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Analyzing Massive Data Sets
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Chapter 3: Spark

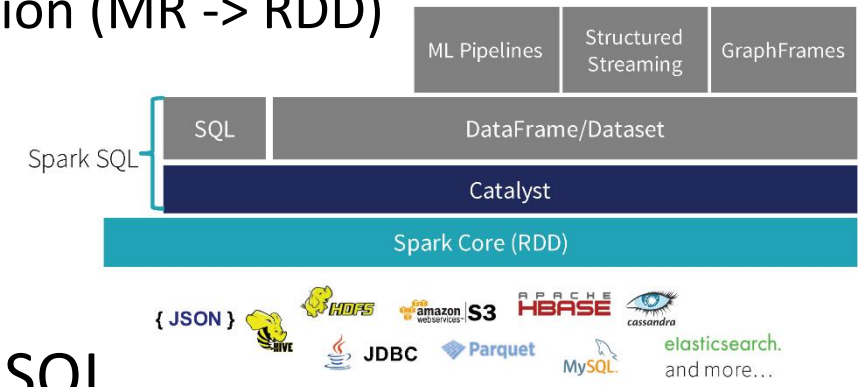
Limitations of Map-Reduce

- No support for general workflows (single-stage map-group-reduce)
- No support for iterative workloads (graph algorithms, learning methods)
- Restricted set of operations
- Low level of abstraction (-> specialized hooks into M/R: combiner, partitioner, …
- Low operational efficiency due to
  - mandatory materialization (failure resilience)
  - lack of data type knowledge
- Long response times (batch processing)

Apache Spark

think map / reduce

- Core Idea: Distributed, shared memory with coarse transformations (RDD)
- Support (and integration) for various different processing requirements
  - Unstructured, general distribution (MR -> RDD)
  - Structured querying (SQL)
  - Data Streams: ordered, infinite
  - Graphs: iteration
  - Machine Learning



native

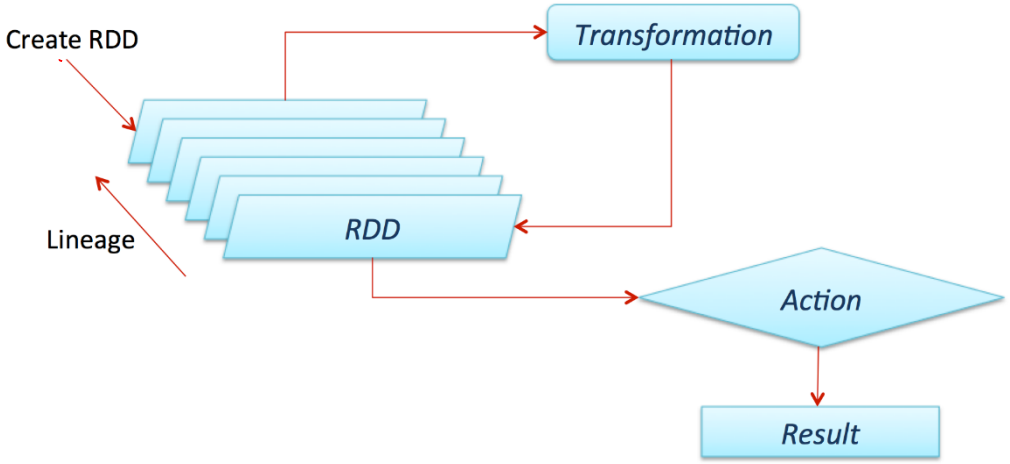
- APIs in Scala, Java, Python, R, SQL
- Integrates into cluster managers (Hadoop YARN, Kubernetes, Mesos) as well as standalone
- Ingestion of various data formats from wide range of source platforms (HDFS, K/V stores, (No)SQL DB)

RDDs (old core API)

- **Distributed** collection
  - In-memory caching
  - Programmable partitioning and co-locationing
- **Parallel**, **coarse** transformations
  - Richer set of operations than map and reduce
- **Immutable** data
  - Transformations generate new RDD
  - No locking, coordination
  - Possibly higher memory consumption
- Fault Tolerance via **Lineage**
  - Recompute results from input dependencies
  - Checkpointing only as optimization
- **Lazy** evaluation
  - Compute only when results are requested

