

DSC 102


Systems for Scalable Analytics

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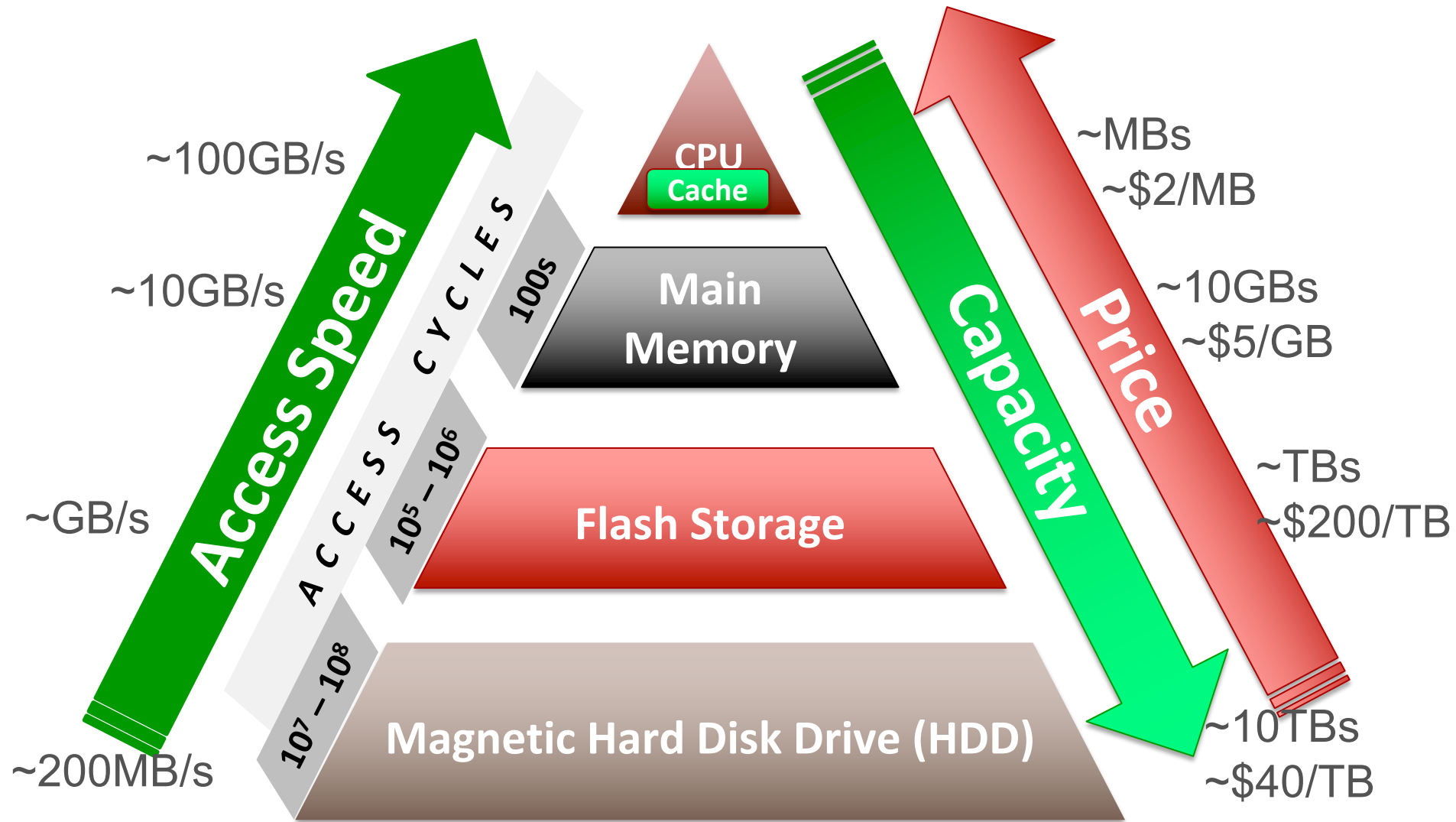
Topic 3: Parallel and Scalable Data Processing
Part 2: Scalable Data Access

Ch. 9.4, 12.2, 14.1.1, 14.6, 22.1-22.3, 22.4.1, 22.8 of Cow Book
Ch. 5, 6.1, 6.3, 6.4 of MLSys Book

Outline

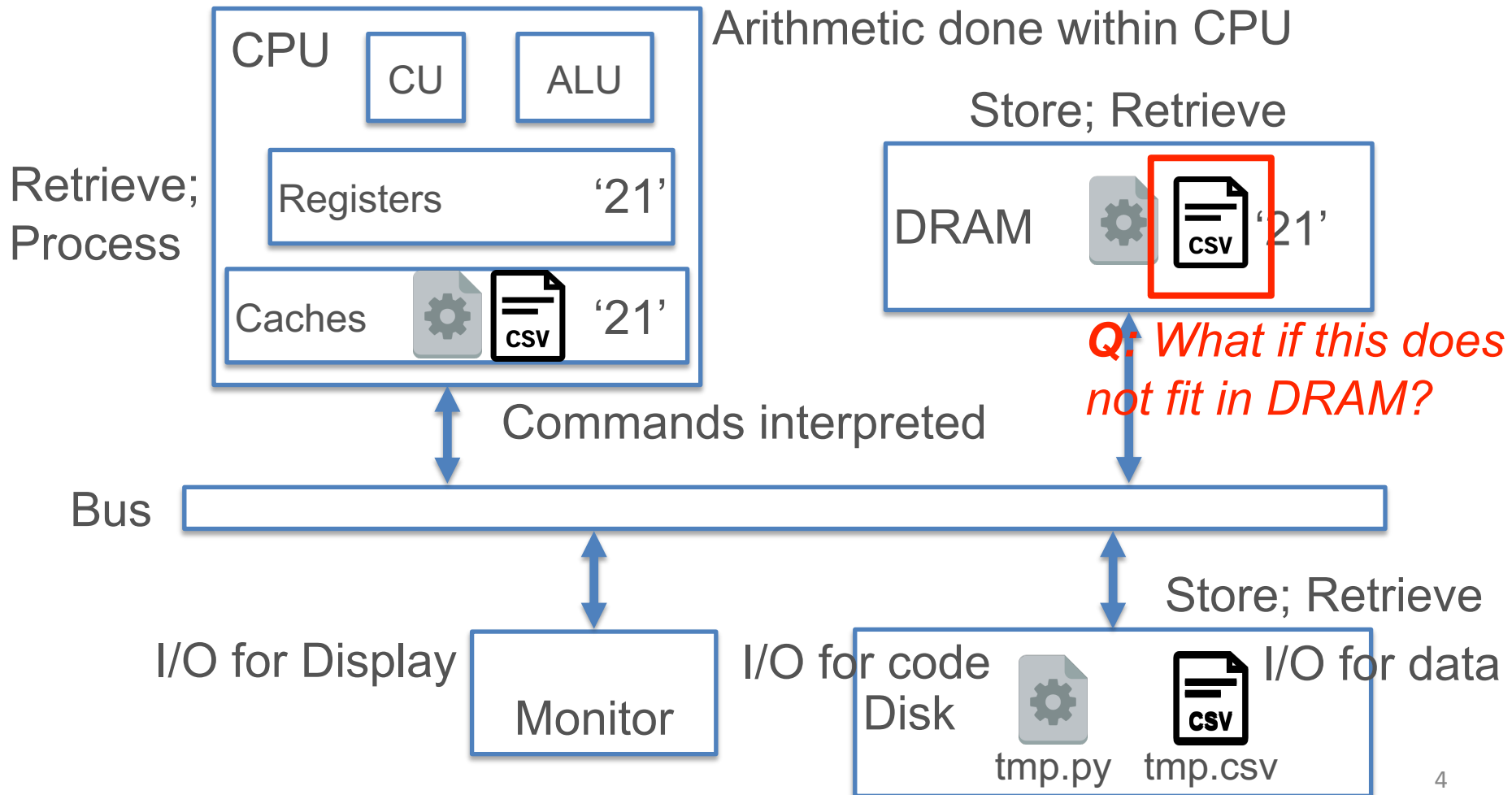
- ❖ Basics of Parallelism
 - ❖ Task Parallelism; Dask
 - ❖ Single-Node Multi-Core; SIMD; Accelerators
-  ❖ Basics of Scalable Data Access
 - ❖ Paged Access; I/O Costs; Layouts/Access Patterns
 - ❖ Scaling Data Science Operations
- ❖ Data Parallelism: Parallelism + Scalability
 - ❖ Data-Parallel Data Science Operations
 - ❖ Optimizations and Hybrid Parallelism

