Infrastructure for Data Analytics and Machine Learning

Part 2 - Large-scale batch processing

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Plan for this lecture

- What is and why we need batch processing?
- How do large-scale data processing engines work?
- How can we use them effectively?

What is batch processing?

Batch processing - processing large volumes of data at once (in batches collected over some time)

batch (n.) - a quantity required for or produced as the result of one operation [1]

- *mixed a batch of cement*; *a batch of cookies*

Stream processing - processing stream of events as they are produced continuously piece-by-piece in (more or less) real-time

1 - https://www.thefreedictionary.com/batch

Use cases - batch processing

- training machine learning models
  - book and product recommendations
  - image classification, object recognition
- computing user-tailored offers (e.g. credit cards offers)
- processing international money transfers
- processing call records to create monthly billing invoices
- various background processes
  - compressing/re-encoding video
  - performing speech-recognition to add subtitles
- data mining

Use cases - stream processing

- fraud detection (must be real-time to prevent detected frauds)
- real-time stock trading
- social media sentiment analysis
- up-to-the-minute retail inventory management
- log and status monitoring, anomaly detection
- load controlling - adjusting service level to current number of requests

When to choose batch processing?

Batch processing works well when:

- you don’t need **real-time** analytics results
- it's more important to process **larger volumes** of data
  - e.g. **wider context** is needed
    - full user purchase history instead of last order event
    - to join and aggregate data from different sources
- **more computation** is needed than stream processing pipeline can handle
  - generally (even in real life) batching is faster because you can reduce various overheads
  - since there is no "real-time" requirement, there's more time and flexibility, e.g.
    - we can store intermediate results on a slower medium if it does not fit in the memory
    - we can perform more precise computations (e.g. increase number of epochs in an iterative algorithm)

When to choose batch processing? (2)

This is not black or white situation, we can:

- process and **prepare data** as much as possible during stream processing to simplify later batch processing
  - compute aggregates
  - partially sort data
  - perform partial joins
  - shard or partition data
- solve some of our (sub-)problems using a dedicated database (e.g. BigQuery, ClickHouse) instead of writing Map/Reduce jobs

Example - computing recommendations

Computing product recommendations is a good example use case for batch processing.

Imagine you have to create recommendation model for a platform:

- with 2 000 000 000 **products**
- using 355 000 000 000 **events**:
    - "user XYZ was searching for a product ABC"
    - "user ZYX added product CBA to basket"

Assuming we only use 8 bytes for product and user identifiers, 4 bytes for a event time stamp, and one byte for event type, thats 6.7 TiB of efficiently written **essential input** data.

- in real world, to extract that essential data you need to process 300-600 TiB of data first
- reading 600 TiB from a single hard drive would take about 36 days. Just to read input data.

To compute recommendation model we need to: sort and group events, compute sparse $\mathbb{R}^{2*10^9 \times 2*10^9}$ Item-Item matrix, factorize it, fine tune recommendations on GPUs using various machine learning techniques, create ANN index, and store recommendations.

Data processing engines

How to approach such task?

There are multiple ways, for example:

1. Creating custom solution from the scratch
2. Using existing Big Data frameworks:
    - Hadoop Map/Reduce, Apache Hive, Apache Spark, Apache Flink, Presto, BigQuery ...
3. Mixing both approaches

Apache Spark - prerequisites

Before we can use Apache Spark for large scale batch processing you need at least:

- **Computing cluster** - machines with reasonable amount of RAM and CPUs
- **Distributed file system** or object storage - that can store input, output and maybe intermediate data
- **Resource Manager/Scheduler** - that manages our computing cluster

Apache Spark - prerequisites (2)

The most popular setup is:

- using **HDFS** (Hadoop Distributed File System) as a distributed storage
- HDFS data nodes that store the data blocks are also used as **computing nodes**
  - data nodes don't need a lot of RAM nor CPU cores, but they need network card, motherboard, PSU, ...
  - also performing computations close to data can be very efficient
    - no need to send data over network, OS page cache can be used for frequently accessed files
- using Apache Hadoop **YARN** as a Scheduler and Resource Manager
  - Instead of YARN, Kubernetes can be used as a cluster manager, but support for that setting is not very mature

Apache Spark - prerequisites (3)

Alternative approach is to use managed Hadoop in the cloud (e.g. Google Dataproc, Amazon EMR):

- either using standard Spark + HDFS + YARN combination
- or without using HDFS - AWS S3 or Google Cloud Storage can be used as a distributed storage