Working with RDDs

- Create RDD from
  - Normal collections
  - External sources (File, HDFS, …)
- Transformations
  - Bulk operation on existing RDDs
  - Define new RDD
  - Keep track of input RDD(s): lineage
- Actions:
  - Turn RDD into "normal" values /collections
  - Trigger the execution → lazy execution

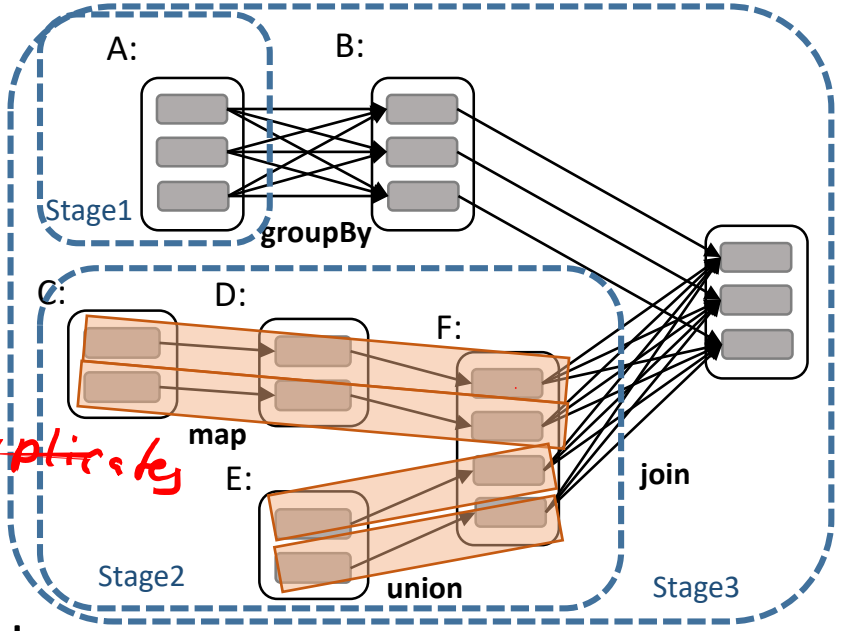


Examples of RDD operations

```
List<Integer> data = Arrays.asList(1, 2, 3, 4, 5);
JavaRDD<Integer> distData = sc.parallelize(data);


JavaRDD<String> distFile = sc.textFile("data.txt");

rdd.filter(p -> p.getAge() < 21)   // transformation, lambda expression
   .map(p -> p.getLast())          // transformation
   .saveAsObjectFile("under21.bin"); // action

JavaRDD<Integer> lineLengths = lines.map(s -> s.length());
int totalLength = lineLengths.reduce((a, b) -> a + b);


pairs = lines.map(lambda s: (s, 1))  # Python
counts = pairs.reduceByKey(lambda a, b: a + b)
```