Recap: Memory Hierarchy



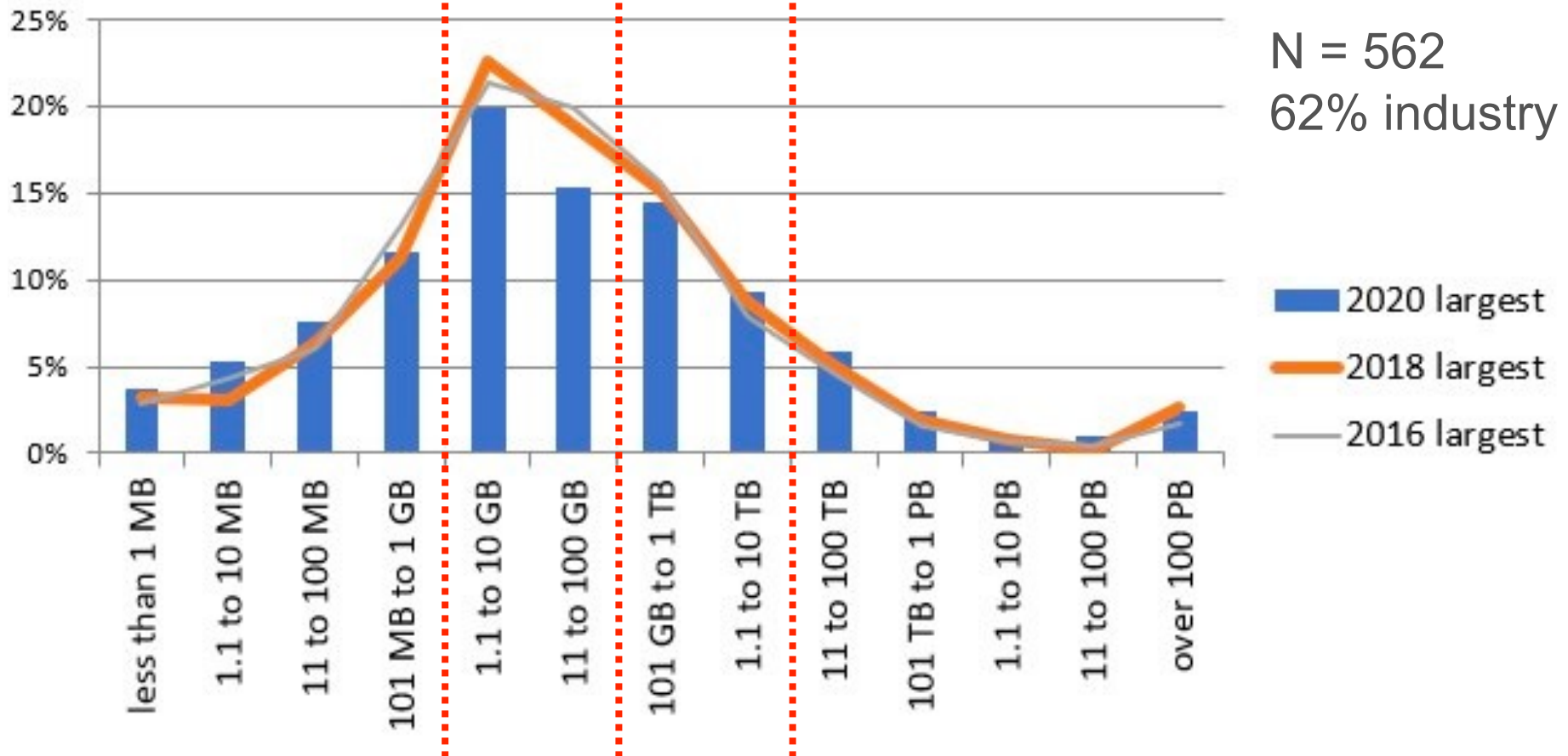
Memory Hierarchy in Action

Rough sequence of events when program is executed



Scale of Datasets in Practice

**KDnuggets 2020 Poll:
Largest Dataset Analyzed**



Scalable Data Access

Central Issue: Large data file does not fit entirely in DRAM


Basic Idea: Divide-and-conquer again!

“Split” data file (virtually or physically) and stage reads of its pages from disk to DRAM; vice versa for writes

4 key regimes of scalability / staging reads:

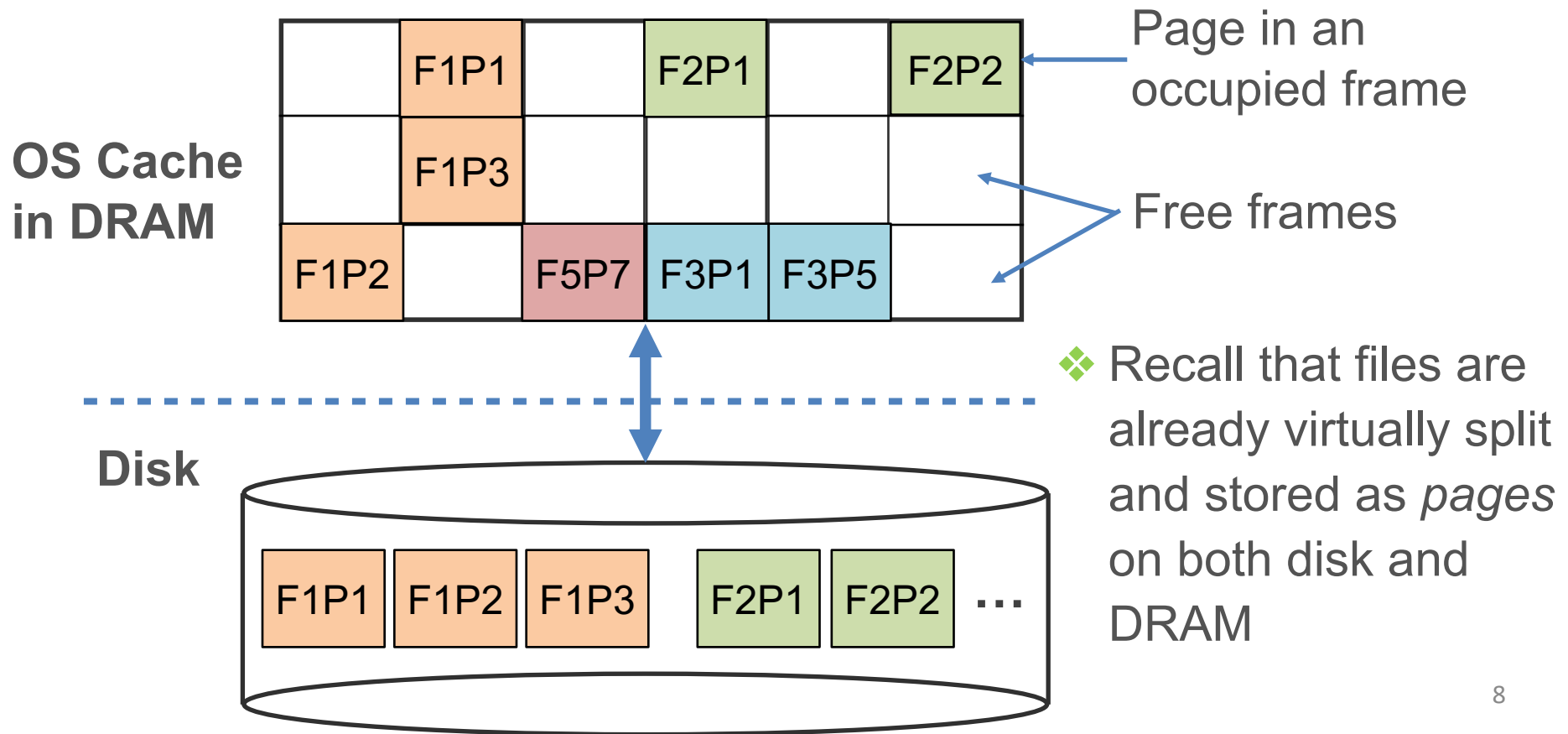
- ❖ **Single-node disk:** Paged access from file on local disk
- ❖ **Remote read:** Paged access from disk(s) over a network
- ❖ **Distributed memory:** Data fits on a cluster’s total DRAM
- ❖ **Distributed disk:** Use entire memory hierarchy of cluster

