Data Engineering

LTAT.02.007

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https://courses.cs.ut.ee/2020/dataeng

Forum

Moodle

Data Pipeline

A pipeline is a set of data processing elements connected in series, where the output of one element is the input of the next one.

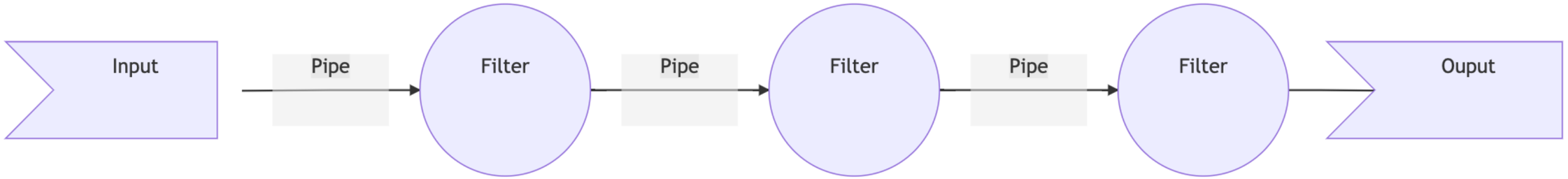
The elements of a pipeline are often executed in parallel or in time-sliced fashion; in that case, some amount of buffer **storage** is often inserted between elements.

Data pipelines Then

The concept of a pipeline began from the good old Unix "Pipe" symbol (|).

The output of one "process" (on left side of the pipe) to be given as "input" to another process (which was on the right side of the pipe).

Elements of a Data Pipeline



Pipes are connectors which send data from one component (filter) to another.

Filters do actual data "processing" (transformation/cleansing/scrubbing/munging... whatever)

Input or **Source** is the actual data source (database output/text file/SQL resultset/raw text)

Output or **Sink** is the final output at the end of this chain.

Big Data Pipeline[1]

The big data world brings velocity, which forced a paradigm shift in data architectures.

Streaming data gave rise to some interesting data pipeline implementations.

[1] The reason as to why Airflow does not support streaming is that there are no obvious behavior rules that could be set so that the airflow scheduler could deterministically check if it has been completed or not.

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  - standardize data in data elements based on field type
- join or merge (in a rule driven way) with other data sources

Big Data Pipeline - Batch

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- [[MapReduce]]

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- [[FlumeJava]]
- [[Apache Airflow]]

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- Hadoop provides the open source implementation of that model
- It was believed that all sorts of large-scale data processing can be tackled by MapReduce, [this is not true as you will see in future lectures]{style="color: red"}

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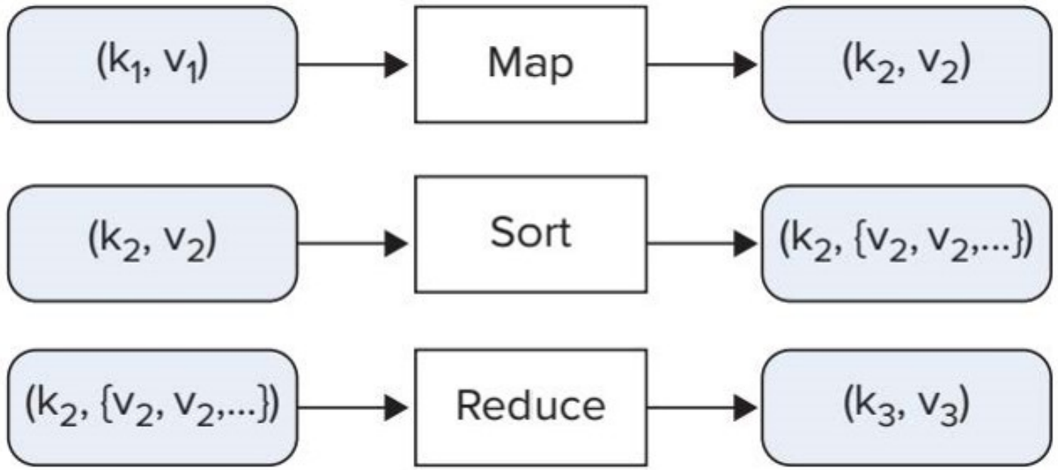
(k_1, v_1)
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(k_2, v_2)
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$(k_2, \{v_2, v_2, \ldots\})$
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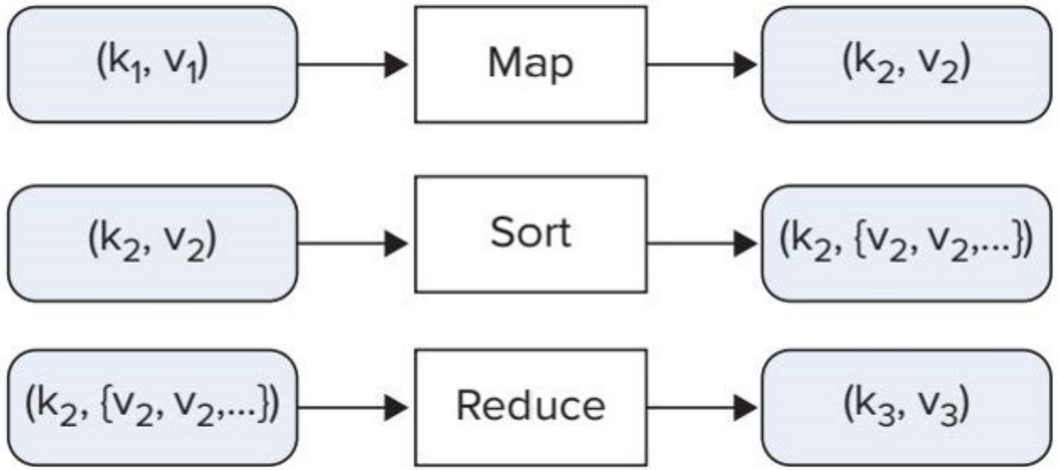

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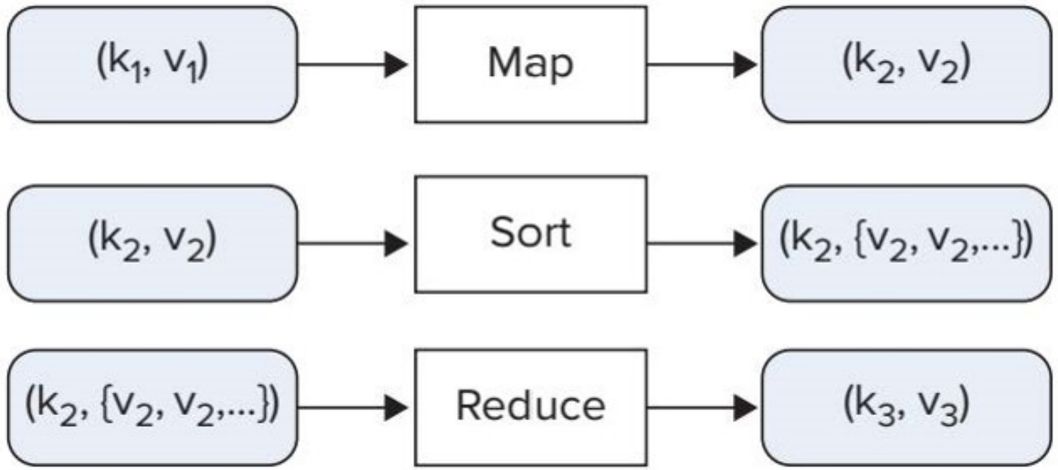

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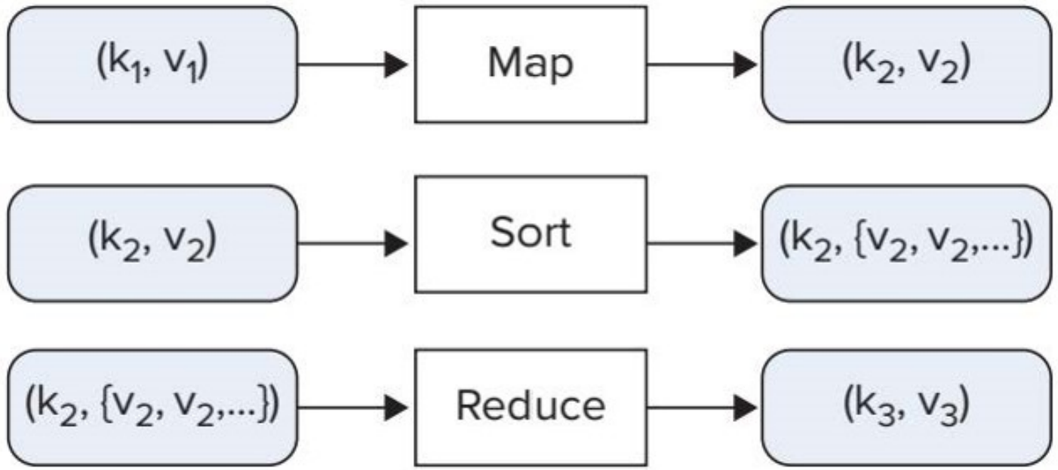

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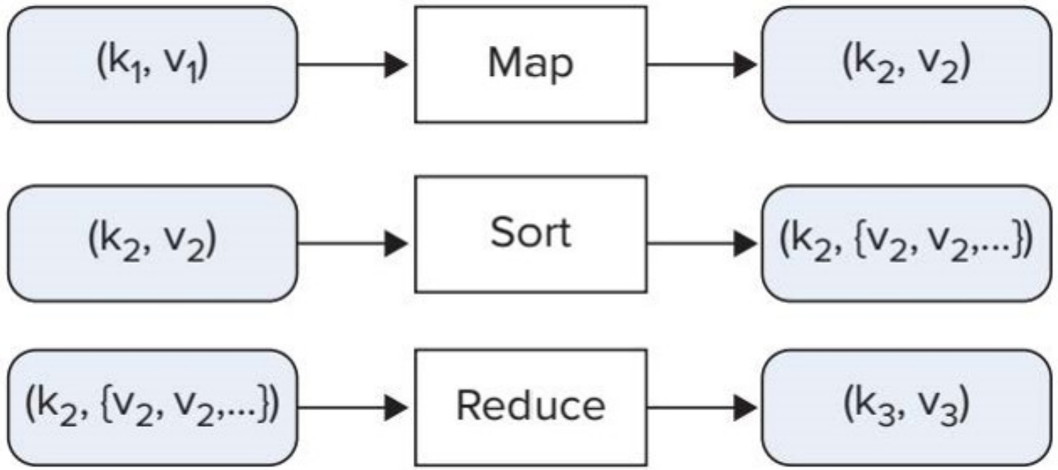

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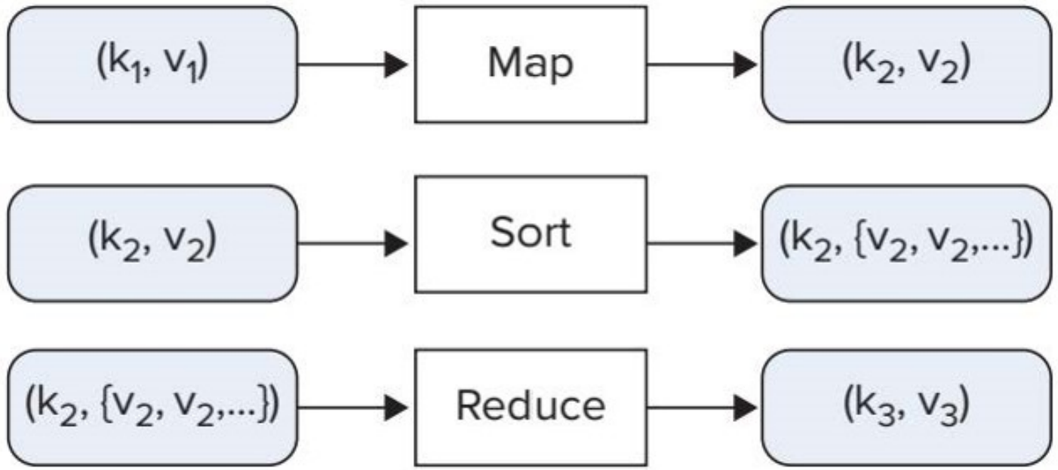