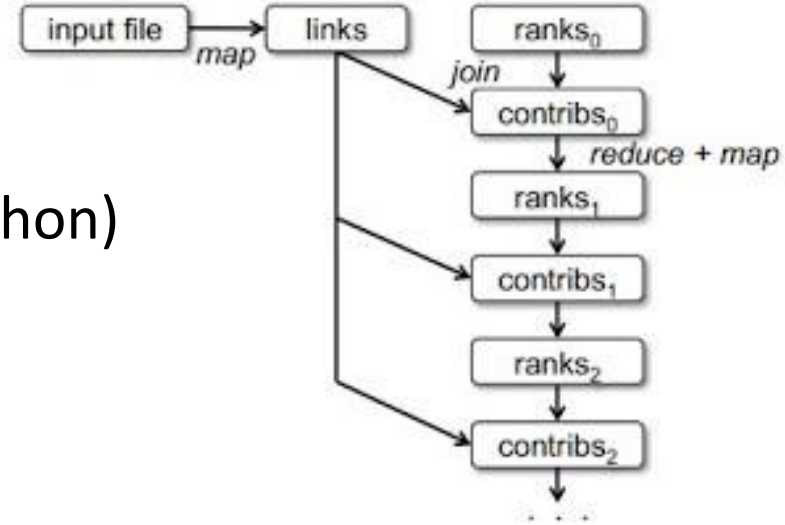
Representing and Executing RDDs

- Native objects in memory, Java/Kryo serialization when transferring over the network
- Controllable partitioning
- Two dependency types:
  - **Narrow**: Each parent partitions contributes to exactly one child partition:
    - map, filter, union, join with fitting partitions
  - **Wide**: At least one parent contributes to multiple children:
    - group by, general join, distinct, …
- Narrow dependencies can be co-scheduled: stages



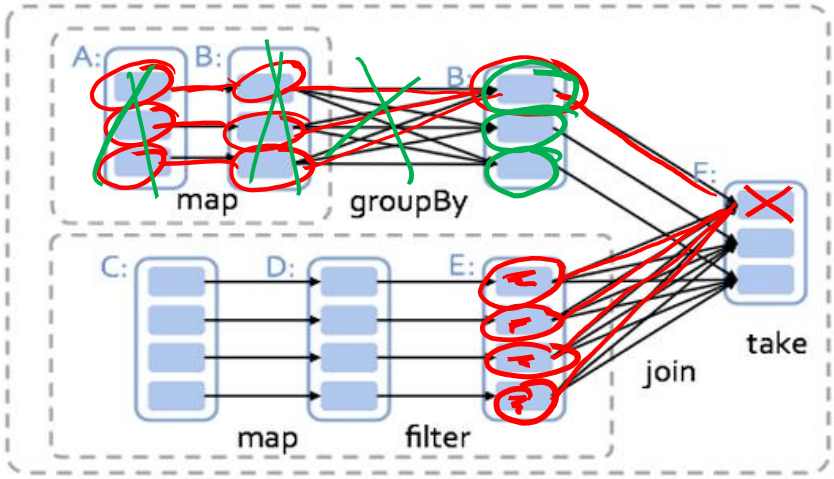
Persisting RDDs

- Framework as well as users can decide if an RDD should persisted
- If an RDD is not persisted, partitions could be discarded when memory is limited
- Explicitly persisting useful for many iterative workloads: cache network structure for path computation, pagerank, …
- Various levels of persistence
  - Original in memory (Java, Python)
  - Serialized in memory (bytes)
  - On disk (bytes)
  - Replication (orthogonal)



Recovery and Fault Tolerance

- If nodes containing RDDs fail, the partitions can be recomputed based on the dependencies
- Walk back to input in stable storage and restore
- Narrow dependencies easy to recover
- Wide dependencies trigger large recomputations
- Cached RDDs can be reused
- Checkpoints
  - Store RDD in stable storage (e.g., HDFS)
  - Truncate lineage before (optional)
  - Speed up recovery



DataFrames

- Key idea: Declarative API, typed storage, optimizations
- Inspired by, but not identical to Python/R Data Frames
- Tabular structure with different data types (vs object collection in RDDs)
- Nested relational format like PIG, Hive (<-> JSON)
  - Atomic types (strings, integers, float)
  - Sequences, maps, …
- Define or imply schema from sources
- Example expressions:

```
df.filter("age > 21"); // SQL style query string
df.filter(df.col("age").gt(21)); // expression builder
df.filter(df.col(“happy”) == true) instead of
rdd.filter(lambda x: x.happy == true))
```

Assessment of DataFrames

Strengths

+ Declarativity allows query plan optimization
+ Strongly typed data model allows for optimized storage
+ Query compilation avoid interpretation overhead

Limitations

- Compile time type checking restricted:
  df.col(“happy”) may yield a runtime error
- No custom lambdas possible,
  DataFrames first need to be converted to RDDs
- No syntax checking in Spark SQL
- DataFrame API somewhat limited