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Paged Data Access to DRAM

Basic Idea: “Split” data file (virtually or physically) and stage reads of its pages from disk to DRAM (vice versa for writes)



Page Management in DRAM Cache

- ❖ **Caching:** Retaining pages read from disk in DRAM
- ❖ **Eviction:** Removing a page frame's content in DRAM
- ❖ **Spilling:** Writing out pages from DRAM to disk
 - ❖ If a page in DRAM is “**dirty**” (i.e., some bytes were written), eviction requires a spill; o/w, ignore that page
- ❖ The set of DRAM-resident pages typically changes over the lifetime of a process
- ❖ **Cache Replacement Policy:** The algorithm that chooses which page frame(s) to evict when a new page has to be cached but the OS cache in DRAM is full
 - ❖ Popular policies include Least Recently Used, Most Recently Used, etc. (more shortly)

Quantifying I/O: Disk and Network

- ❖ Page reads/writes to/from DRAM from/to disk incur latency
- ❖ **Disk I/O Cost:** Abstract counting of number of page I/Os; can map to bytes given page size
- ❖ Sometimes, programs read/write data over network
- ❖ **Communication/Network I/O Cost:** Abstract counting of number of pages/bytes sent/received over network
- ❖ I/O cost is *abstract*; mapping to latency is *hardware-specific*

Example: Suppose a data file is 40GB; page size is 4KB

I/O cost to read file = 10 million page I/Os

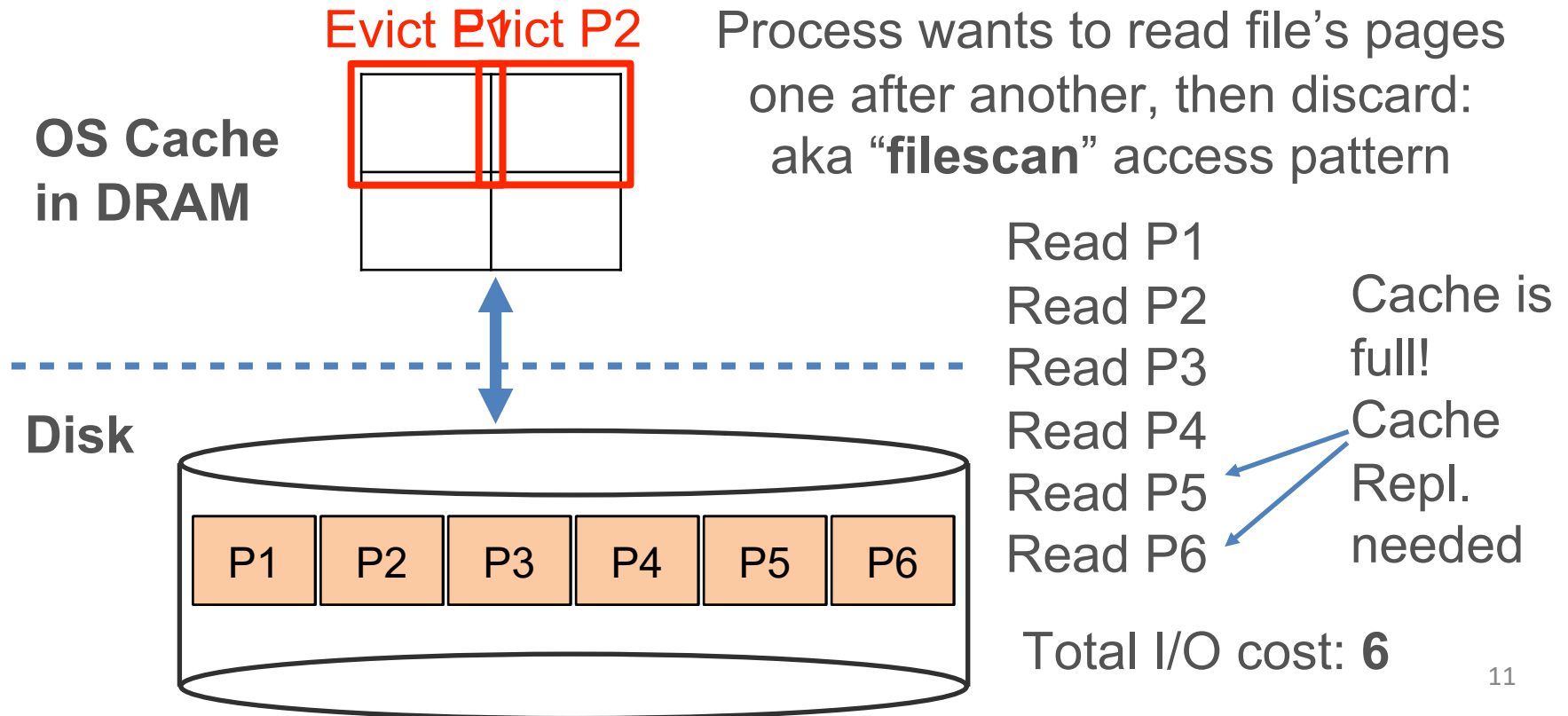
Disk with I/O throughput: 800 MB/s \longrightarrow $40\text{GB}/800\text{MBps} = 50\text{s}$

Network with speed: 200 MB/s \longrightarrow $40\text{GB}/200\text{MBps} = 200\text{s}$

Scaling to (Local) Disk

Basic Idea: Split data file (virtually or physically) and stage reads of its pages from disk to DRAM (vice versa for writes)

Suppose OS Cache has only 4 frames; initially empty



Scaling to (Local) Disk

- ❖ In general, scalable programs stage access to pages of file on disk and efficiently use available DRAM
 - ❖ Recall that typically DRAM size \ll Disk size
- ❖ Modern machines have 10s of GBs DRAM; so, read a “chunk”/“block” of file at a time (say, 1000s of pages)
 - ❖ On HDDs, such chunking leads to *more sequential I/Os*, raising throughput and lowering latency
 - ❖ Similarly, write a chunk of dirtied pages at a time

Data Layouts and Access Patterns

- ❖ **Data Layout:** Order in which data is laid out on storage; property of physical level of database
- ❖ **Data Access Pattern:** Order in which a program needs to access data for its computations; property of the program
- ❖ Together, the above two affect what data subset gets cached in higher level of memory hierarchy
- ❖ **Key Principle:** Optimizing data layout on disk based on data access pattern can help reduce I/O costs and latency
 - ❖ Applies to both HDDs and SSDs but especially critical for HDDs due to its random vs. sequential access latency gap

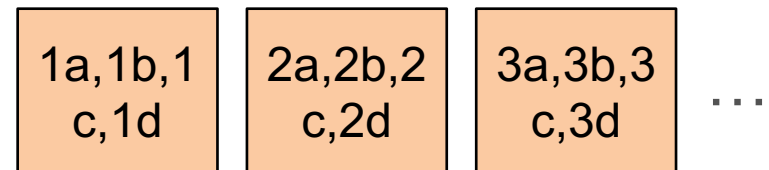
Row-store vs Column-store Layouts

- ❖ A common dichotomy when serializing 2-D structured data (relations, matrices, DataFrames) to file on disk

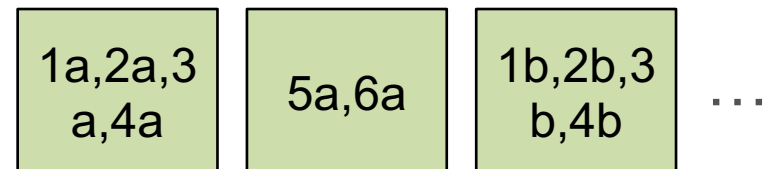
A	B	C	D
1a	1b	1c	1d
2a	2b	2c	2d
3a	3b	3c	3d
4a	4b	4c	4d
5a	5b	5c	5d
6a	6b	6c	6d

Say, a page can fit only 4 cell values

Row-store:



Col-store:



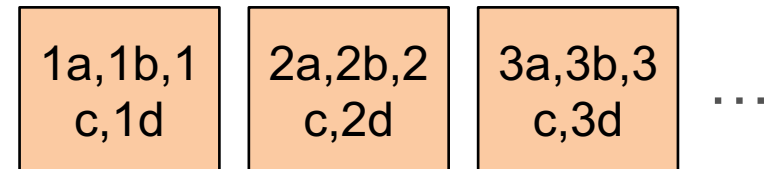
- ❖ Based on data access pattern of program, I/O costs with row- vs col-store can be orders of magnitude apart!