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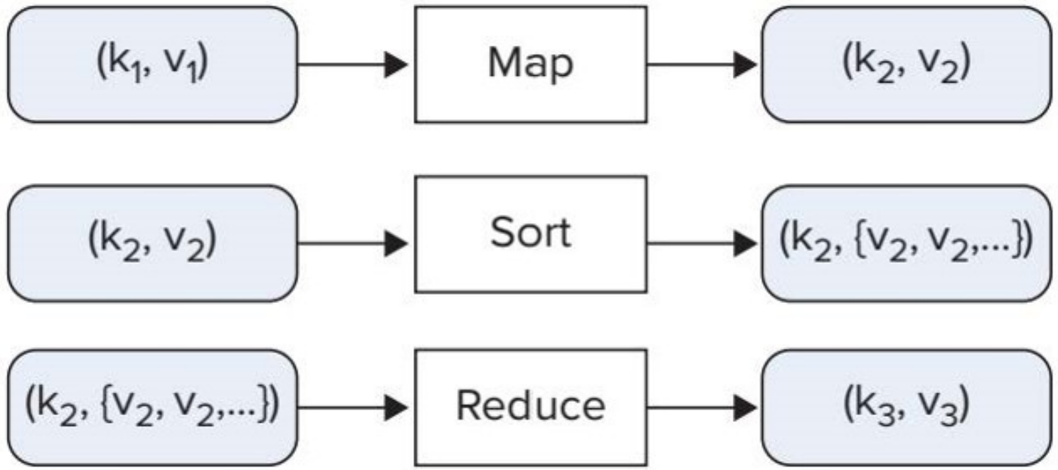

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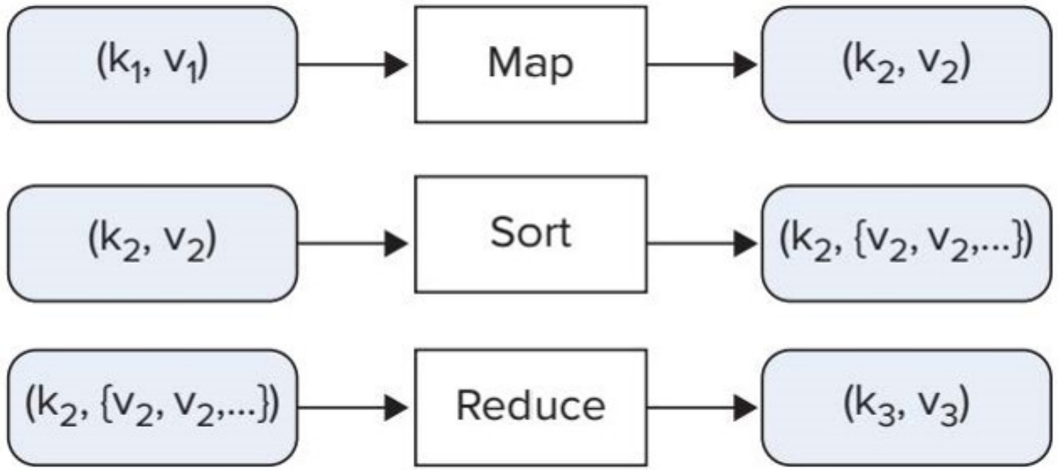

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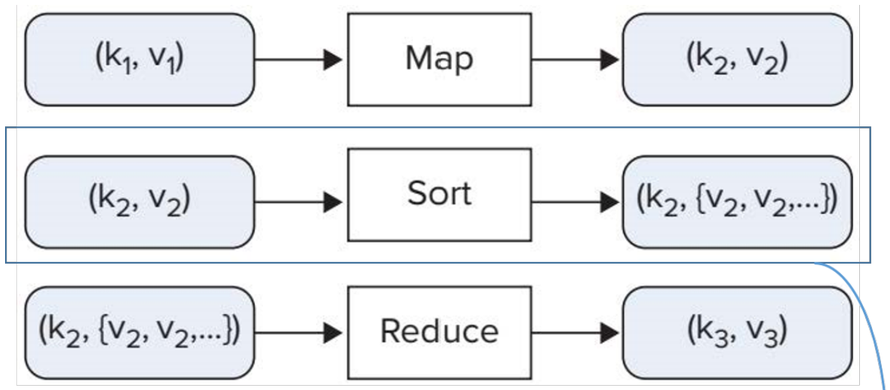
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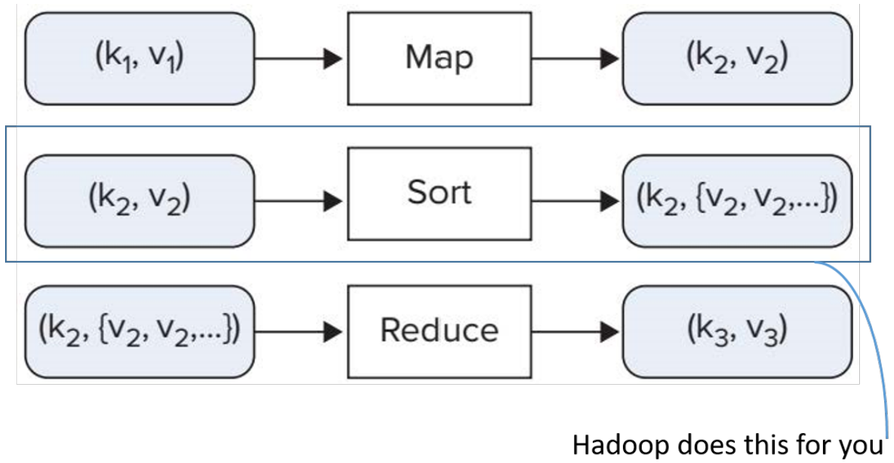

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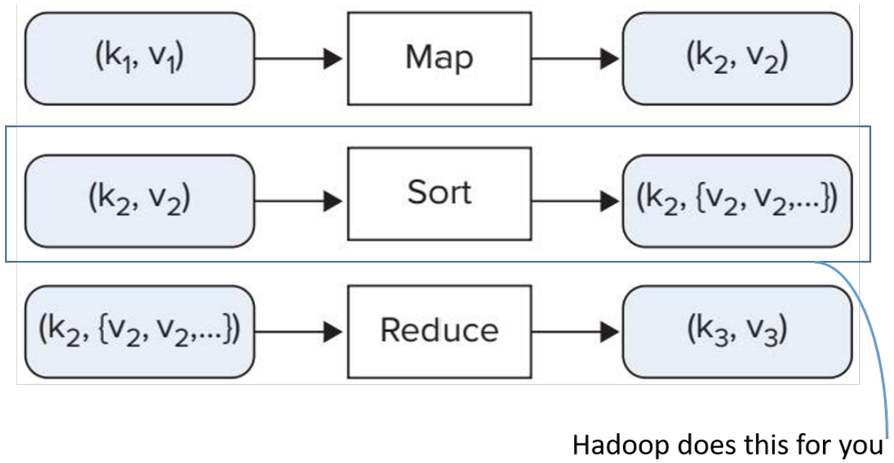

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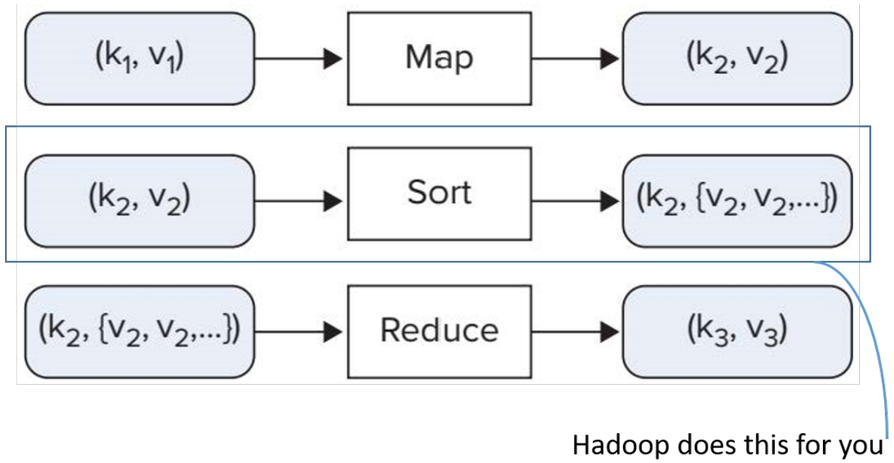

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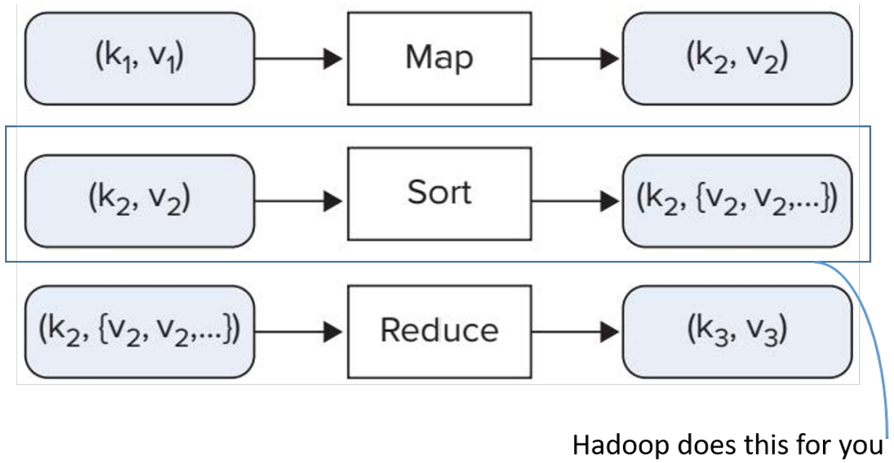

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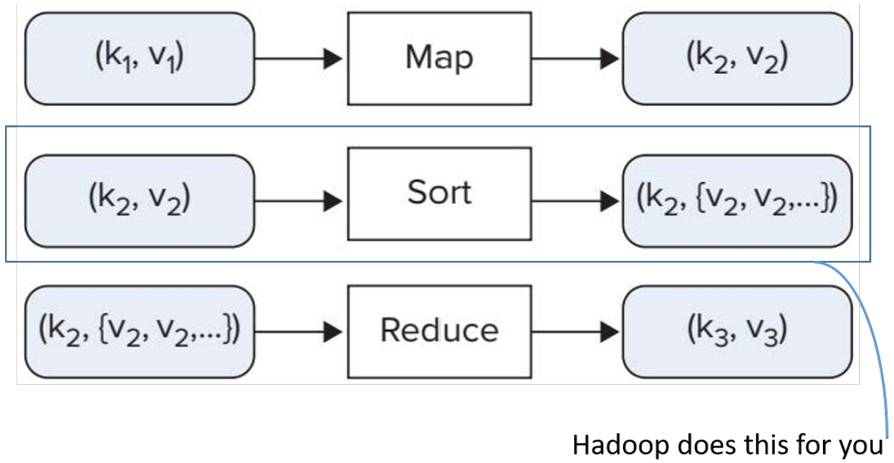

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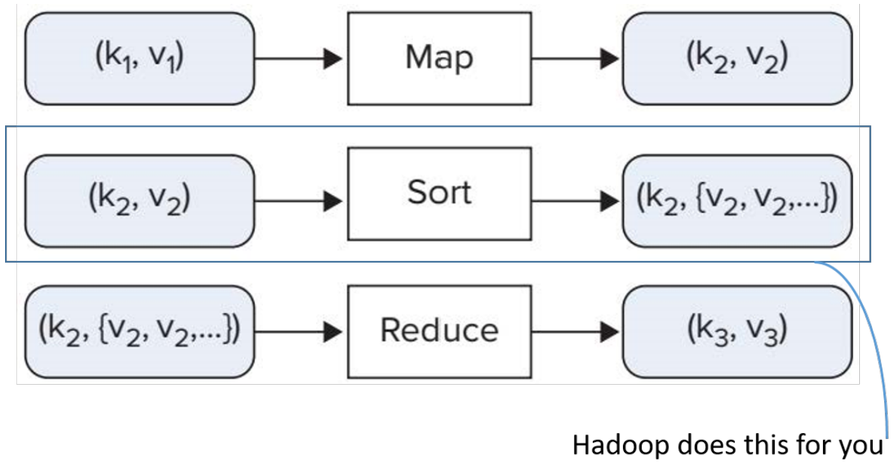