Apache Spark - overview

Spark (Java/Scala) application consists of:

- single **driver** program that orchestrates and executes parallel operations
- those operations are performed by multiple **executors**

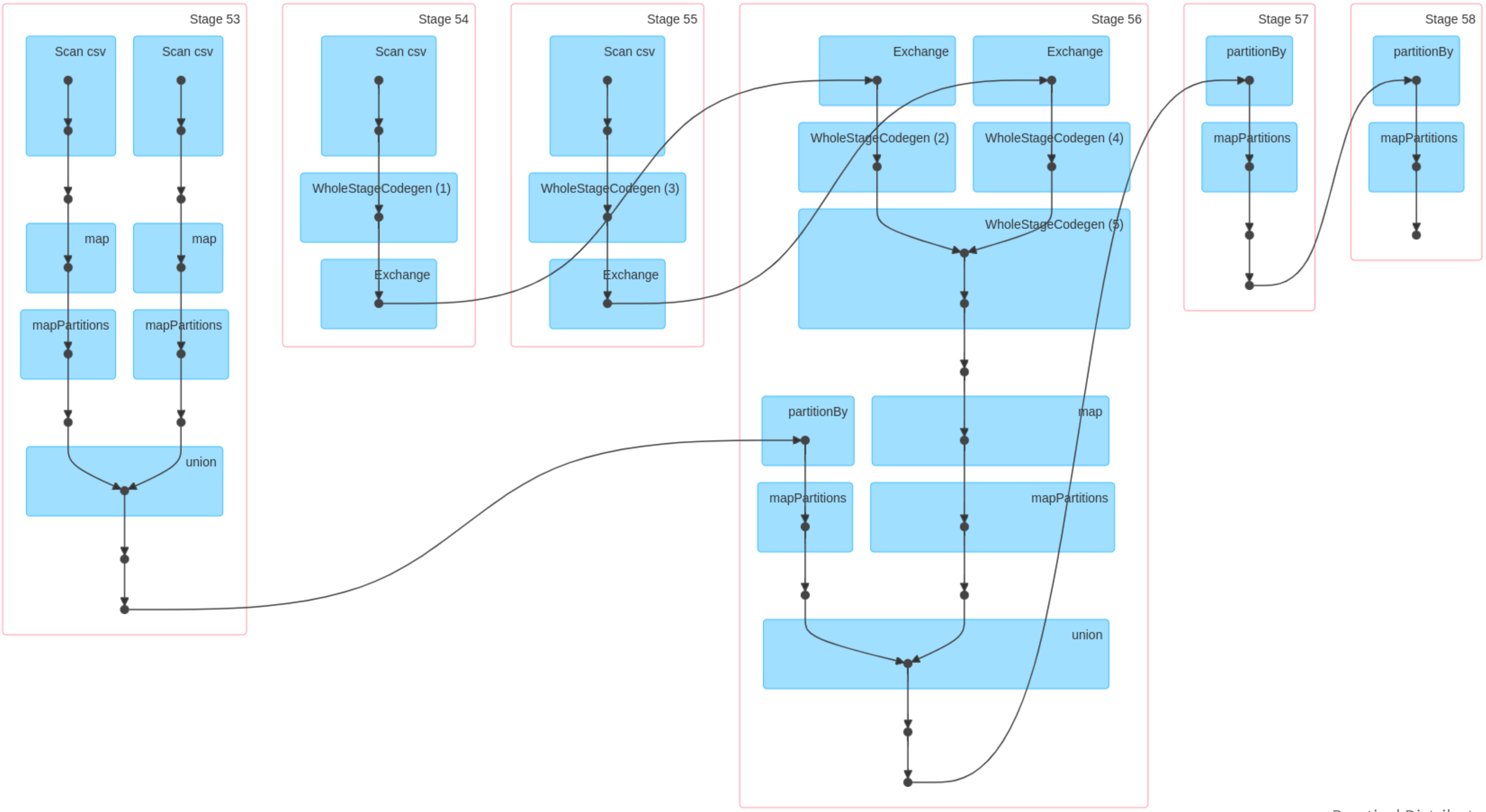
The main abstractions are:

- **Resilient Distributed Dataset (RDD)** - collection of elements partitioned across cluster nodes
  - e.g. having 100 000 files on HDFS (each with multiple records) can result in a RDD with 100 partitions
  - RDDs can be operated in parallel
  - RDDs can be transformed, persisted (to disk or to memory), and recomputed in case of node failure
- **Broadcast variables** - shared (read-only) variables available on all executors