Row-store vs Column-store Layouts

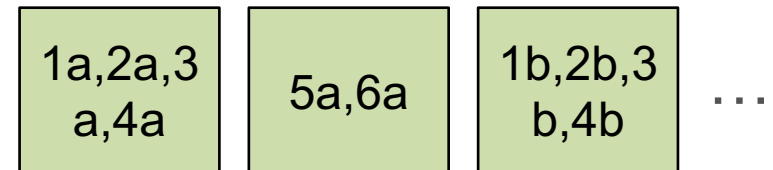
A	B	C	D
1a	1b	1c	1d
2a	2b	2c	2d
3a	3b	3c	3d
4a	4b	4c	4d
5a	5b	5c	5d
6a	6b	6c	6d

Say, a page can fit only 4 cell values

Row-store:



Col-store:



Q: What is the I/O cost with each to compute, say, a sum over B?

- ❖ With row-store: need to fetch *all* pages; I/O cost: 6 pages
- ❖ With col-store: need to fetch only B's pages; I/O cost: 2 pages
- ❖ This difference generalizes to higher dim. for tensors

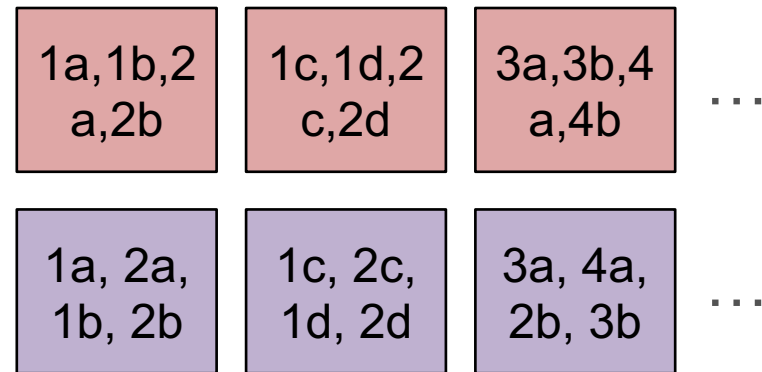
Hybrid/Tiled/“Blocked” Layouts

- ❖ Sometimes, it is beneficial to do a hybrid, especially for analytical RDBMSs and matrix/tensor processing systems

A	B	C	D
1a	1b	1c	1d
2a	2b	2c	2d
3a	3b	3c	3d
4a	4b	4c	4d
5a	5b	5c	5d
6a	6b	6c	6d

Say, a page can fit only 4 cell values

Hybrid stores with 2x2 tiled layout:

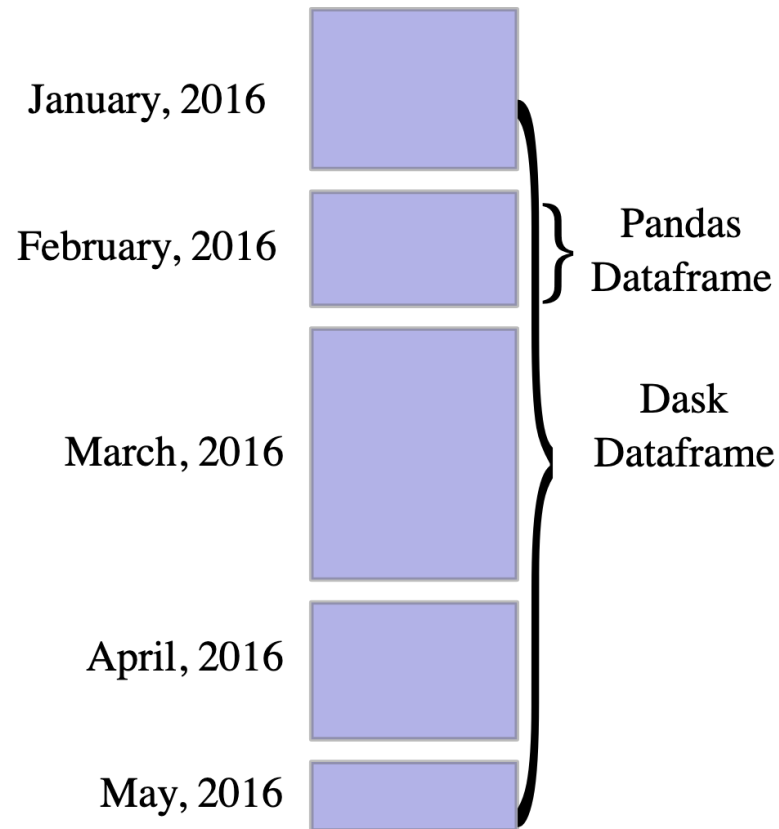


Key Principle: Which data layout will yield lower I/O costs (row vs. col vs tiled) depends on data access pattern of the program!

Example: Dask's DataFrame

Basic Idea: Split data file (virtually or physically) and stage reads of its pages from disk to DRAM (vice versa for writes)

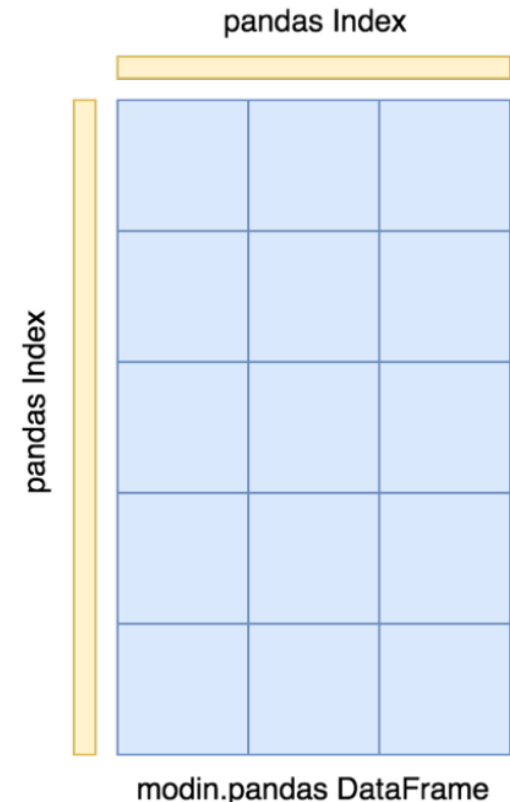
- ❖ Dask DF scales to disk-resident data via a row-store
- ❖ “Virtual” split: each split is a Pandas DF under the hood
- ❖ Dask API is a “wrapper” around Pandas API to scale ops to splits and put all results together
- ❖ If file is too large for DRAM, need manual *repartition()* to get physically smaller splits (< ~1GB)



Example: Modin's DataFrame

Basic Idea: Split data file (virtually or physically) and stage reads of its pages from disk to DRAM (vice versa for writes)

- ❖ Modin's DF aims to scale to disk-resident data via a tiled store
- ❖ Enables seamless scaling along *both* dimensions
- ❖ Easier use of multi-core parallelism
- ❖ Many in-memory RDBMSs had this, e.g., SAP HANA, Oracle TimesTen
- ❖ ScaLAPACK had this for matrices



Scaling with Remote Reads


Basic Idea: Split data file (virtually or physically) and stage reads of its pages from disk to DRAM (vice versa for writes)

- ❖ Similar to scaling to local disk but not “local”:
 - ❖ Stage page reads from remote disk/disks over the network (e.g., from S3)
- ❖ *More restrictive* than scaling with local disk, since spilling is not possible or requires costly network I/Os
 - ❖ OK for a *one-shot* filescan access pattern
 - ❖ Use DRAM to cache; repl. policies
 - ❖ Can also use smaller local disk as cache; you did this in PA1

Peer Instruction Activity

(Switch slides)

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Scaling Data Science Operations

- ❖ Scalable data access for key representative examples of programs/operations that are ubiquitous in data science:



- ❖ DB systems:

- ❖ Select
- ❖ Non-deduplicating project
- ❖ Simple SQL aggregates
- ❖ GROUP BY aggregates

- ❖ ML systems:

- ❖ Matrix sum/norms
- ❖ (Stochastic) Gradient Descent

Scaling to Disk: Relational Select

A	B	C	D
1a	1b	1c	1d
2a	2b	2c	2d
3a	3b	3c	3d
4a	4b	4c	4d
5a	5b	5c	5d
6a	6b	6c	6d

R

$$\sigma_{B="3b"}(R)$$

Row-store:

1a,1b,1 c,1d	2a,2b,2 c,2d	3a,3b,3 c,3d
4a,4b,4 c,4d	5a,5b,5 c,5d	6a,6b,6 c,6d

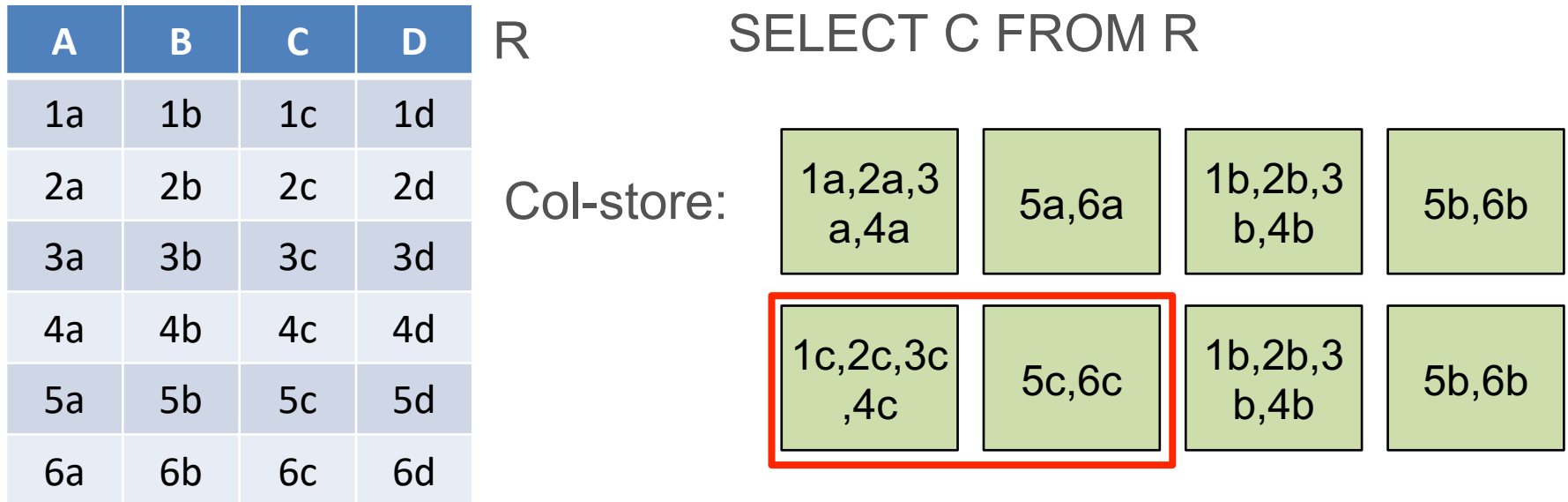
- ❖ Straightforward **filescan** data access pattern
 - ❖ Read pages/chunks from disk to DRAM one by one
 - ❖ CPU applies predicate to tuples in pages in DRAM
 - ❖ Copy satisfying tuples to temporary output pages
 - ❖ Use LRU for cache replacement, if needed
- ❖ I/O cost: 6 (read) + output # pages (write)

Scaling to Disk: Non-dedup. Project

A	B	C	D	R	SELECT C FROM R		
1a	1b	1c	1d	Row-store:	1a,1b,1 c,1d	2a,2b,2 c,2d	3a,3b,3 c,3d
2a	2b	2c	2d				
3a	3b	3c	3d		4a,4b,4 c,4d	5a,5b,5 c,5d	6a,6b,6 c,6d
4a	4b	4c	4d				
5a	5b	5c	5d				
6a	6b	6c	6d				

- ❖ Straightforward **filescan** data access pattern
 - ❖ Read one page at a time into DRAM; may need cache repl.
 - ❖ Drop unneeded columns from tuples on the fly
- ❖ I/O cost: 6 (read) + output # pages (write)

Scaling to Disk: Non-dedup. Project



- ❖ Since we only need col C, no need to read other pages
- ❖ I/O cost: **2** (read) + output # pages (write)
- ❖ Big advantage for col-stores over row-stores for SQL analytics queries (projects, aggregates, etc.), aka “OLAP”
 - ❖ Rationale for col-store RDBMS (e.g., Vertica) and Parquet

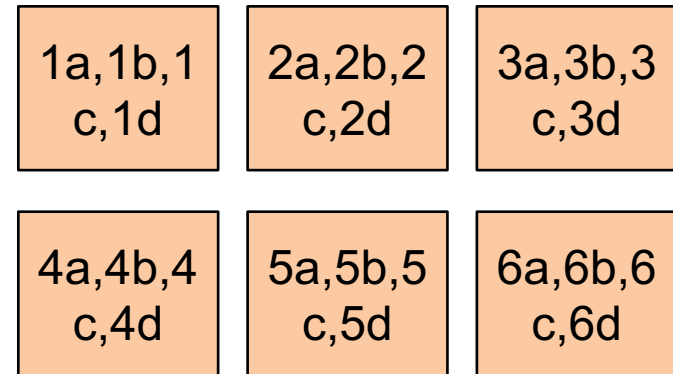
Scaling to Disk: Simple Aggregates

A	B	C	D
1a	1b	1c	1d
2a	2b	2c	2d
3a	3b	3c	3d
4a	4b	4c	4d
5a	5b	5c	5d
6a	6b	6c	6d

R

SELECT MAX(A) FROM R

Row-store:



- ❖ Again, straightforward **filescan** data access pattern
 - ❖ Similar I/O behavior as non-deduplicating project
- ❖ I/O cost: 6 (read) + output # pages (write)

Scaling to Disk: Simple Aggregates

A	B	C	D	R	SELECT MAX(A) FROM R			
1a	1b	1c	1d	Col-store:	1a,2a,3a,4a	5a,6a	1b,2b,3b,4b	5b,6b
2a	2b	2c	2d					
3a	3b	3c	3d		1c,2c,3c,4c	5c,6c	1b,2b,3b,4b	5b,6b
4a	4b	4c	4d					
5a	5b	5c	5d					
6a	6b	6c	6d					

- ❖ Similar to the non-dedup. project, we only need col A; no need to read other pages!
- ❖ I/O cost: **2** (read) + output # pages (write)

Scaling to Disk: Group By Aggregate

A	B	C	D
a1	1b	1c	4
a2	2b	2c	3
a1	3b	3c	5
a3	4b	4c	1
a2	5b	5c	10
a1	6b	6c	8

R

```
SELECT A, SUM(D)
FROM R GROUP BY A
```

- ❖ Now it is not straightforward due to the **GROUP BY**!
- ❖ Need to “collect” all tuples in a group and apply agg. func. to each
- ❖ Typically done with a **hash table** maintained in DRAM
 - ❖ Has 1 record per group and maintains “running information” for that group’s agg. func.
 - ❖ Built on the fly during filescan of R; holds the output in the end

Hash table (output)

A	Running Info.
a1	17
a2	13
a3	1

Scaling to Disk: Group By Aggregate

A	B	C	D
a1	1b	1c	4
a2	2b	2c	3
a1	3b	3c	5
a3	4b	4c	1
a2	5b	5c	10
a1	6b	6c	8

R

SELECT A, SUM(D)
FROM R GROUP BY A

Row-store:

a1,1b,1 c,4	a2,2b,2 c,3	a1,3b,3 c,5
a3,4b,4 c,1	a2,5b,5 c,10	a1,6b,6 c,8

Hash table in DRAM

A	Running Info.
a1	4 -> 9 -> 17
a2	3 -> 13
a3	1

- ❖ Note that the sum for each group is constructed *incrementally*
- ❖ I/O cost: 6 (read) + output # pages (write); just one filescan again!

Q: But what if hash table > DRAM size?!