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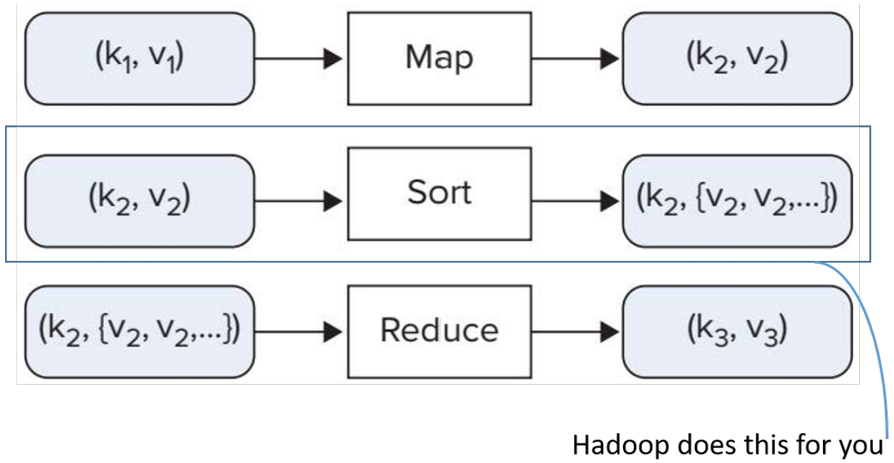
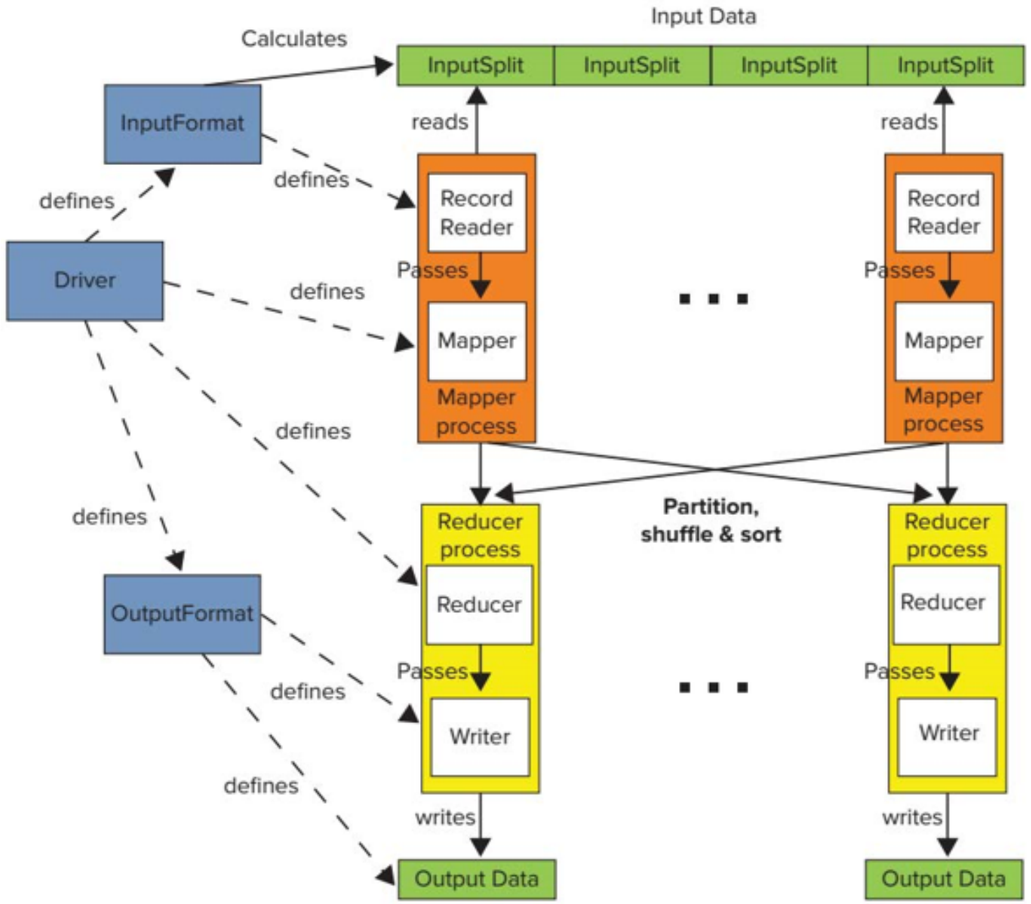


Workflow


Input Data
Calculates
InputSplit
InputSplit
InputSplit
InputSplit
InputFormat
reads
reads
defines
defines
Record Reader
Record Reader
Driver
Passes
Passes
defines
Mapper
Mapper
Mapper process
Mapper process
defines
defines
Partition, shuffle & sort
Reducer process
Reducer process
OutputFormat
Reducer
Reducer
Passes
Passes
defines
Writer
Writer
defines
writes
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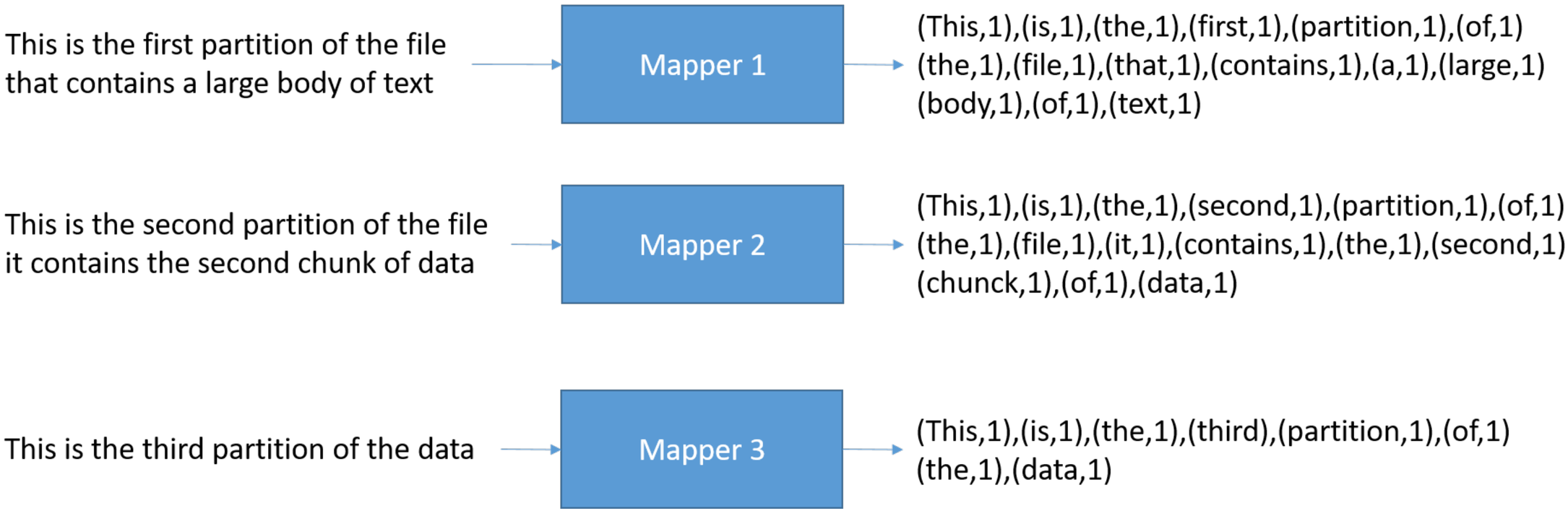
Output Data
Output Data

Example: Word Count

Word Count Mapper



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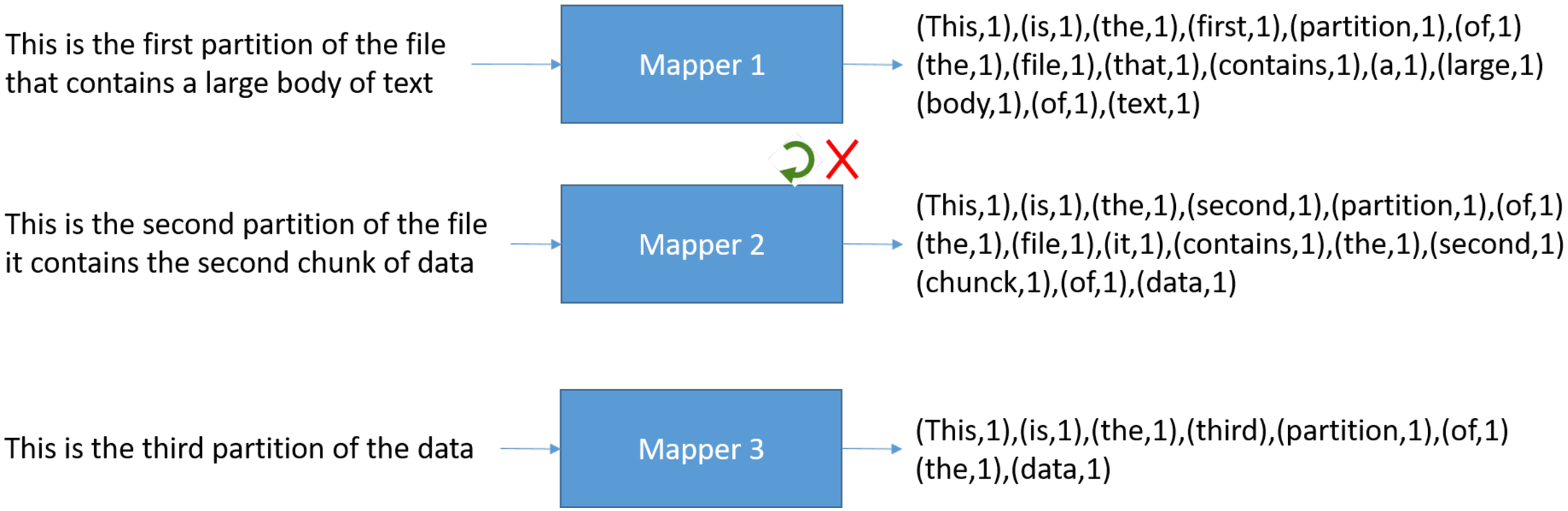
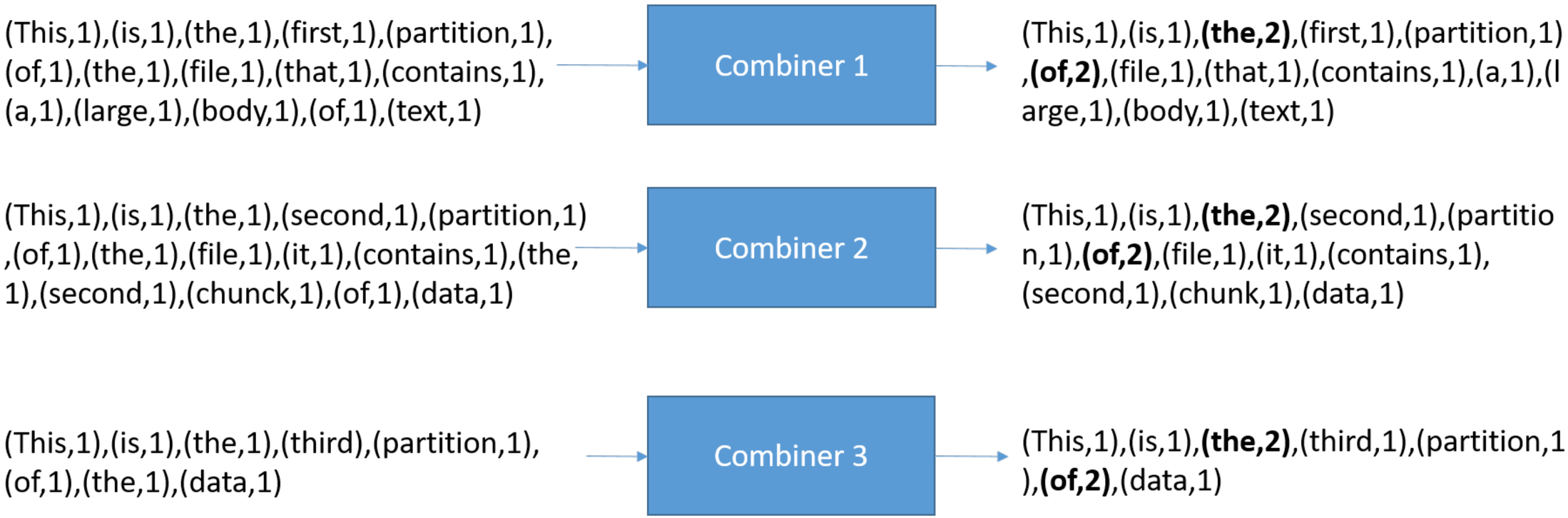


Word Count Combiner (optional) (local reducer)



Combiners run locally on the node where the mapper runs. They can be used to reduce the number of records emitted to the next phase

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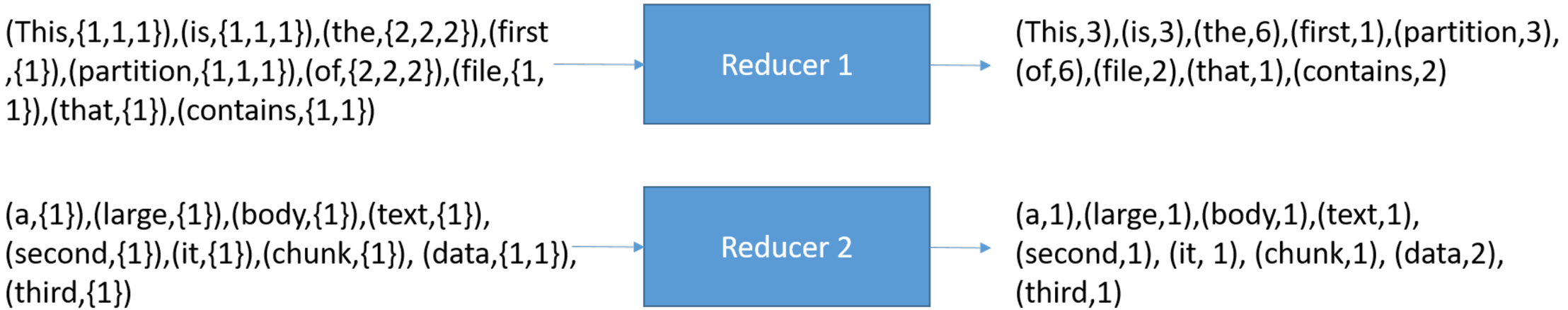
  - Transforms (k,v1), (k,v2), (k,v3) (kx,{v1,v2,v3})

Word Count Reducer



There will be two files written to the specified output path. The number is equivalent to the number of reducers.