RDDs

- **transformations** - operations on RDD that are performed lazily, e.g.
  - `map()`, `filter()`, `groupByKey()`, `reduceByKey()`, `join()`, `union()`, `sortByKey()`
- **actions** - operations on RDD that are performed eagerly and trigger computation of DAGs composed from lazy transformations, e.g.:
  - e.g. `count()`, `collect()`, `reduce()`, `saveAsXYZ()`

Computations DAGs



Apache Spark API - example program (1)

Example: E-commerce order logs

Input

Multiple files on HDFS inside `/warehouse/purchase_logs/`, e.g.:

```
/warehouse/order_logs/log-1652658664132_40_hXMzbDepoC.txt
/warehouse/order_logs/log-1652658665521_70_aXZzbDCEPQ.txt
...
/warehouse/order_logs/log-1652658278519_13_xiTNJreBBT.txt
```

Each file contains multiple entries with information about products bought by users, e.g.:

```
# <timestamp> <country> <customer_id> <product_id> <product_price>
2022-01-23 17:31:00.131, Poland, User123, ProductABC, 129.99
2022-01-23 17:31:03.217, Brazil, User456, ProductDEF, 499.99
2022-01-23 17:39:03.217, Poland, User123, ProductGHI, 450.79
...
```

Information about the same user (or product) can occur in multiple files.

Apache Spark API - example program (2)

Goal: find top 100 customers from Poland that spend the most money in the store

Apache Spark API - example program (2)

Goal: find top 100 customers from Poland that spend the most money in the store

```
type UserId = String; type Price = Float
case class OrderRow(timestamp: String, country: String, userId: UserId, productId: String, price: Price)

val lines: RDD[String] = sparkContext.textFile("/warehouse/order_logs/log-*.txt")
val parsedLines: RDD[Array[String]] = lines.map(line => line.split(", ?"))

val orderRows: RDD[OrderRow] = parsedLines
    .map(words => OrderRow(words[0], word[1], words[2], word[3], word[3].toFloat))

val ordersFromPoland = orderRows.filter(order => order.country == "Poland")

val userPrices: RDD[(UserId, Price)] = ordersFromPoland.map(order => (order.userId, order.price))
val summedUserPrices: RDD[(UserId, Price)] = userPrices.reduceByKey((price1, price2) => price1 + price2)
val top100Users: Array[(UserId, Price)] = summedUserPrices
    .sortBy({ case (userId, priceSum) => -priceSum })
    .take(100)
```

Execution of the example program (1)

- DAG of computations will be materialized, then
- for each file, one RDD partition will be created

```
task_00: read_lines(file_00) => partition_00 == stream_of[line1, line2, ...]
task_01: read_lines(file_01) => partition_01 == stream_of[line1, line2, line3, ...]
...
task_99: read_lines(file_99) => partition_99 == stream_of[line1]
```

- every executor will process multiple RDD partitions (perform multiple tasks):

```
executor_00: [task_01, task_17, task_87, task_99]
executor_01: [task_02, task_05, task_43, task_66]
...
executor_19: [task_55, task_77, task_88, task_98]
```

Execution of the example program (2)

- To execute `task_01`, Spark Driver has to **serialize closure** of a function that has to be executed remotely and send it to every executor
    - e.g. `fun: Array[String] => OrderRow = { words => OrderRow(words[0], word[1], words[2], word[3], word[3].toFloat) }`
- Then executor merges subsequent transformations and produces **stream** of results with approximately following semantic:

```
lines_stream.
    .map(line => line.split(", ?"))
    .map(words => OrderRow(words[0], word[1], words[2], word[3], word[3].toFloat))
    .filter(order => order.country == "Poland")
    .map(order => (order.userId, order.price))
```

- If our application called `ordersFromPoland.saveAsTextFile("/warehouse/temp/orders_from_poland")` instead of `reduceByKey(...)`, we could read and write multiple files sequentially in parallel using constant memory

Execution of the example program - shuffle (1)

- Certain Spark operations trigger a slow and complex event called **shuffle**
- Shuffle is a mechanism for re-distributing and re-grouping data across partitions.
- This usually involves **copying data between executors** (all-to-all),
  - and if shuffled data is too large to fit in RAM, writing intermediate results to disk
  - it also requires serializing data and network I/O