Data Sets

- Key idea: Combination of RDD and DataFrames
  + When fully using strong typing everything is checked during compile time
  + Optionally also weakly typed objects usable
  + Retains optimizability and code compilation
- Like DataFrames, Dataset API's are internally mapped to RDDs, share lineage, recovery, execution,…

Sample expressions:

```
dataset.filter(person -> person.getAge() < 21);
```

- Spark 2.0 unifies Data Sets and DataFrames (~DataSet[Row])
- Python/R only use DataFrames (lack of type information)

Common Generic Transformations

- Single input RDD
  - map, flatMap
  - filter
  - distinct
  - sample
- Multiple input RDDs
  - union
  - Intersection
  - subtract (set)
  - cartesian / crossproduct
- Operations on specialized RDDs
  - numeric: count, sum, mean, max
  - key/value: group, reduce, (outer) join, cogroup, sort

Common RDD Actions

- Collect (all elements to an array)
- Count
- countByValue
- Take (n elements)
- First/Top
- takeOrdered
- Reduce/fold/aggregate
- Foreach
- saveAs{Text/Sequence/Object}File

- Produce non-RDD output

Dataset/Frame Operations

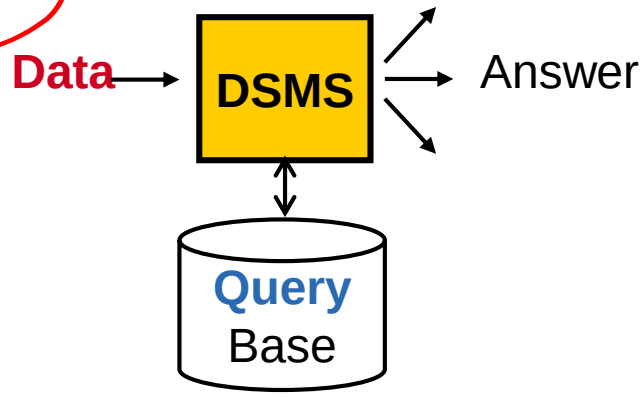
- select, as, drop
- filter, where
- head/limit
- Distinct
- Union, except, intersect
- Join, crossJoin
- Map, MapPartitions
- Aggregations (global)
- groupBy
- cube/rollup
- Metadata: columns, dtypes, count
- cache/persist, unpersist, Checkpoint, storageLevel
- toRDD, write, toDF

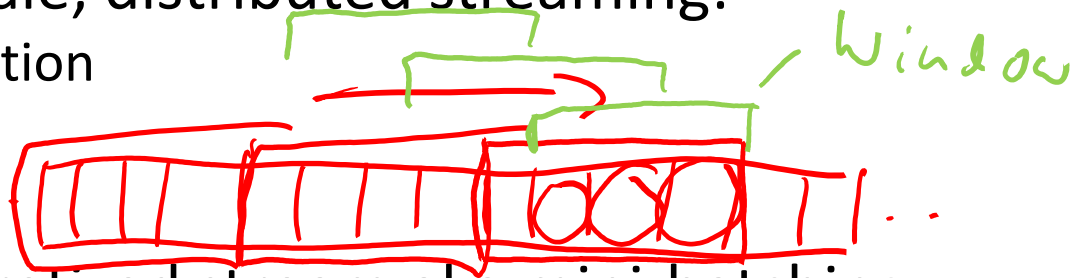
Spark and SQL

- Express SQL queries directly on dataframe/sets
- Fully composable with expressions
- SQL dialect close to HiveQL
  - Analytical SQL: SQL 92+nested columns, windows, cube,…
  - DDL with partitioning information
  - User-defined functions in Scala, Java, Python
- Tungsten:
  - Type-specialized, column storage based on Schema
  - Java bytecode generation instead of iterators
  - vectorization in recent versions
- Catalyst: cost-based, extensible query optimizer
- Input/Output to JSON, Parquet, relational DB
- Expression pushdown even into sources (JDBC database, Parquet file)