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    - However, this will come with a large overhead as shuffle and sort will be invoked

FlumeJava[1]

Easy, Efficient Data-Parallel Pipelines

[1] The reason as to why Airflow does not support streaming is that there are no obvious behavior rules that could be set so that the airflow scheduler could deterministically check if it has been completed or not.

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- Many real-world computations require a chain of MapReduce works, e.g., graph analytics
- Additional coordination code chains together the separate MapReduce stages, requiring additional work to manage the intermediate results

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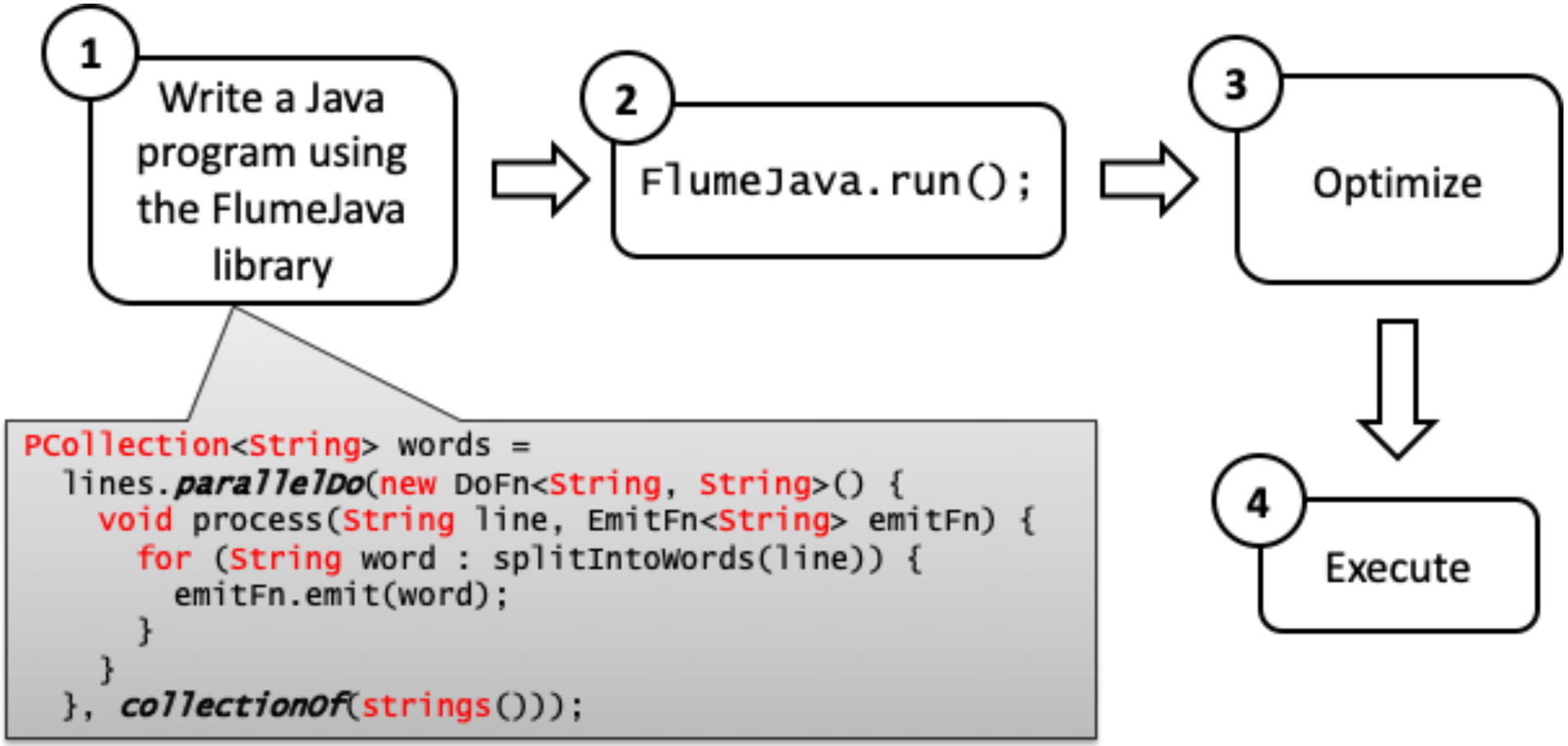
- abstract away the details of how data is represented, including whether the data is represented as an in-memory data structure
- FlumeJava evaluation is lazy: The invocation of a parallel operation does not actually run the operation, but instead simply records the operation and its arguments in an internal execution plan graph structure.

FlumeJava Workflow



Core Abstractions

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  - In Java, PTable<K,V> is a subclass of PCollection<Pair<K,V>>
- **PObjects**<T> is a container for a single Java object of type T that acts much like a future. Like PCollections, PObjects can be either deferred or materialized, allowing them to be computed as results of deferred operations in pipelines.

Parallel Operations (Primitives)

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- **parallelDo**() higher-order function that supports element-wise computation over an input PCollection<T>

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WordCount in Primitive FlumeJava

Sentences to Words

```
PCollection<String> words =
    lines.parallelDo(new DoFn<String,String>() {
        void process(String line, EmitFn<String> emitFn) {
            for (String word : splitIntoWords(line)) {
                emitFn.emit(word);
            }
        }
    }, collectionOf(strings()));
```

Words Occurrences

```
PTable<String,Integer> wordsWithOnes =
    words.parallelDo(
        new DoFn<String, Pair<String,Integer>>() {
            void process(String word,
                EmitFn<Pair<String,Integer>> emitFn) {
                    emitFn.emit(Pair.of(word, 1));
            }
    }, tableOf(strings(), ints()));
```

Occurrences to Counts

```
PTable<String,Collection<Integer>> gwOnes = wordsWithOnes.groupByKey();

PTable<String,Integer> wordCounts = gwOnes.combineValues(SUM_INTS);
```

Derived operations

Derived operations

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PTable<String,Integer> wordCounts = gwOnes.combineValues(SUM_INTS);
```

OR