Scaling to Disk: Group By Aggregate

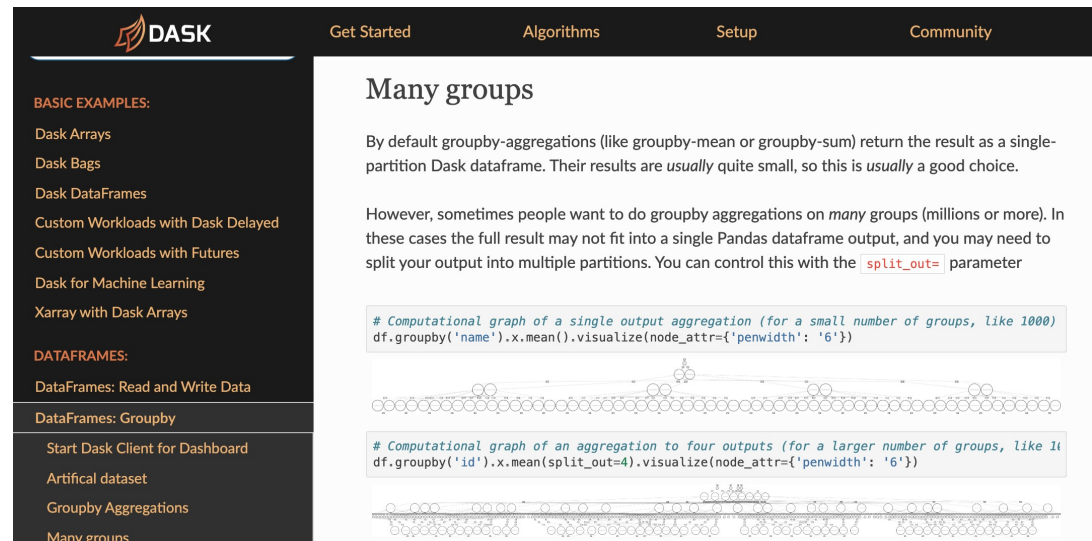
SELECT A, SUM(D) FROM R GROUP BY A

Q: But what if hash table > DRAM size?

- ❖ Program will likely just crash! OS may keep swapping pages of hash table to/from disk; aka “thrashing”

Q: How to scale to large number of groups?

- ❖ Divide and conquer!
Split up R based on values of A
- ❖ HT for each split may fit in DRAM alone
- ❖ Reduce running info. size if possible



The screenshot shows the Dask documentation website. The left sidebar contains a navigation menu with sections: BASIC EXAMPLES (Dask Arrays, Dask Bags, Dask DataFrames, Custom Workloads with Dask Delayed, Custom Workloads with Futures, Dask for Machine Learning, Xarray with Dask Arrays), DATAFRAMES: (DataFrames: Read and Write Data, DataFrames: Groupby), and a list of topics (Start Dask Client for Dashboard, Artificial dataset, Groupby Aggregations, Many groups). The main content area is titled 'Many groups' and explains that by default groupby-aggregations return a single-partition Dask dataframe. It notes that for many groups (millions or more), the full result may not fit into a single Pandas dataframe, and the `split_out` parameter can be used to control this. Two computational graphs are shown: one for a single output aggregation (for a small number of groups, like 1000) and one for an aggregation to four outputs (for a larger number of groups, like 1k).

Ad: Take CSE 132C for more on how GROUP BY is scaled

Scaling Data Science Operations

- ❖ Scalable data access for key representative examples of programs/operations that are ubiquitous in data science:

- ❖ DB systems:

- ❖ Select
- ❖ Non-deduplicating project
- ❖ Simple SQL aggregates
- ❖ GROUP BY aggregates



- ❖ ML systems:

- ❖ Matrix sum/norms
- ❖ (Stochastic) Gradient Descent

Scaling to Disk: Matrix Sum/Norms

2	1	0	0
2	1	0	0
0	1	0	2
0	0	1	2
3	0	1	0
3	0	1	0

$M_{6 \times 4}$

$$\|M\|_2^2$$

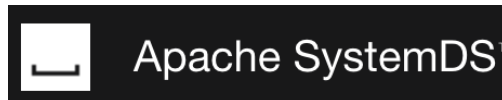
Row-store:

2,1, 0,0	2,1 0,0	0,1, 0,2
0,0, 1,2	3,0, 1,0	3,0, 1,0

- ❖ Again, straightforward **filescan** data access pattern
 - ❖ Very similar to relational simple aggregate
 - ❖ Running info. in DRAM for sum of squares of cells
 - ❖ 0 -> 5 -> 10 -> 15 -> 20 -> 30 -> 40
- ❖ I/O cost: 6 (read) + output # pages (write)
- ❖ Col-store and tiled-store also have I/O cost 6; why?

Scalable Matrix/Tensor Algebra

- ❖ In general, tiled partitioning is more common for matrix/tensor ops
 - ❖ More DRAM/cache-efficient implementations
- ❖ DRAM-to-disk scaling:
 - ❖ pBDR, SystemDS, and Dask Arrays for matrices
 - ❖ SciDB, Xarray for n-d arrays
- ❖ CUDA for DRAM-GPU caches scaling of matrix/tensor ops



The screenshot shows the Dask Arrays website with the 'Create Random array' example. The page includes a sidebar with navigation links, a main content area with a description and code, and a table comparing array and chunk properties.

DASK

Text Vectorization Pipeline
Hyperparameter optimization with Dask
Scale XGBoost
Use Voting Classifiers
Automate Machine Learning with TPOT
Generalized Linear Models
Singular Value Decomposition

APPLICATIONS:

Analyze web-hosted JSON data
Async/Await and Non-Blocking Execution
Asynchronous Computation: Web Servers + Dask
Embarrassingly parallel Workloads
Handle Evolving Workflows
Image Processing

Create Random array

This creates a 10000x10000 array of random numbers, represented as 1000x1000 (or smaller if the array cannot be divided evenly). In terms of numpy arrays of size 1000x1000.

```
import dask.array as da
x = da.random.random((10000, 10000), chunks=(1000, 1000))
x
```

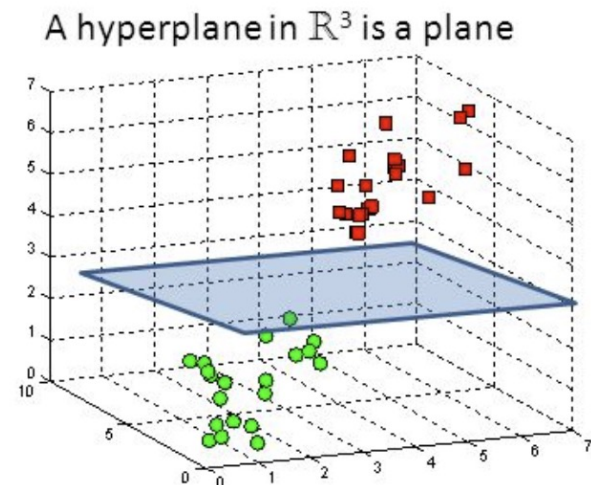
	Array	Chunk
Bytes	800.00 MB	8.00 MB
Shape	(10000, 10000)	(1000, 1000)
Count	100 Tasks	100 Chunks
Type	float64	numpy.ndarray

Numerical Optimization in ML

- ❖ Many regression and classification models in ML are formulated as a (constrained) *minimization* problem
 - ❖ E.g., logistic and linear regression, linear SVM, etc.
 - ❖ Aka “Empirical Risk Minimization” (ERM) approach
 - ❖ Computes “loss” of predictions over labeled examples

$$\mathbf{w}^* = \operatorname{argmin}_{\mathbf{w}} \sum_{i=1}^n l(y_i, f(\mathbf{w}, x_i))$$

- ❖ Hyperplane-based models aka Generalized Linear Models (GLMs) use $f()$ that is a scalar function of distances: $\mathbf{w}^T x_i$