Streams

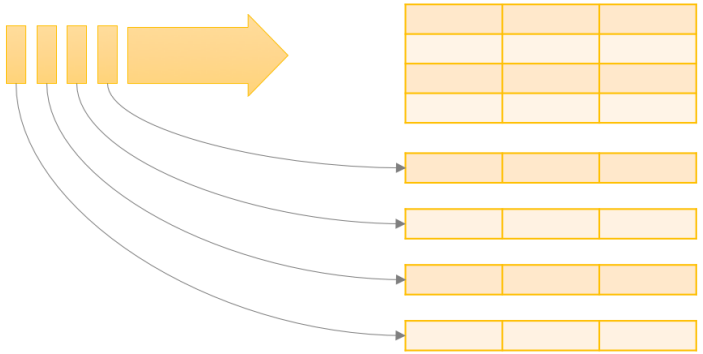
- **Continuous queries** over **ordered**, possibly **infinite data**
- Often:
  - Varying and/or very high data rates
  - Low response times required
- Standard approach:
  - Process data without storing
  - Tuple-at-a-time (low latency)
- Challenges in large-scale, distributed streaming:
  - Consistency/Coordination
  - Recovery
  - Out-of-order arrival
- Spark Streaming: discretized stream aka mini-batching

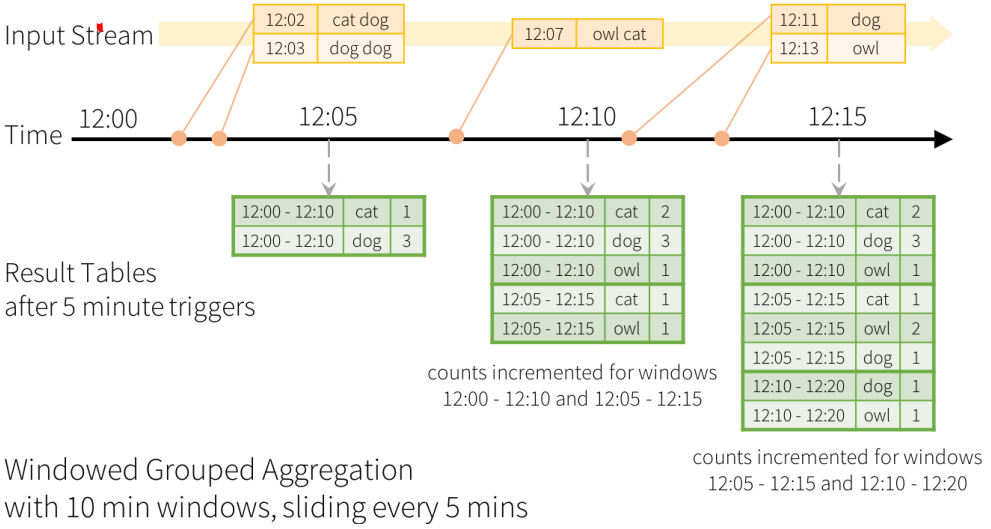




Structured Streaming

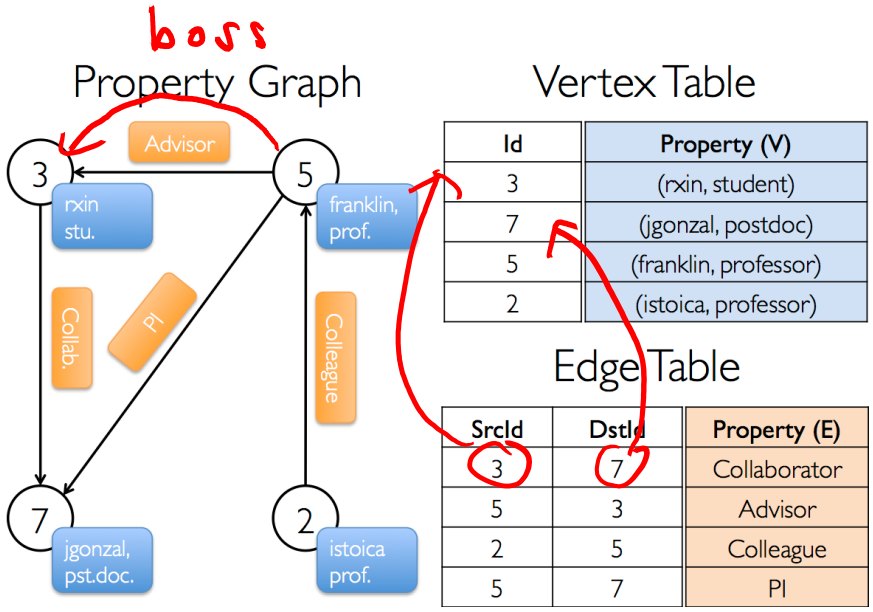
- Unbounded Data Frame:
  - append new rows
  - Keep old rows as long as expressions request them
- Execute queries in regular, short intervals (100 ms)
- Bound relevant state using window expressions
- Watermarking for late arrivals
- Limited support for streaming expressions
- Higher latency
- Easier integration with other models