```
PTable<String,Integer> wordCounts = words.count();
```

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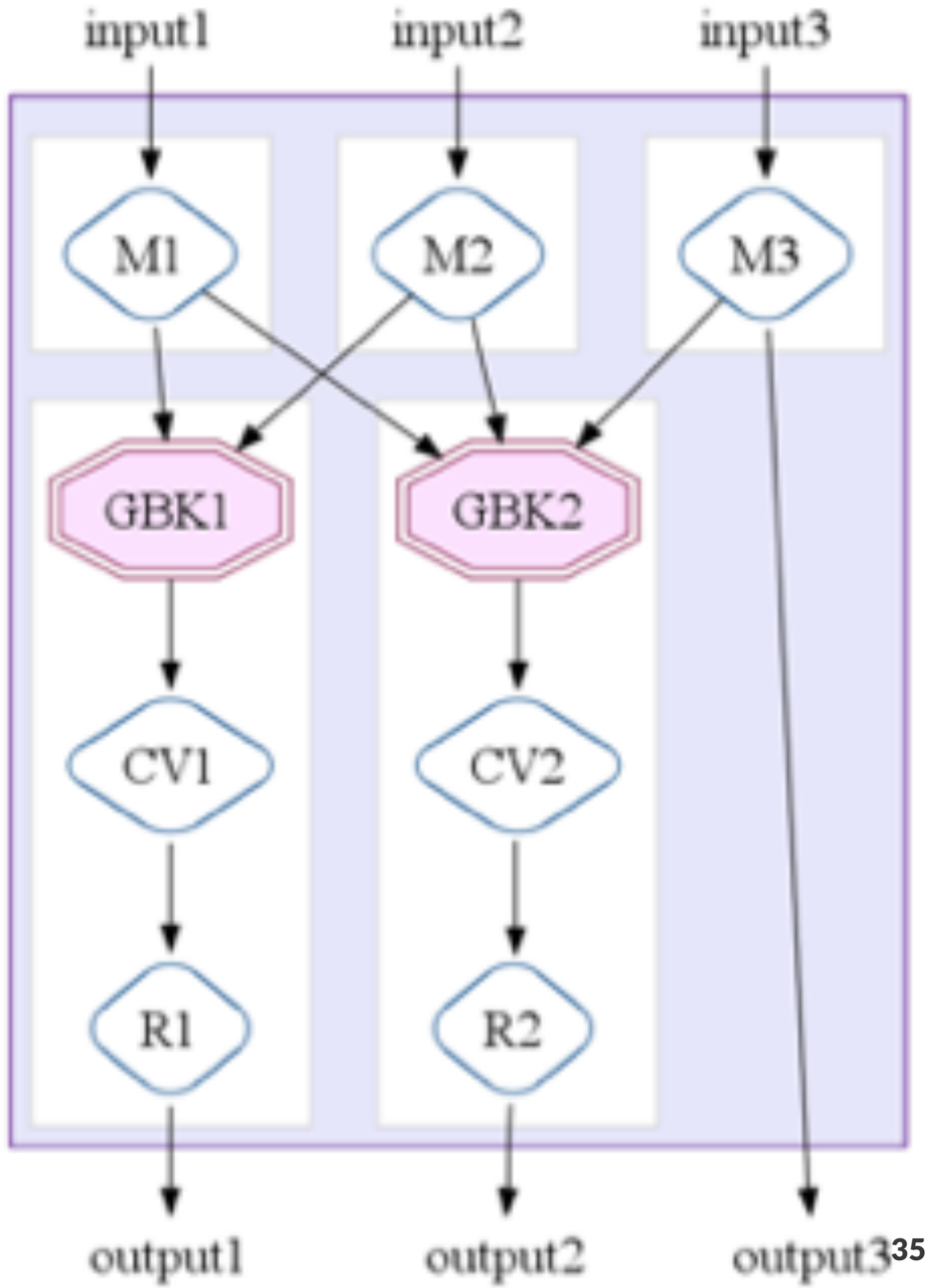
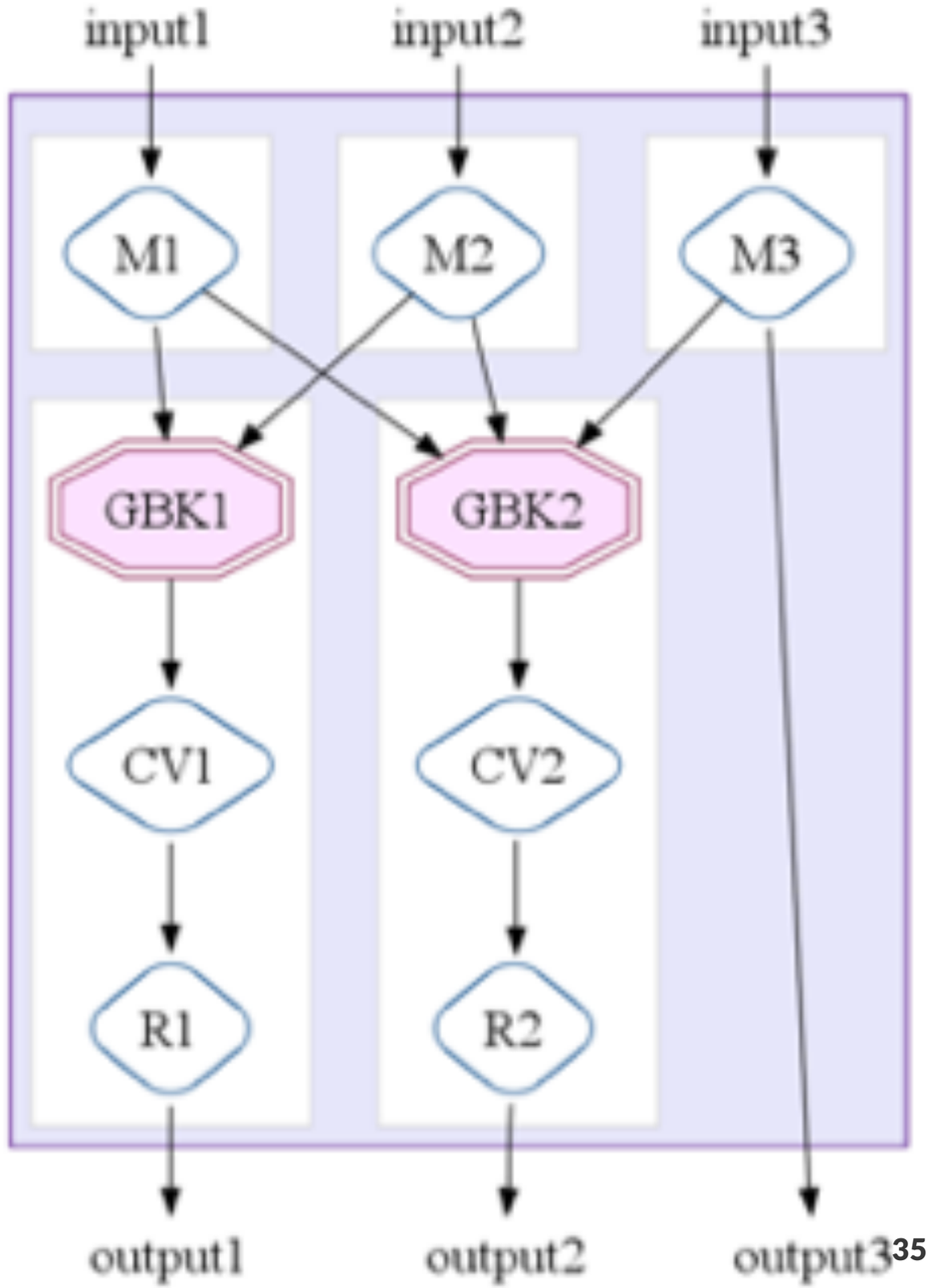
- **top**() which takes a comparison function and a count N and returns the greatest N elements of its receiver PCollection according to the comparison function.

MapShuffleCombineReduce (MSCR)



MapShuffleCombineReduce (MSCR)

- Transform combinations of the four primitives into single MapReduce



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- Transform combinations of the four primitives into single MapReduce
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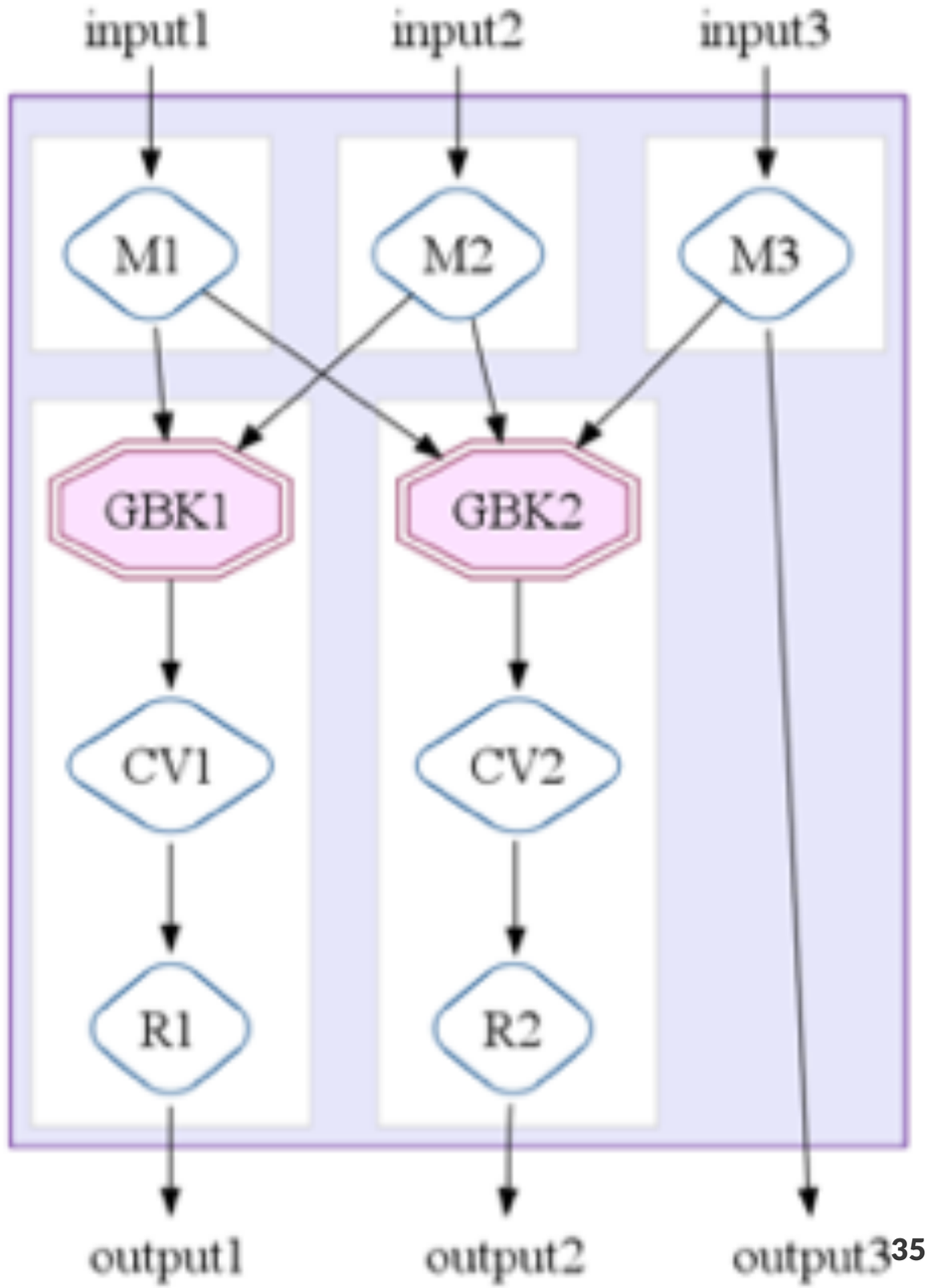

MapShuffleCombineReduce (MSCR)

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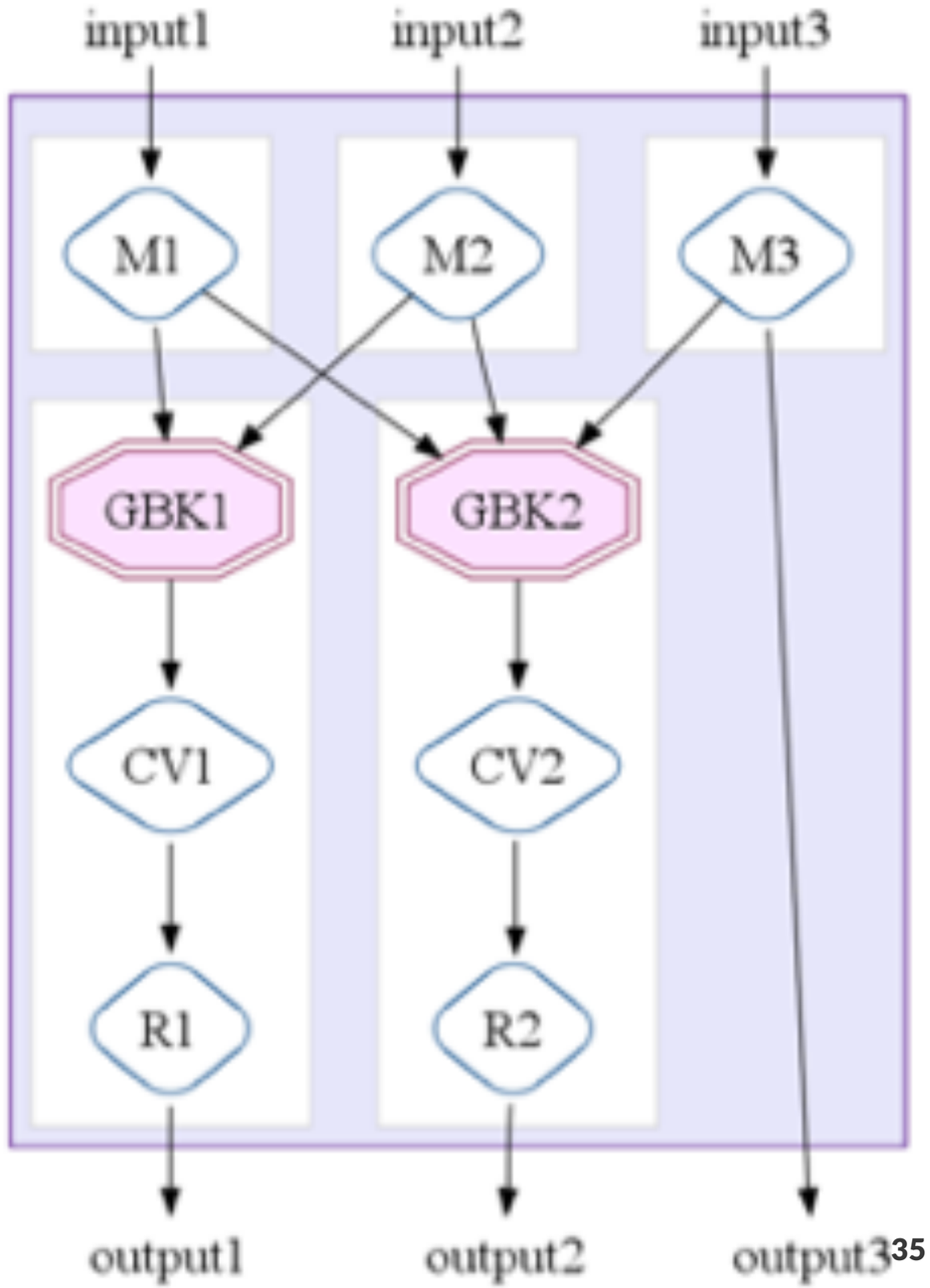
  - Multiple reducers/combiners



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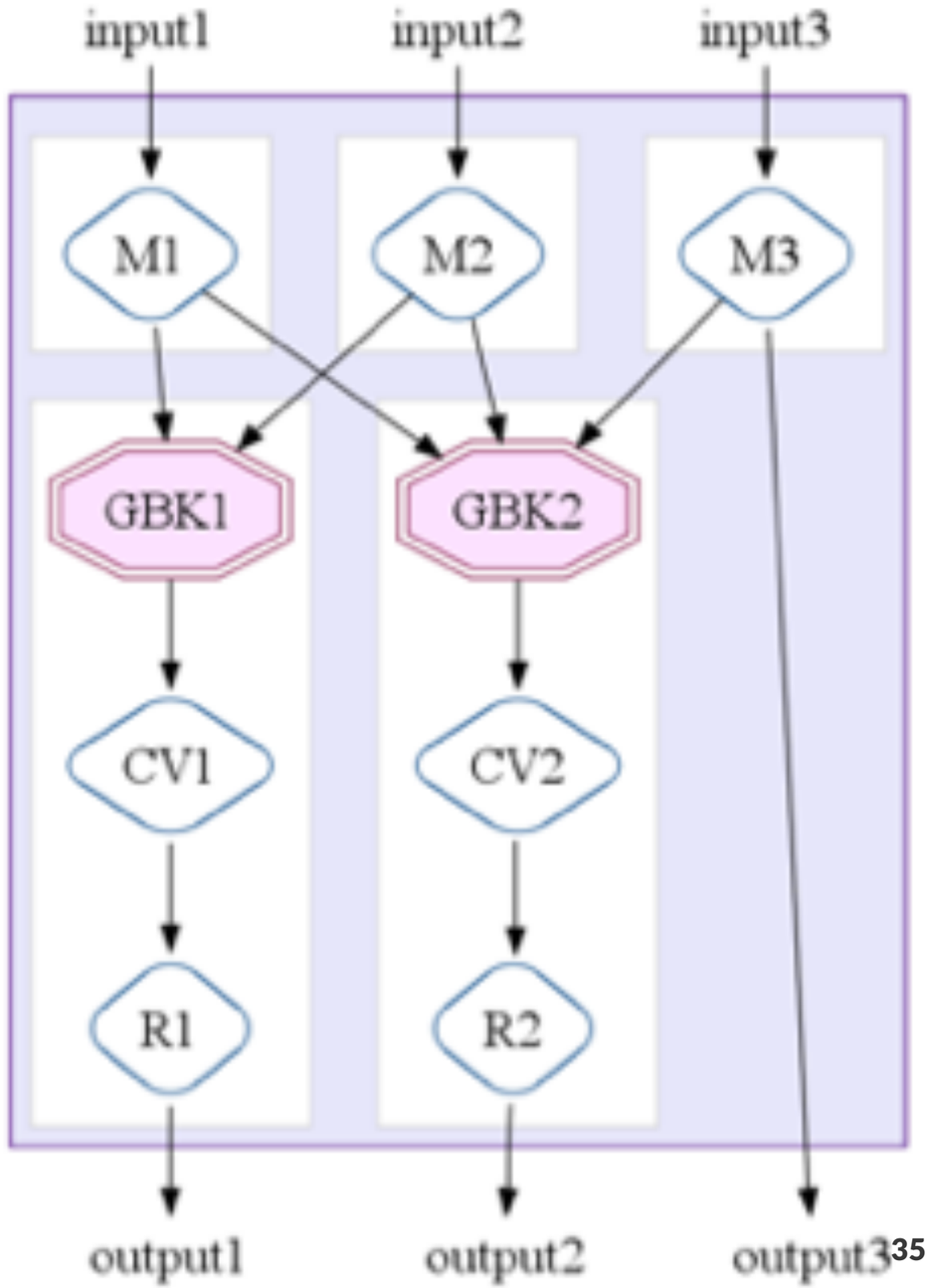

MapShuffleCombineReduce (MSCR)

- Transform combinations of the four primitives into single MapReduce
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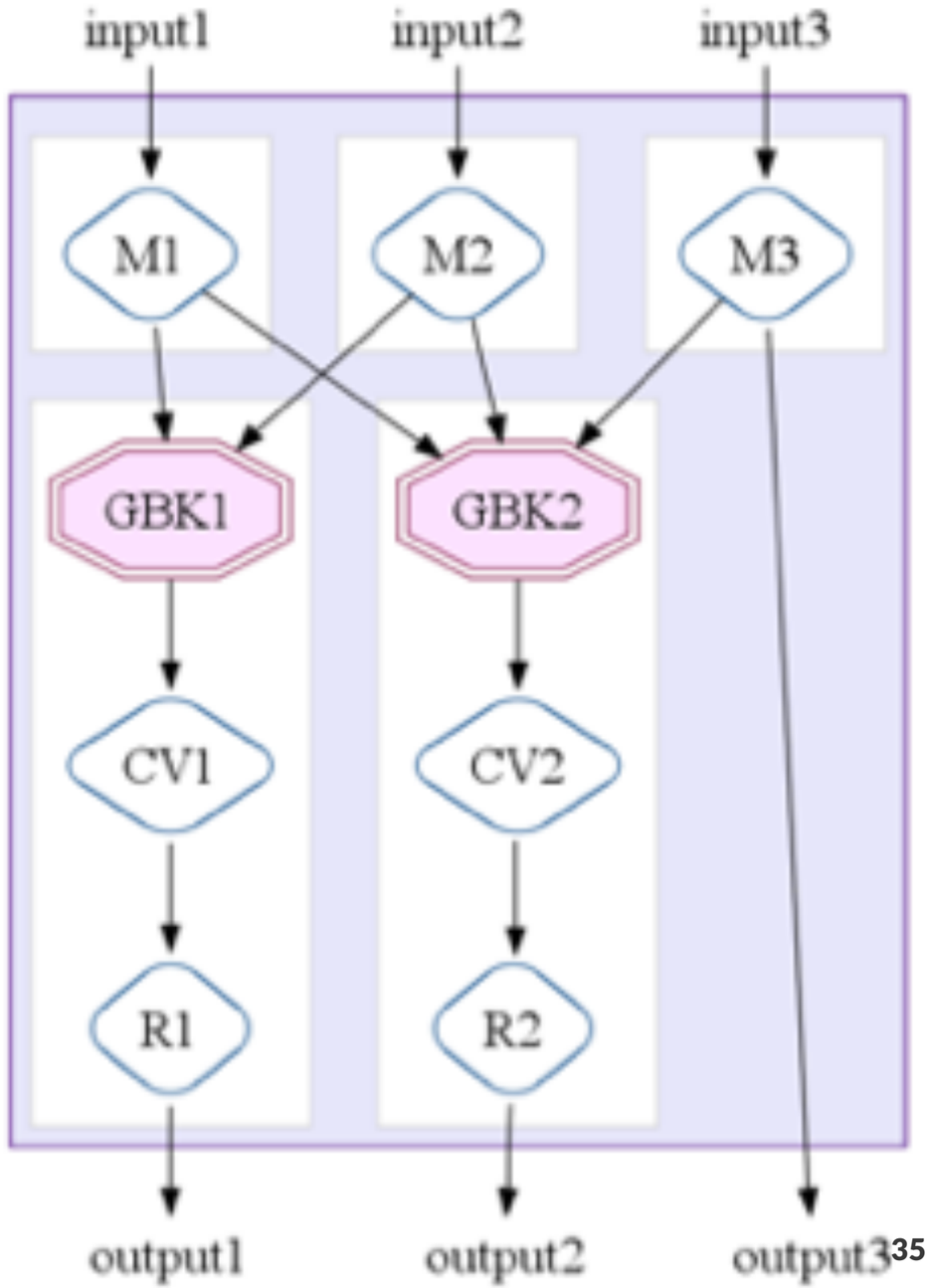
  - Multiple output per reducer
  - Pass-through outputs



Optimizer

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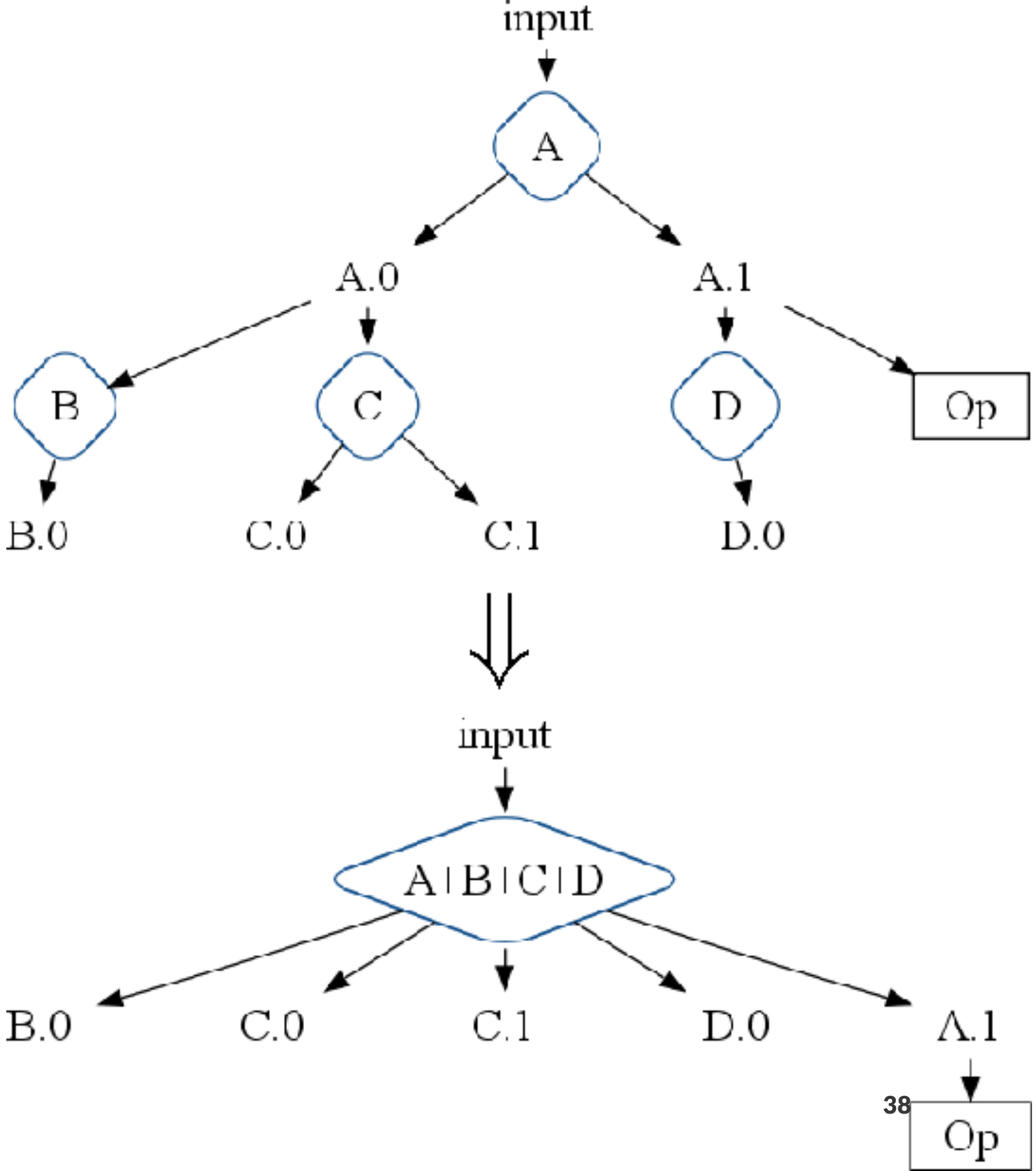