Execution of the example program - shuffle (2)

- Every task operates on a single partition and is executed by one executor, so to perform:

```
userPrices // : RDD[(UserId, Price)]
    .reduceByKey((price1, price2) => price1 + price2)
```

- which corresponds to:

```
for user in userPrices.keys():
    group: List[Price] = { find all records where record.key == user }
    aggregated_value = group.reduce((price1, price2) => price1 + price2)
    output(user, aggregated_value)
```

- we need to **re-group** all records with given key so that they are located within **the same partition** an can be processed efficiently by a single executor

Execution of the example program - shuffle (3)

There are at least two ways to perform shuffle:

- **sort based** (used by Hadoop Map/Reduce and Spark)
  - (on-disk) sort records by key using multiple files on HDFS
    - this complex parallel external sort
  - process sorted results in parallel so that all adjacent records with given key are processed by a single Reduce Task
- **hash-based** (used by Spark)
  - hash keys and write records to resulting buckets (`hash(key) % num_buckets`)
    - spilling intermediate data on disk, when they don't fit into memory
  - process each bucket by one executor

We can reduce work by performing map-side reduces.

Spark SQL, DataFrames and Datasets

- RDD is the low-level Spark API
- Spark also provides less flexible but (in some cases) more performant APIs:
  - Dataset interface
  - Pandas DataFrame-like interface
  - Spark SQL interface
- **Extra information** about data and computations allows for **additional optimizations**
  - e.g. reading only a subset of columns, choosing the best join method, reordering of operations
- There's also PySpark interface, ML and Graph processing on top of Spark

```
data
  .filter(col("country").equalTo("Mexico"))
  .groupBy(col("age"))
  .count()
```

```
spark.sql("""
SELECT age, count(1)
FROM table_from_rdd
WHERE country = 'Mexico'
GROUP BY age
""")
```

Useful techniques in batch processing

Partitioning and clustering

- organizing files to allow common tasks to read only necessary subsets of data
  - by type, by date, by region, vendor or category
- storing the same events multiple times in multiple clusters

```
/warehouse/products/...
/warehouse/user-reviews/...
/warehouse/browsing_events/...
/warehouse/browsing_events/2022-05-01/...
/warehouse/browsing_events/2022-05-02/...
/warehouse/browsing_events/2022-05-03/...
/warehouse/browsing_events/2022-05-04/region=us/...
/warehouse/browsing_events/2022-05-04/region=eu/log-1652658664132_40_hXMzbDepoC.avro.snappy
/warehouse/browsing_events/2022-05-04/region=eu/log-1652658665521_70_aXZzbDCEPQ.avro.snappy
/warehouse/browsing_events/2022-05-04/region=eu/log-1652658278519_13_xiTNJreBBT.avro.snappy
/warehouse/browsing_events/2022-05-04/region=eu/...
/warehouse/subscriptions/...
/warehouse/purchases/...
```

Sharding

Sharding - partitioning data or computations horizontally so that each data shard is stored or handled by a different server, process, thread etc.

- similar to partitioning
- but it's rather related to spreading load/computations/responsibility evenly
  - compared to reducing amount of data read

```
def process_single_event(event):
    computed_result = compute(event)
    shard_id = hash(event.user_id) % NUM_SHARDS
    write_to(computed_result, f"/temp/stage-delta/shard.{worker_id}.{shard_id}.avro")

input_files.map(process_single_event)

for shard_id in range(NUM_SHARDS):
    sort_in_memory(get_paths("/temp/stage-delta/shard.*.{shard_id}.avro"),
        output="/temp/stage-gamma/shard.{shard_id}.avro") # sort by user_id

def process_full_user_history(event):
    while event.user_id == previous_user_id:
        ...

read_avros("/temp/stage-gamma/shard.*.avro")
    .map(process_full_user_history)
```

Sampling

- sometimes we are not able store all data
- sometimes processing all data is too slow and increasing amount of processed data gives diminishing gains
- for many tasks and queries using sample of data is enough
- sometimes we need samples from different distributions:
  - ```
    if random() < 0.1:
        write_sample(event)
    ```
  - ```
    if hash(event.user_id) % 1000 < 100:
        write_sample(event)
    ```
- sometimes can keep all important events (e.g. conversions) and sample of ordinary events (home page visits)
- nothing prevents us from having sampled and whole dataset at the same time:

```
/warehouse/browsing_events/2022-05-04/sample=1/..   # 10 GB
/warehouse/browsing_events/2022-05-04/sample=10/..  # 90 GB
/warehouse/browsing_events/2022-05-04/sample=100/.. # 900 GB
```

