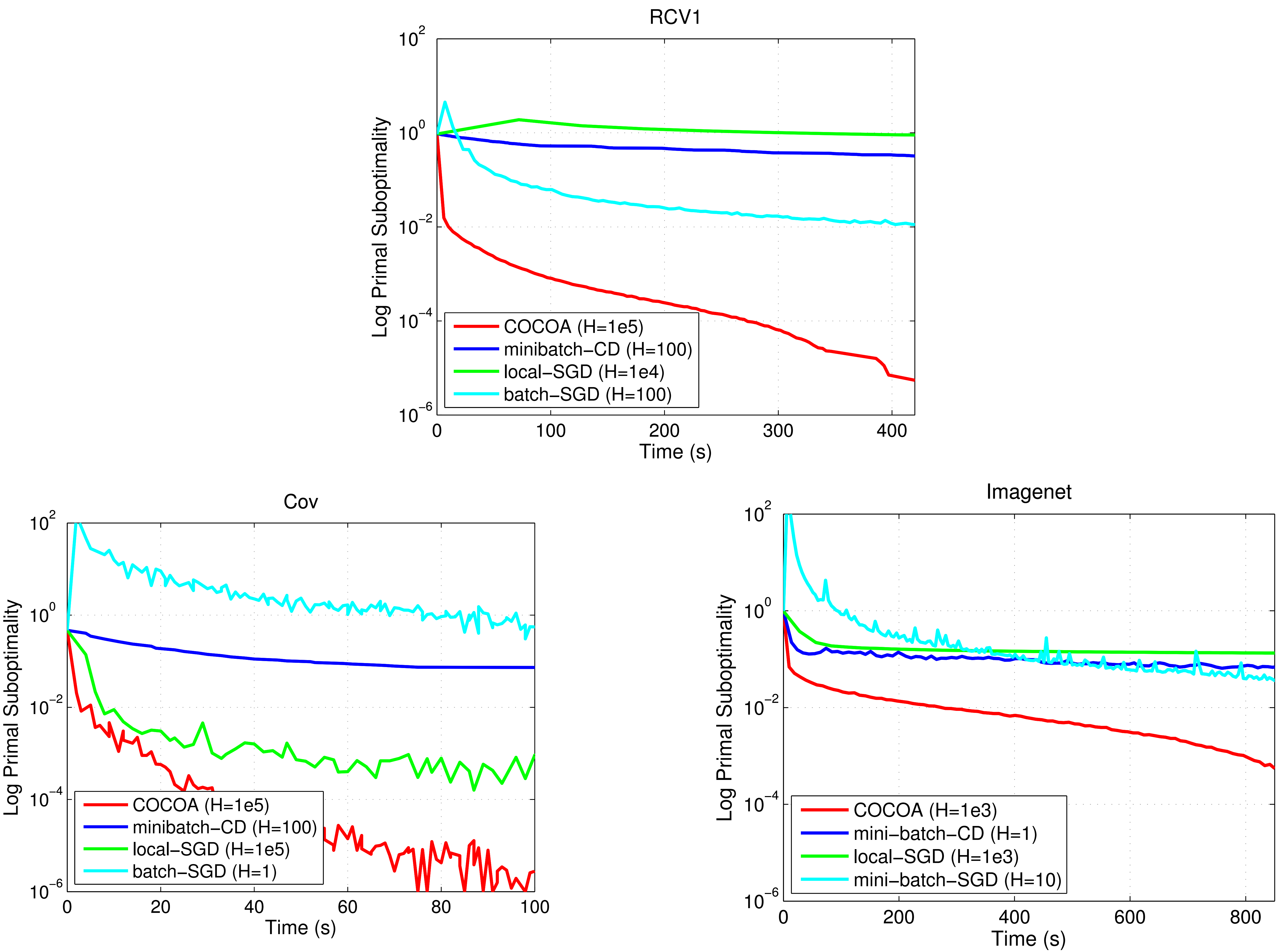
CoCoA

**RESULTS!**

# Empirical Results in Spark

| Dataset | Training (n) | Features (d) | Sparsity | Workers (K) |
|---|---|---|---|---|
| Cov | 522,911 | 54 | 22.22% | 4 |
| Rcv1 | 677,399 | 47,236 | 0.16% | 8 |
| Imagenet | 32,751 | 160,000 | 100% | 32 |