ParallelDo Fusion

One of the simplest and most intuitive optimizations is ParallelDo producer-consumer fusion.



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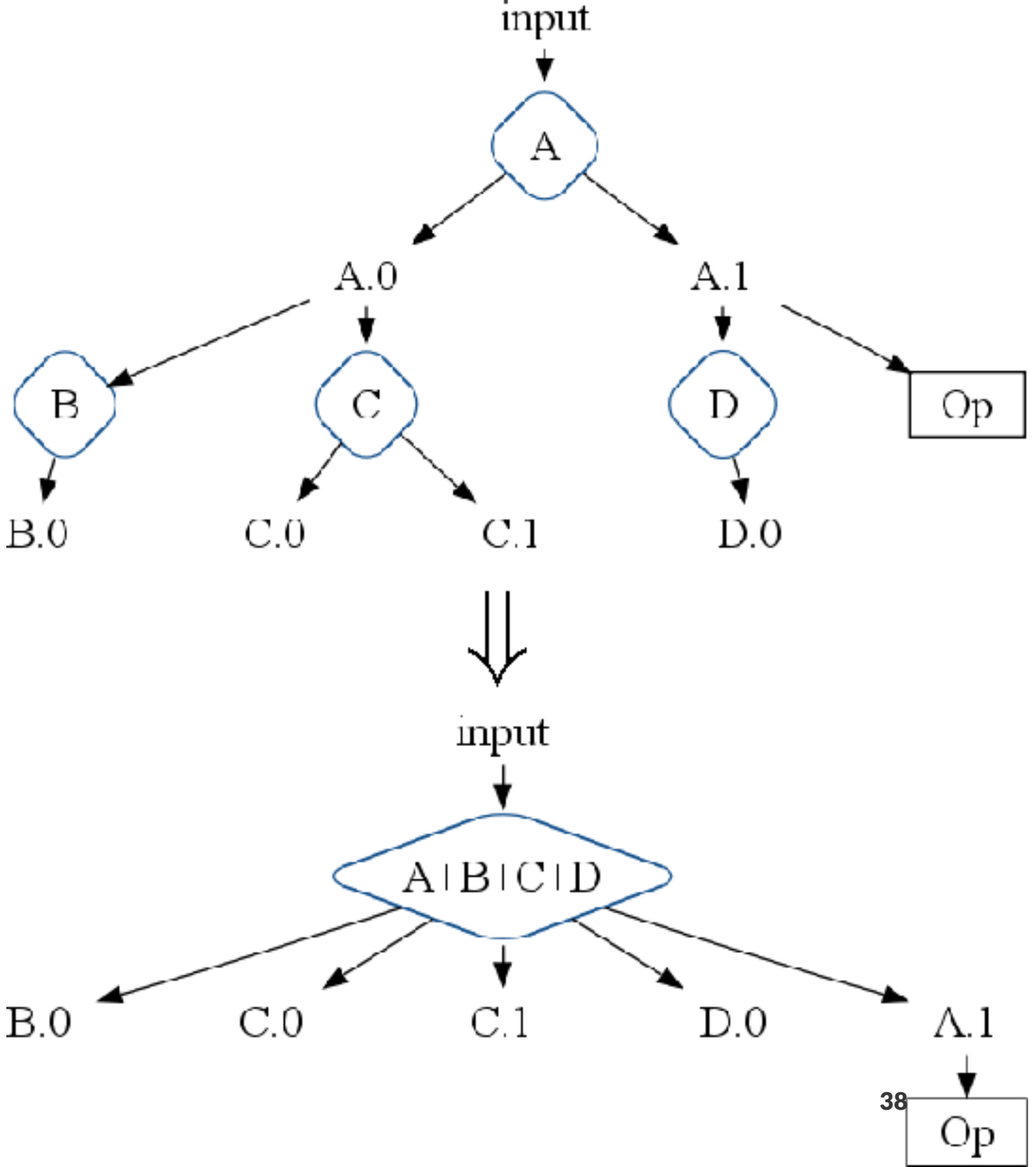

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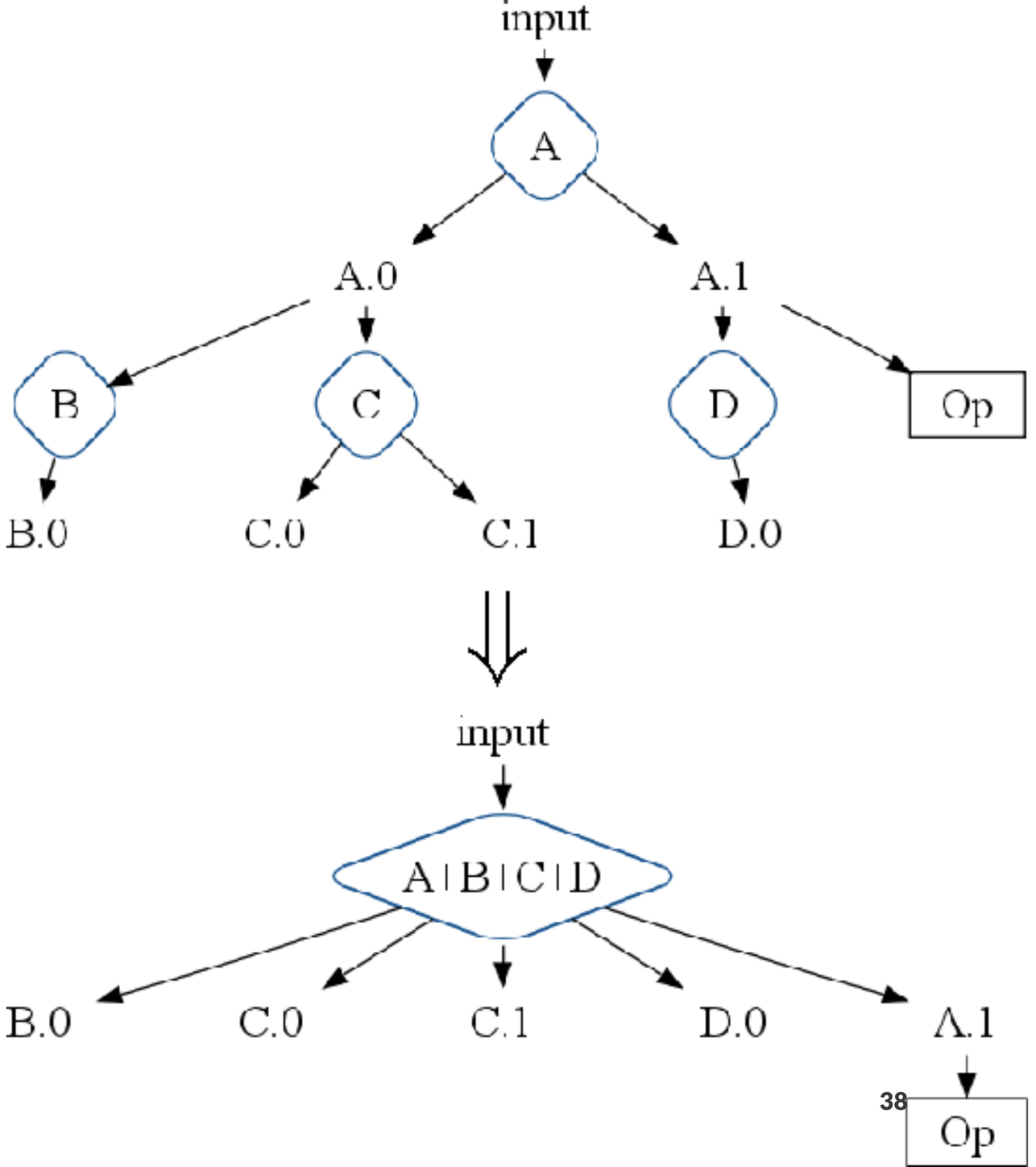
- **sibling fusion** when two or more ParallelDo operations read the same input they are fused into a single multi-output ParallelDo operation that computes the results of all the fused operations in a single pass over the input.



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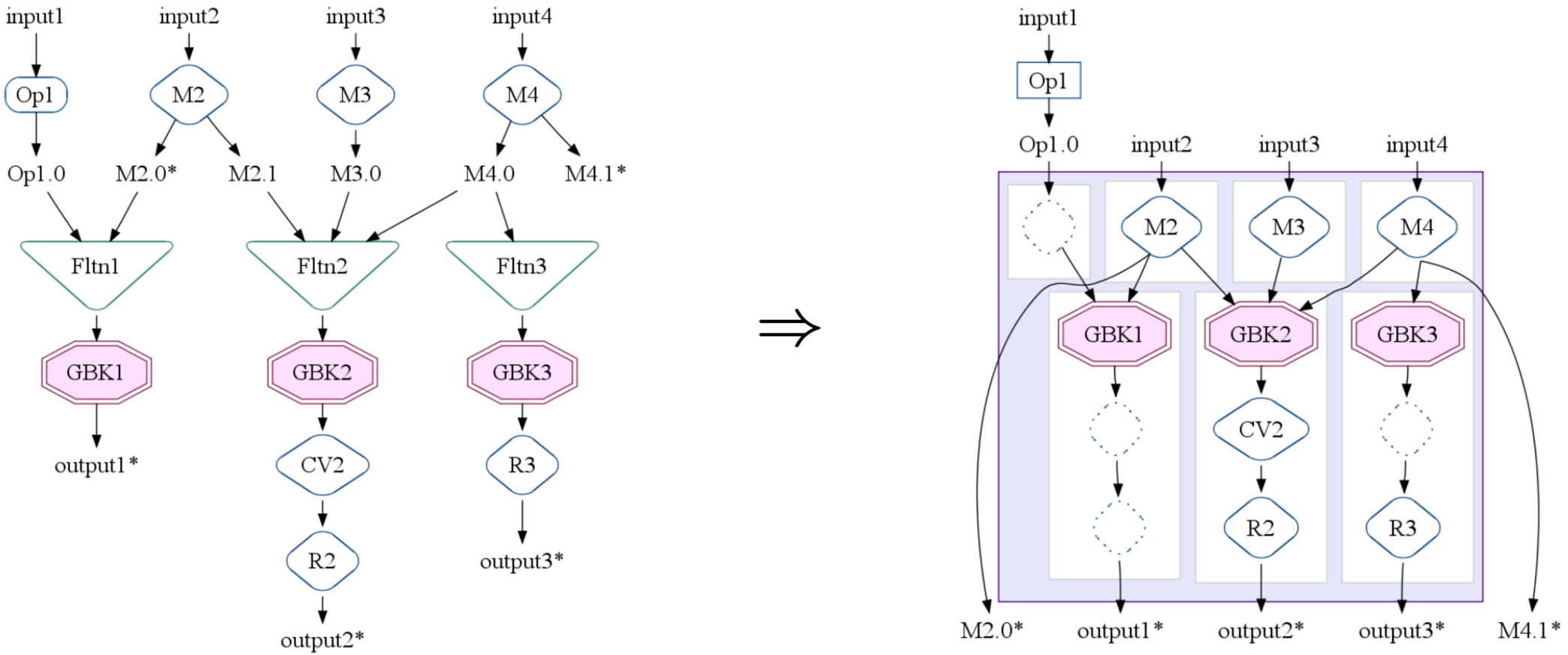
- **Fuse ParallelDos**
- **Fuse MSCRs**

MSCR Fusion

An MSCR operation is produced from a set of related GroupByKey operations.

In turn, GroupByKey operations are related if they consume the same inputs created by the same (fused) ParallelDo operations.



The resulting MSCR operation has 4 input channels and 5 output channels

Apache Airflow

Apache
Airflow

What Airflow is...

Apache Airflow is a dataflow orchestrator to define data engineering workflows

Airflow allows to parallelize jobs, schedule them appropriately with dependencies and historically reprocess data when needed.

Airflow glues all the data engineering steps, i.e., ingest, transform, store.

What Airflow is not...