Sorting and merging

Having sorted data can be useful

- we can use binary search, skip-list-like or sampled indices
- we **merge multiple sorted streams** - very useful operation
  - joining two "tables" using common key
  - processing multiple shards
  - merge sorting
- we can reduce by key easily when data is sorted
- sorted data compresses better

Reducing amount of stored and processed information

- sometimes it's worth re-examine stored data and decide if everything we write is useful
  - maybe some fields or columns are no longer needed or redundant?
- during processing **the faster we reduce every record to minimum needed the better**
  - this reduces amount of data that need to be serialized, send over network, shuffled, sorted, spilled to disks, kept in RAM, etc.
- also parsing and casting done early can reduce amount of processed data (e.g. converting time stamp strings to `int64`)

Pushing projections up

In some cases in may be better to perform redundant computations to reduce amount of processed data

```
val userSessions: RDD[(UserId, (SessionStartDate, List[UserAction]))] = ... # 200 TB of data
val lastUserSessions = user_sessions
    .reduceByKey(takeMoreRecentSession) # for every user, find his latest session

lastUserSessions
    .mapValues(session => computeFraudScore(session)) # detect suspicioius users using heavy ML algorithm
    .filterValues(fraudScore => fraudScore > 0.8)
    .saveAsAvro("suspiciousUsers.avro")
```

and

```
val userSessions: RDD[(UserId, (SessionStartDate, List[UserAction]))] = ... # 200 TB of data
val suspiciousSessions : RDD[(UserId, (SessionStartDate, Float))] = userSessions
    .mapValues(session => computeFraudScore(session))
    .filterValues(fraudScore => fraudScore > 0.8)

suspiciousSessions # 5 GB of data
    .reduceByKey(takeMoreRecentSession) # for every user, find his latest session
    .saveAsAvro("suspiciousUsers.avro")
```

Denormalization

Sometimes to avoid complex joins it's worth to consider keeping:

- **raw events**
- (redundant) big **complex snapshots** (e.g. snapshot of all records related to user XYZ)
  - those can be stored
    - periodically (e.g. every day at midnight)
    - or even with every request
- optionally, redundant **periodical deltas** containing consolidated information that changed since last snapshot

In our example, to materialize user profile at requested point of time

- instead of reading all records about user XYZ stored in hundreds of files created during last 2 years
- we could use the latest snapshot of user XYZ history + few deltas + few raw events

Storing redundant materialized snapshots will consume **huge amounts of storage space**, but it's worth considering as it might speed up **simplify** batch processing.

Caching and precomputing

- caching **can introduce subtle bugs**, but it's worth considering caching, especially if
  - performed computation is slow or cached computation result is smaller than data needed to compute that result
- we can cache things in memory or store intermediate results on to disk to read it multiple times
- we can also cache results computed by previous batch processing jobs, for example:
  - if every day we process rolling window consisting of data from last n days
  - we can change our algorithm to reuse previous results, i.e.
  - remove data from $n+1$ day ago and use changes from the newest day

Tiering, prefetching and buffering

Tiering - arranging something in tiers (layers)

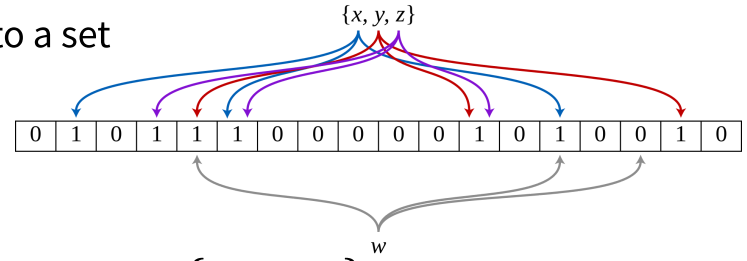
We should keep in mind speeds, properties and capacities of various memory types, e.g.

- keep frequently accessed data (or data that need random access) on SSD or in RAM
- using fact that we can read from HDD faster if we read large continuous chunks of data
    - so if we expect data to be read in the near future we can prefetch it the background or keep constant read-ahead buffer
- sometimes manually juggling data paired with sharding can give spectacular effects

Bloom filters and sketches (1)

Bloom filter is a compact probabilistic data structure that can be used to test if an element is a member of a set.