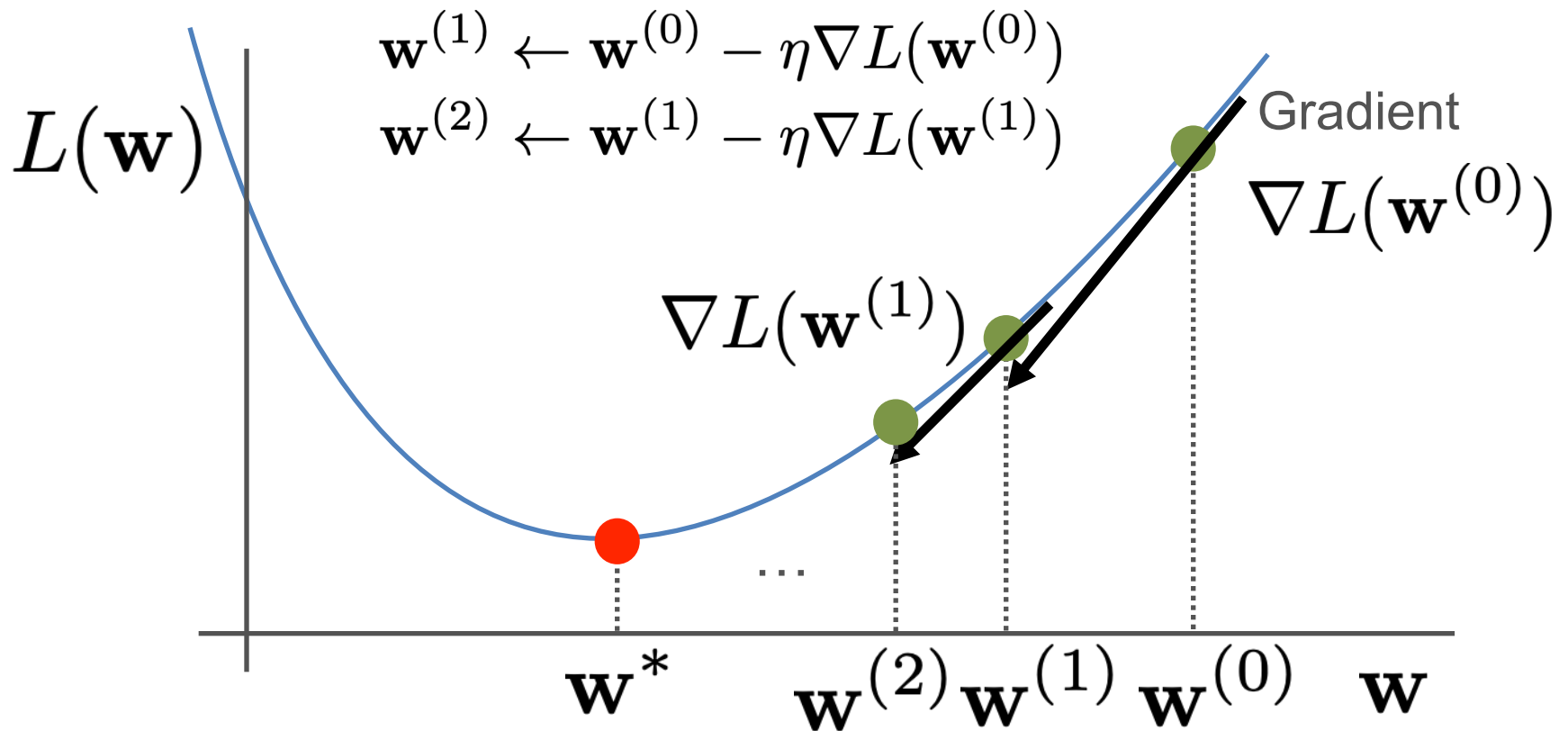


Batch Gradient Descent for ML

$$L(\mathbf{w}) = \sum_{i=1}^n l(y_i, f(\mathbf{w}, x_i))$$

- ❖ In many cases, **loss function** $l()$ is **convex**; so is $L()$
- ❖ Closed-form minimization typically infeasible
- ❖ **Batch Gradient Descent:**
 - ❖ Iterative numerical procedure to find an optimal \mathbf{w}
 - ❖ Initialize \mathbf{w} to some value $\mathbf{w}^{(0)}$
 - ❖ Compute **gradient**:
$$\nabla L(\mathbf{w}^{(k)}) = \sum_{i=1}^n \nabla l(y_i, f(\mathbf{w}^{(k)}, x_i))$$
 - ❖ Descend along gradient:
(Aka **Update Rule**)
$$\mathbf{w}^{(k+1)} \leftarrow \mathbf{w}^{(k)} - \eta \nabla L(\mathbf{w}^{(k)})$$
- ❖ Repeat until we get close to \mathbf{w}^* , aka **convergence**

Batch Gradient Descent for ML



- ❖ Learning rate is a **hyper-parameter** selected by user or “AutoML” tuning procedures
- ❖ Number of iterations/epochs of BGD also hyper-parameter

Data Access Pattern of BGD at Scale

- ❖ The data-intensive computation in BGD is the gradient
 - ❖ In scalable ML, dataset D may not fit in DRAM
 - ❖ Model \mathbf{w} is typically small and DRAM-resident

$$\nabla L(\mathbf{w}^{(k)}) = \sum_{i=1}^n \nabla l(y_i, f(\mathbf{w}^{(k)}, x_i))$$

Q: What SQL op is this reminiscent of?

- ❖ Gradient is like SQL SUM over vectors (one per example)
- ❖ At each epoch, 1 **filescan** over D to get gradient
- ❖ Update of \mathbf{w} happens normally in DRAM
- ❖ Monitoring across epochs for convergence needed
- ❖ Loss function $L()$ is also just a SUM in a similar manner

I/O Cost of Scalable BGD

D

Y	X1	X2	X3
0	1b	1c	1d
1	2b	2c	2d
1	3b	3c	3d
0	4b	4c	4d
1	5b	5c	5d
0	6b	6c	6d

$$\nabla L(\mathbf{w}^{(k)}) = \sum_{i=1}^n \nabla l(y_i, f(\mathbf{w}^{(k)}, x_i))$$

Row-store:

0,1b, 1c,1d	1,2b, 2c,2d	1,3b, 3c,3d
0,4b, 4c,4d	1,5b, 5c,5d	0,6b, 6c,6d

- ❖ Straightforward **filescan** data access pattern for SUM
 - ❖ Similar I/O behavior as non-dedup. project and simple SQL aggregates
- ❖ I/O cost: **6** (read) + output # pages (write for final \mathbf{w})