Graphs: GraphX

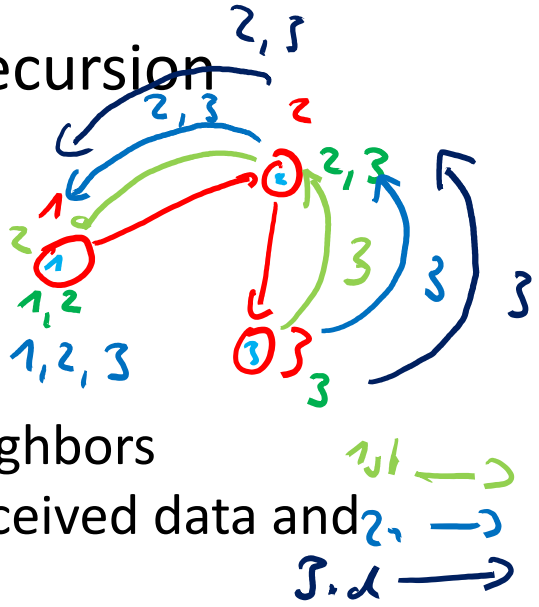
- Property Graph Model
  - Vertices (with id) & Directed edges (multigraph)
  - Properties at vertices and edges → attributes
  - behave like RDDs (immutable, distributed)
  - Implemented as pair of typed RDDs (vertex, edge)



- Property Operators: map() on vertices, edges, triple <e,v,e>
- Simple Structural operations:
  - subgraphs: on edge/vertex predicates, mask with existing graph,
  - reverse edges
  - combine parallel edges into one
- Join graph with RDDs
- Collect neighborhood data – follow edges

GraphX – Iterative Computation

- Many graphs problem require iteration/recursion
  - Reachability / Connected Components
  - Shortest path
  - Pagerank
- Pregel API - Vertex-centric iteration
  - All vertices collect information from their neighbors
  - All vertices perform a computation on the received data and their state
  - All vertices propagate information to their neighbors
  - There is a global synchronization barrier (bulk synchronous): next round can only start after all vertices finished
  - Iteration ends at fixed point (no more changes) or after a count
- Spark maps this graph parallelism to RDD data parallelism



Machine Learning Support

- MLLib (RDDs, focus on methods, no longer developed) and ML (DataFrames, focus on orchestration, catching up in features)
- Core Concept of ML – Pipelines:
  - Dataframes (as defined before)
  - Transformers: add new columns
    - feature transformation (e.g. text to feature vector)
    - learned models (predicted vales)
  - Estimator: fit data, generate model
- Supported operations:
  - Feature extraction and selection
  - Classification/Regression
  - Clustering
  - Recommendations
  - Model selection and tuning

Wrap up

- Big data analytics is evolving to include
  - More **complex** analytics (e.g. graphs, machine learning)
  - More **interactive** ad-hoc queries
  - More **real-time** stream processing
- Spark provides broad support and unification
- Concepts
  - Distributed shared memory
  - coarse-grained transformation
  - Lineage-based recovery
  - Type information
  - Mix of imperative and declarative expressions -> optimizer
- Ongoing arms race with other big data platforms for speed, functionality, usability