- no false negatives – if tested element belongs to a set, bloom filter will always return true
- false positives are possible – bloom can return true for element that does not belong to a set



General idea:

- Bloom filter is a bit array of `m` bits, all set to 0.
- when we add an `element` to a set, we hash it using k different hash functions $h_i : Universe \rightarrow \{1, .., m\}$
- we turn on every bit indicated by $h_i(element) : i \in \{1..k\}$
- to test whether element belongs to a set we check that every $bit\_array[h_i(element)] : i \in \{1..k\}$ bits are 1

We can choose n, k, m to get very compact filter with desired False Positive Rate (FPR). A Bloom filter with a 1% FPR and an optimal k needs only ~9.6 bits per element (which can be anything identifier, string, blob of bytes, image).

Examples:

- checking bloom filter before trying to retrieve from slower medium or external source
- using bloom filter for broadcast joins

source: https://en.wikipedia.org/wiki/Bloom_filter#/media/File:Bloom_filter.svg

Bloom filters and sketches (2)

Count–min sketch - probabilistic data structure that serves as a frequency table of events.

- hash functions are used to map events to frequencies
- uses only sub-linear space, but can over count events due to hash collisions

We can use d hash functions $h_i : Universe \rightarrow \{1, .., w\}$, increase $d \times w$ counter matrix accordingly and estimate each element frequency as $min\ \{C[1][(h_1(elem)],\ \ldots,\ C[d][h_d(elem)]\}$

```
        hash_1(elem) % w = 2 --> [    ] [    ] [ +1 ] [    ] [    ] [    ] [    ]
elem -> hash_2(elem) % w = 5 --> [    ] [    ] [    ] [    ] [    ] [ +1 ] [    ]
        hash_d(elem) % w = 3 --> [    ] [    ] [    ] [ +1 ] [    ] [    ] [    ]
```

Bloom filters and sketches (3)

HyperLogLog - probabilistic algorithm for approximating the number of distinct elements in a multiset (i.e. count-distinct problem),

- uses sub-linear memory, at the cost of obtaining only an approximation of the cardinality

The basic idea is to hash elements and use the observation that we can estimate cardinality of a multiset of uniformly distributed random numbers by calculating **maximum number of leading zeros** in binary representation of each number in the set.

```
elem1 ->  hash(elem1) -> . . . 0 0 0 # 3 leading zeros => P(3 zeros) = 1 / 2^3 = 1 / 8
elem2 ->  hash(elem2) -> . . . 0 0 1
elem3 ->  hash(elem3) -> . . . 0 1 0
elem4 ->  hash(elem4) -> . . . 0 1 1
elem5 ->  hash(elem5) -> . . . 1 0 0
elem6 ->  hash(elem6) -> . . . 1 0 1
elem7 ->  hash(elem7) -> . . . 1 1 0
elem8 ->  hash(elem8) -> . . . 1 1 1
```

Effective serialization and file formats (1)

If data elements we process have at least some basic structure we can store the elements either in **columnar format** or **row format**.

Row format:

```
{ name: Jack, age: 23, city: Warsaw }
{ name: Jill, age: 22, city: NULL }
{ name: Bill, age: 21, city: Berlin }
{ name: John, age: 24, city: Berlin }
```

Columnar format:

```
{ name: [Jack, Jill, Bill, John] }
{ age:  [23, 22, 21, 24] }
{ city: [Warsaw, NULL, Berlin, Berlin] }
```

Effective serialization and file formats (2)

Columnar format is useful

- when we process only subset of columns
  - we don't have to read whole file, nor deserialize entire object
  - especially when we have very selective predicate
    - e.g. `dataset.filter(user => user.firstName == 'Gościsław').map(...)`
  - this is common case for query-like workloads
- because it makes compression easier (similar values are close to each other)
- and allows for vectorization and efficient processing (e.g. processing numbers using AVX instructions)