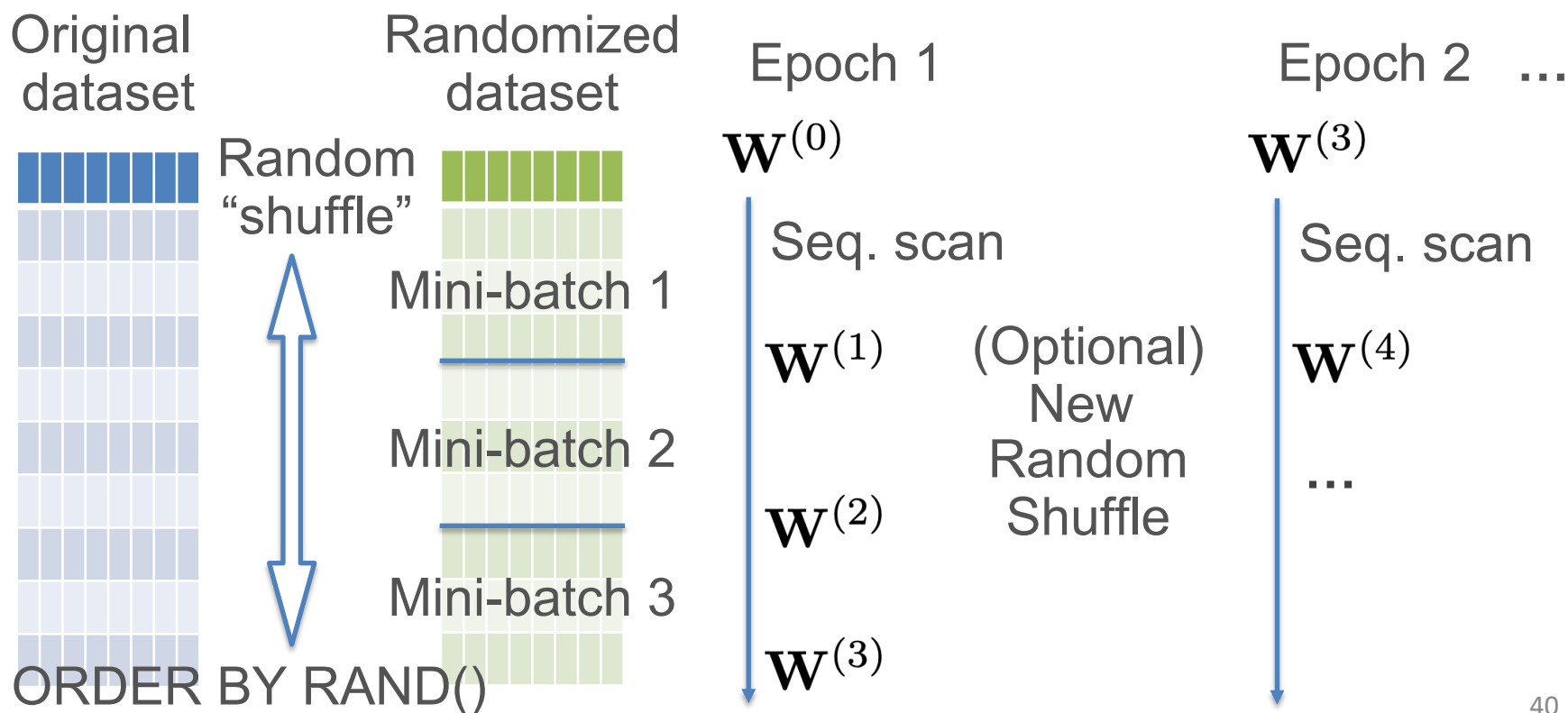
Stochastic Gradient Descent for ML

- ❖ Two key cons of BGD:
 - ❖ Often, too many epochs to reach optimal
 - ❖ Each update of \mathbf{w} needs full scan: costly I/Os
- ❖ Stochastic GD (SGD) mitigates both cons
- ❖ **Basic Idea:** Use a *sample* (**mini-batch**) of D to approximate gradient instead of “full batch” gradient
 - ❖ Done *without replacement*
 - ❖ Randomly reorder/shuffle D before every epoch
 - ❖ Sequential pass: sequence of mini-batches
- ❖ Another big pro of SGD: works well for *non-convex* loss too, especially DL; BGD does not
- ❖ SGD often called the “workhorse” of modern ML/DL

Access Pattern of Scalable SGD

$$\mathbf{W}^{(t+1)} \leftarrow \mathbf{W}^{(t)} - \eta \nabla \tilde{L}(\mathbf{W}^{(t)}) \quad \nabla \tilde{L}(\mathbf{W}) = \sum_{i \in B} \nabla l(y_i, f(\mathbf{W}, x_i))$$

Sample mini-batch from dataset without replacement



I/O Cost of Scalable SGD

- ❖ I/O cost of random shuffle is non-trivial; need so-called “external merge sort” (skipped in this course)
 - ❖ Typically amounts to 1 or 2 passes over file
- ❖ Mini-batch gradient computations: 1 **filescan** per epoch:
 - ❖ As filescan proceeds, count # examples seen, accumulate per-example gradient for mini-batch
 - ❖ Typical mini-batch sizes: 10s to 1000s
 - ❖ Orders of magnitude more model updates than BGD!
- ❖ Total I/O cost per epoch: 1 shuffle cost + 1 filescan cost
 - ❖ Often, shuffling only once upfront suffices
- ❖ Loss function $L()$ computation is same as before (for BGD)

Scaling Data Science Operations

- ❖ Scalable data access for key representative examples of programs/operations that are ubiquitous in data science:
 - ❖ DB systems:
 - ❖ Select
 - ❖ Non-deduplicating project
 - ❖ Simple SQL aggregates
 - ❖ GROUP BY aggregates
 - ❖ ML systems:
 - ❖ Matrix sum/norms
 - ❖ (Stochastic) Gradient Descent

Peer Instruction Activity

(Switch slides)

Review Questions

1. What are the 4 main regimes of scalable data access?
2. Briefly explain 1 pro and 1 con of scaling with local disk vs. scaling with remote reads.
3. You are given a DataFrame serialized as a 100 GB Parquet columnar file. It has 20 columns, all of the same fixed-length data type. You compute a sum over 4 columns. What is the I/O cost (in GB)?
4. Which is the most flexible data layout format for 2-D structured data?
5. You lay out a 1 TB matrix in tile format with a shape 2000x500. What is the I/O cost (in GB) of computing its full matrix sum?
6. Briefly explain 1 pro and 1 con of SGD vs. BGD.
7. Suppose you use scalable SGD to train a DL model. The dataset has 100 million examples. Mini-batch size is set to 50. How many iterations (number of model update steps) will SGD finish in 20 epochs?
8. What is the precise runtime tradeoff involved in shuffle-once-upfront vs. shuffle-every-epoch for SGD?

Outline

- ❖ Basics of Parallelism

- ❖ Task Parallelism; Dask

- ❖ Single-Node Multi-Core; SIMD; Accelerators

- ❖ Basics of Scalable Data Access

- ❖ Paged Access; I/O Costs; Layouts/Access Patterns

- ❖ Scaling Data Science Operations



- ❖ Data Parallelism: Parallelism + Scalability

- ❖ Data-Parallel Data Science Operations

- ❖ Optimizations and Hybrid Parallelism

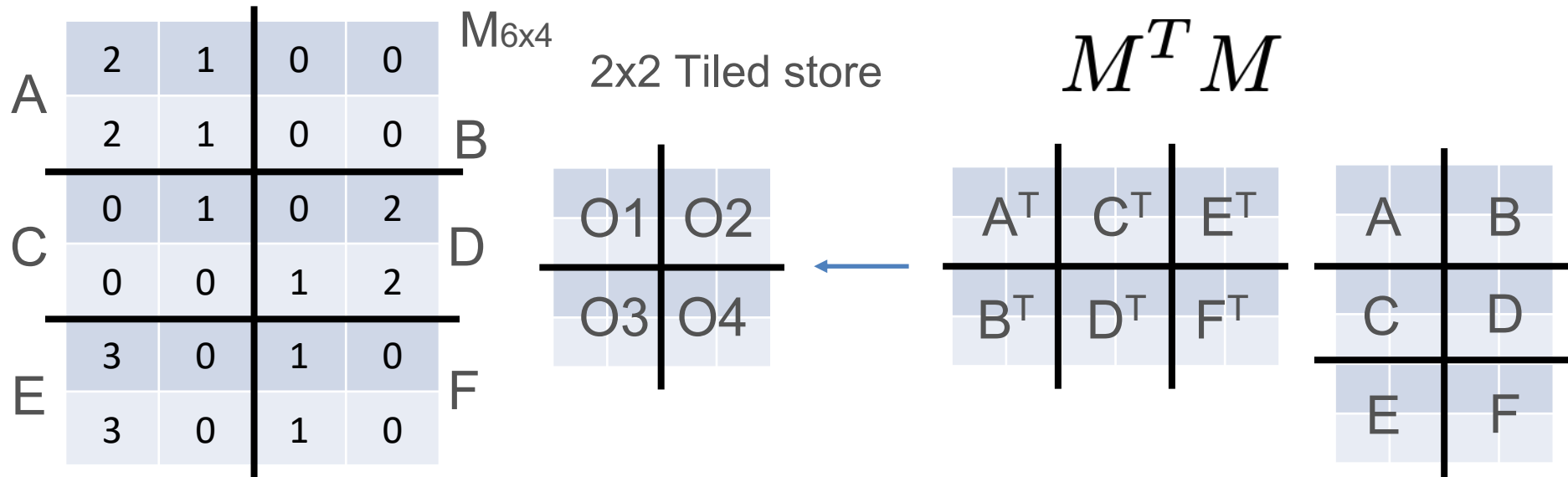
Optional: Another Example of Scaling
Data Science Operations
Not included in syllabus

Scaling to Disk: Gramian Matrix

2	1	0	0	M _{6x4}	$M^T M$			
2	1	0	0					
0	1	0	2		Row-store:	2,1, 0,0	2,1 0,0	0,1, 0,2
0	0	1	2					
3	0	1	0			0,0, 1,2	3,0, 1,0	3,0, 1,0
3	0	1	0					

- ❖ A bit tricky, since output may not fit entirely in DRAM
 - ❖ Similar to GROUP BY difficult case
- ❖ Output here is 4x4, i.e., 4 pages; only 3 can be in DRAM!
 - ❖ Each row will need to update entire output matrix
 - ❖ Row-store can be a poor fit for such matrix algebra
- ❖ What about col-store or tiled-store?

Scaling to Disk: Gramian Matrix



- ❖ Read A, C, E one by one to get $O1 = A^T A + C^T C + E^T E$; $O1$ is incrementally computed; write $O1$ out; I/O: 3 (r) + 1 (w)
- ❖ Likewise with B, D, F for $O4$; I/O: 3 (r) + 1 (w)
- ❖ Read A, B and put $A^T B$ in $O2$; read C, D to add $C^T D$ to $O2$; read E, F to add $E^T F$ to $O2$; write $O2$ out; I/O: 6 + 1
- ❖ Likewise with $B, A; D, C; F, E$ for $O3$; I/O: 6 + 1
- ❖ Max I/O cost: **18** (r) + **4**(w); *scalable on both dimensions!*