Imagenet
Log Primal Suboptimality
$10^{2}$
$10^{0}$
$10^{-2}$
$10^{-4}$
$10^{-6}$
0
200
400
600
800
Time (s)
COCOA (H=1e3)
mini−batch−CD (H=1)
local−SGD (H=1e3)
mini−batch−SGD (H=10)



RCV1
Log Primal Suboptimality
Time (s)
COCOA (H=1e5)
minibatch−CD (H=100)
local−SGD (H=1e4)
batch−SGD (H=100)
Cov
COCOA (H=1e5)
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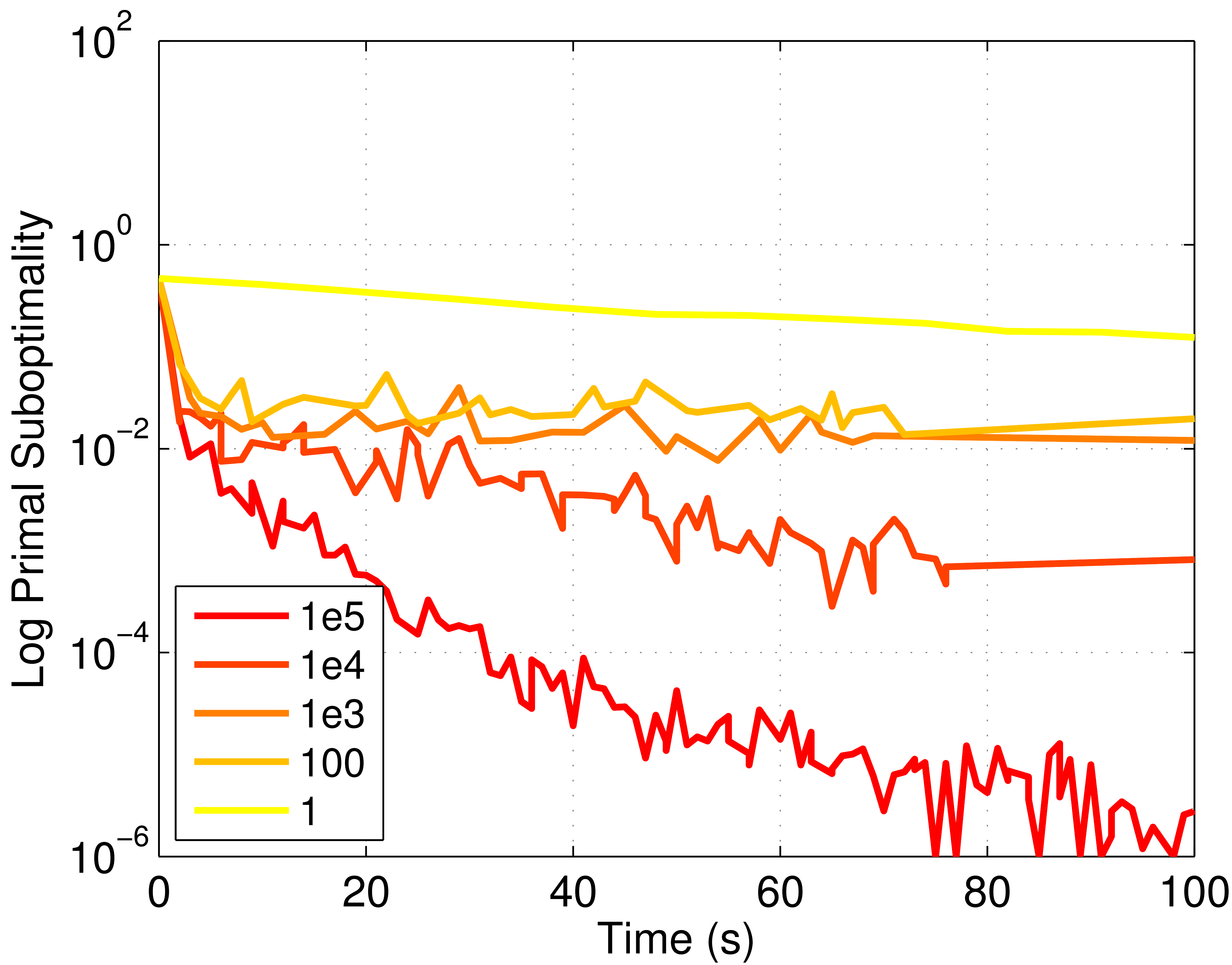
# Effect of H on COCOA



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