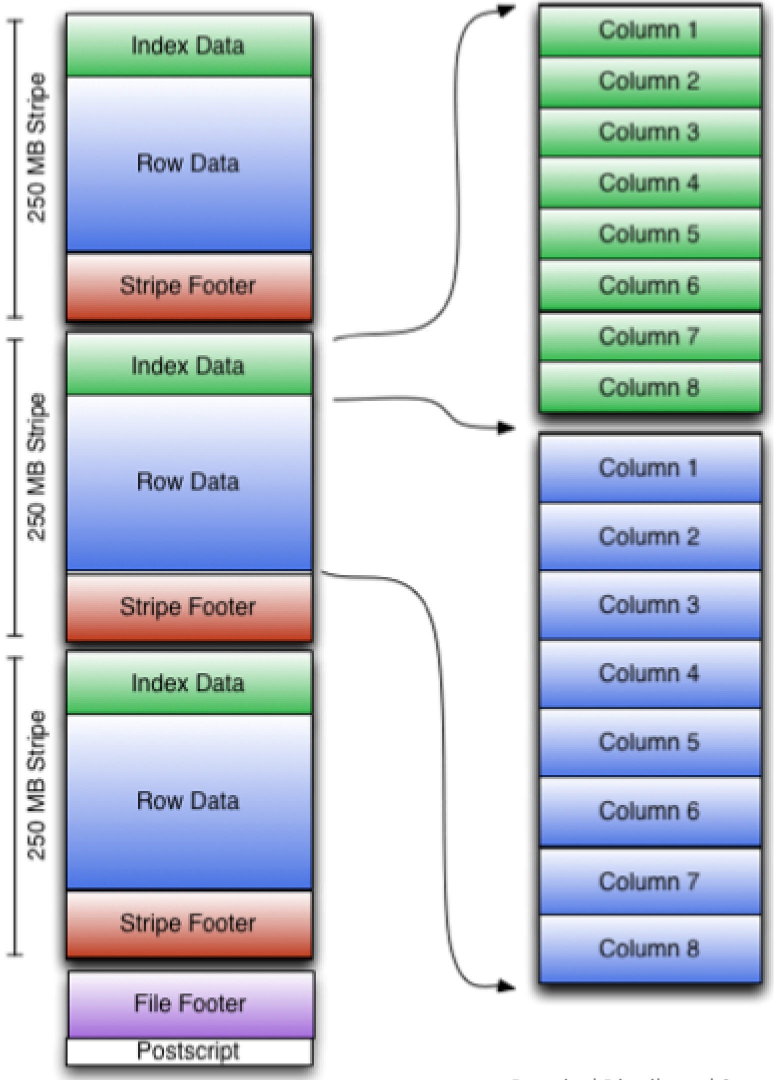
Effective serialization and file formats (3)

Row format is useful

- when we process all fields/columns sequentially
  - accessing n columns would require n disk access
- easier to serialize (no need to buffer multiple rows)

Row-Columnar format:

- we can group rows, and for each group use columnar format
  - e.g. Apache ORC (Optimized Row Columnar)



source: https://cwiki.apache.org/confluence/display/hive/languagemanual+orc

Effective serialization and file formats (4)

Space-efficient and/or fast serialization is very important.

- for data serialized **on disk** we might prefer space-efficient serialization, e.g.
  - compression
  - variable length zig-zag integer encoding
  - encoding enums as bytes, enum sets as bit sets
- for data serialized to be transferred **over network** we might prefer fast serialization, e.g.
  - serializing integers in native byte order
  - keeping padding bytes so structures can be memory mapped

Map-side/Broadcast joins

```
users // large collection
    .join(purchases) // smaller collection
    .keyBy(user => user.id)
    .map({ case (user, order) => (user.email, oder.orderedProducts) })
```

The standard way to perform this join is to use slow sort- of hash-based shuffle join.

But we can also broadcast smaller collection to all workers and perform simple map task.

```
val purchaseMap : Broadcast[HashMap[UserId, List[Product]]] = spark.broadcast(purchases.collect().asMap)
users.map(user => (user.email, purchaseMap.get(user.id, List.empty)))
```

Vertical scaling

If we are able reduce amount of processed data or transform our problem into set of independent tasks we can consider **vertical scaling**.

For example, performing computation using one or few machines with 4TB RAM and 256 CPU threads and fast NVMe SDD RAID-0 disk array can reduce total computation time drastically.

When we perform computations in a single address space on a single machine:

- we don't need to **serialize** data, send it over network nor write to disk
- we can **vectorize** our operations and use native implementations
- we can use efficient data structures and algorithms
- we can use CPU and OS **caches** effectively
- we can reduce various **overheads** related to distributed computing (e.g. no need to use distributed task scheduler)

t: 120 / 86:50

Summary

We have discussed following topics:

- What is and when we need batch processing
- Batch processing using Apache Spark
- Useful techniques in batch processing