A data processing tool. No processing happens in airflow, so there's no ~~need for~~ fault tolerance

Airflow does not provide any built-in workflow versioning

Airflow does not support streaming computation (talk later)[1]

[1] The reason as to why Airflow does not support streaming is that there are no obvious behavior rules that could be set so that the airflow scheduler could deterministically check if it has been completed or not.

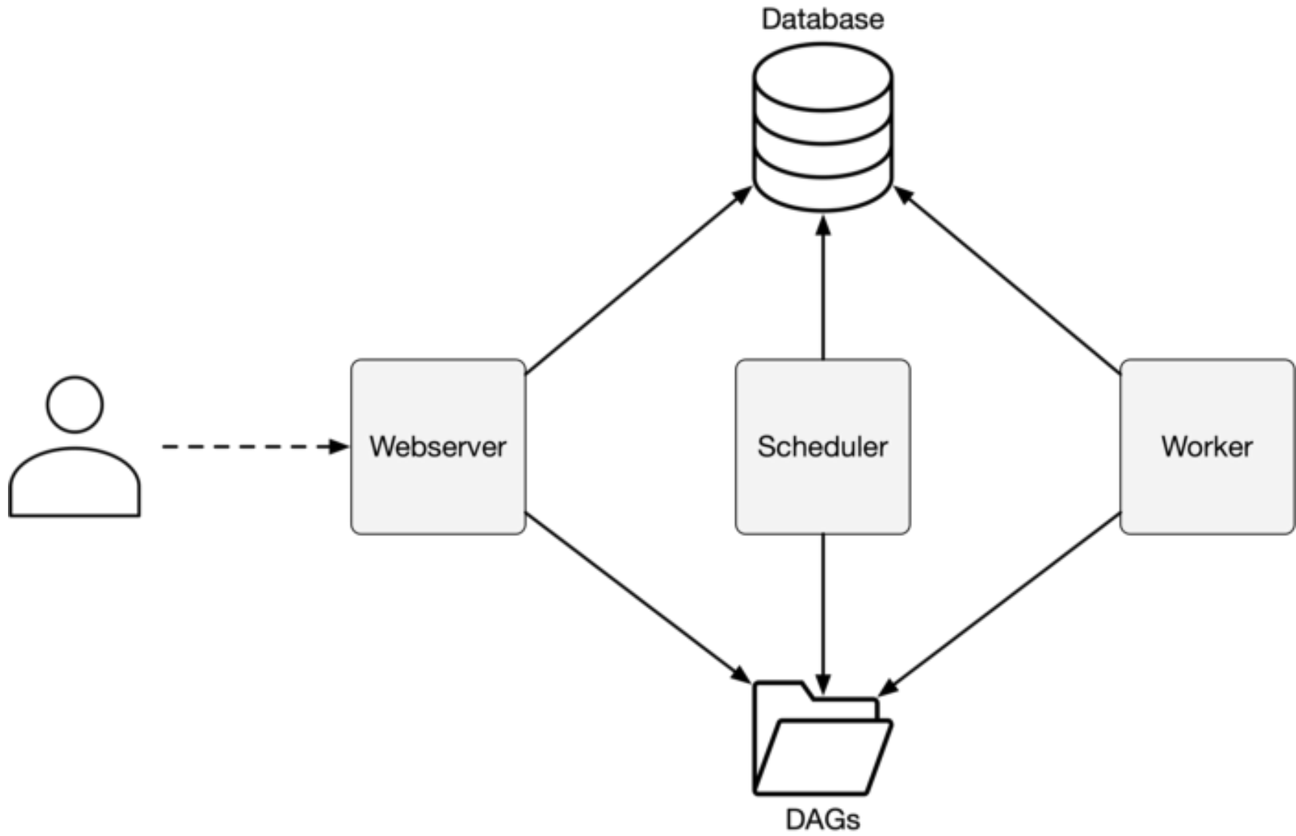
The DAG

Airflow (and almost any orchestrato), organizes the processing in a Directed Acyclic Graph (DAG). Acyclicity is required to reduce ambiguity.

Data engineering tasks are the graph nodes, Edges represent dependency relationships, e.g., if task 1 depends on task 2, then task 2 has to succeed.

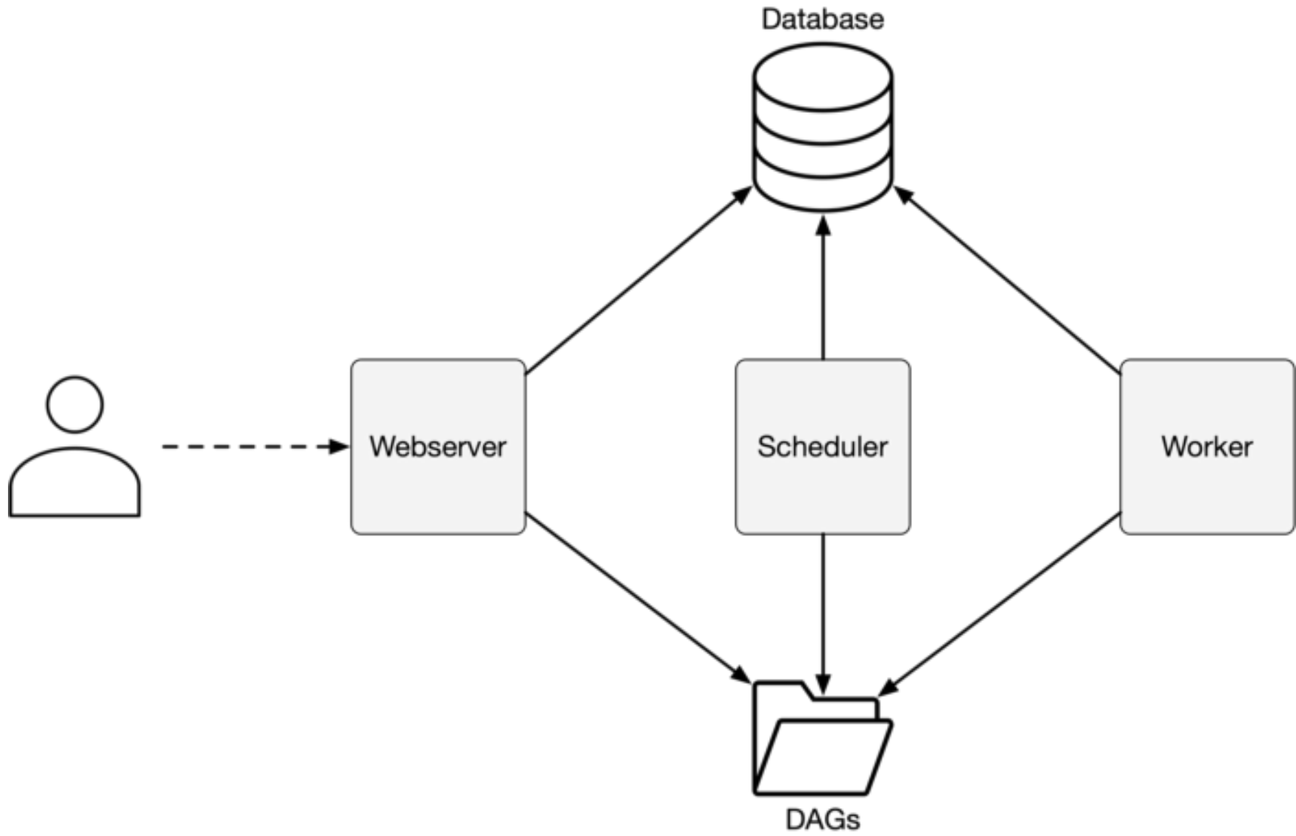
Notably, "success" doesn't have to mean that it has been succesfully completed. It can mean that it hasn't been skipped, for instance.

Airflow architecture



Airflow architecture

- **Web server** - nice GUI with access to the logs and most of Airflow's functionality, such as stopping and clearning DAGs.



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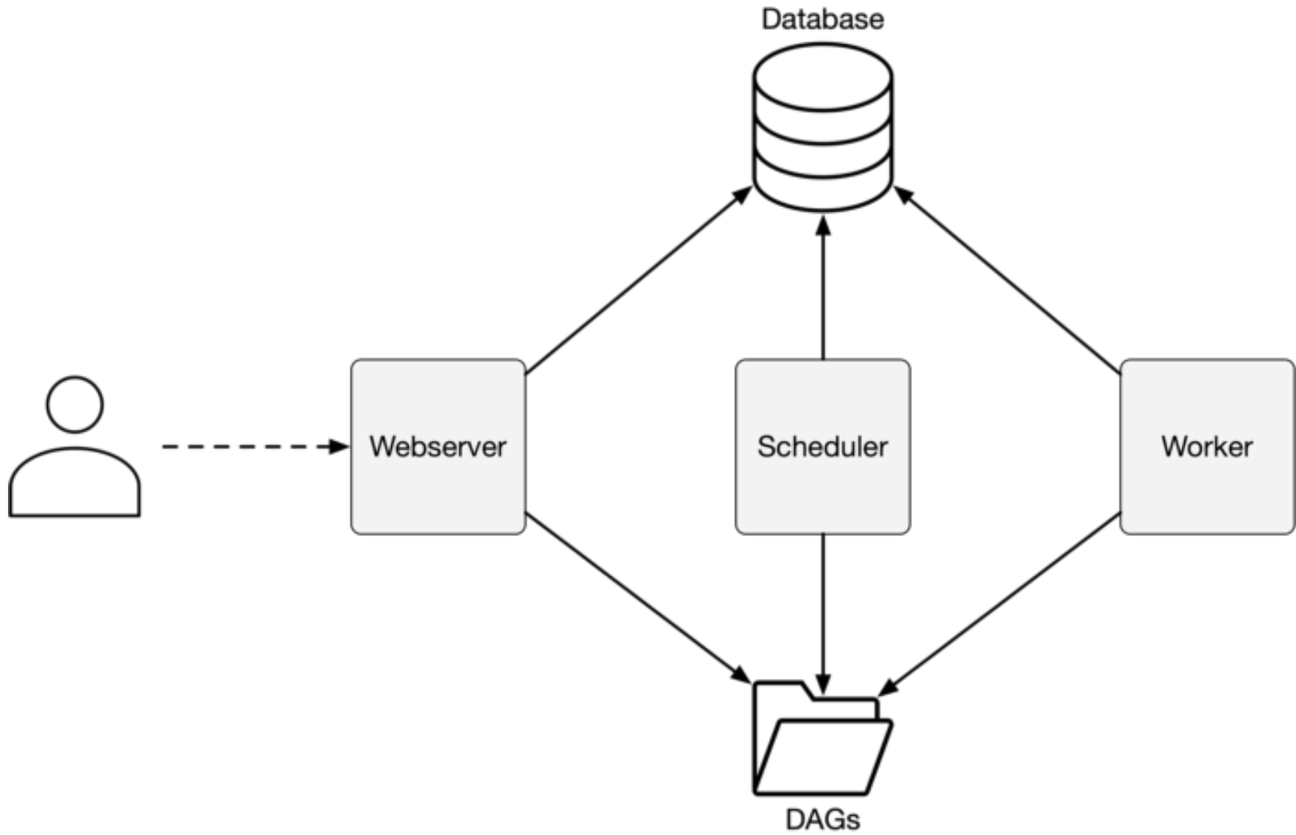
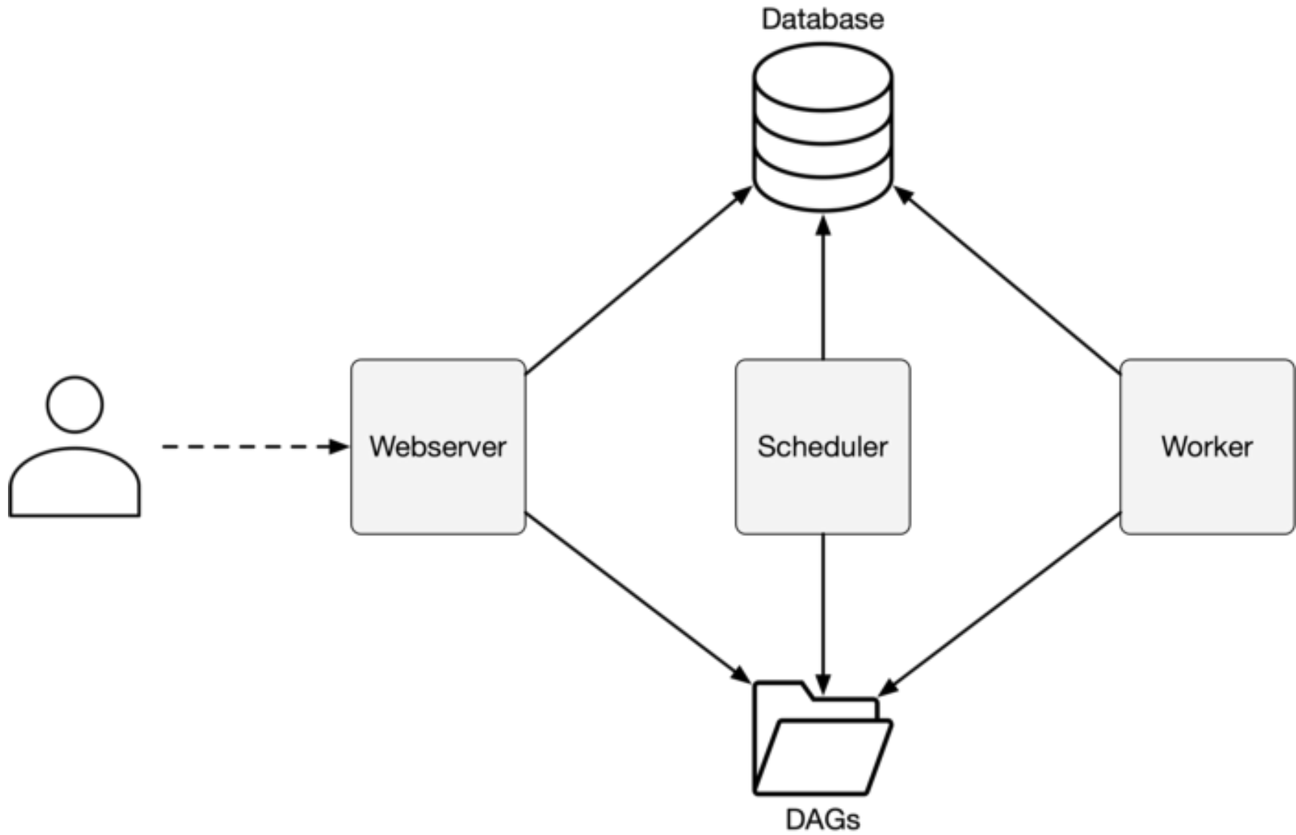


Airflow architecture

- **Web server** - nice GUI with access to the logs and most of Airflow's functionality, such as stopping and clearning DAGs.
- **Scheduler** - Puts the DAGs to action by coordinating the work to be done
- **Workers** - do the job assigned by the scheduler.



Workflows

Workflows are written entirely in Python

The first thing to do is to instance the DAG, declaring a dictionary with default arguments such as *start date*, *concurrency* and *schedule interval*.

```
default_args_dict = {
    'start_date': airflow.utils.dates.days_ago(0),
    'concurrency': 1,
    'schedule_interval': None,
    'retries': 1,
    'retry_delay': datetime.timedelta(minutes=5),
}

first_dag = DAG(
    dag_id='first_dag',
    default_args=default_args_dict,
    catchup=False,
)
```

Idiosyncrasies

If you thought it would **start** at the moment of **start***date, you thought wrong~~, haha~~. The first task will actually start on start*date + schedule_interval.

In case you tried to run a DAG, for the first time, with a start date of let's say, 1 month ago, and a schedule interval of 5 minutes, then airflow would generate 8640 runs, which is the amount of 5 minute intervals within a month.

In case you didn't put `catchup=False` you will be in for a treat next time you start it, since airflow will re-run the DAG for n schedule intervals between when you turned it off and the moment of turning it on again.

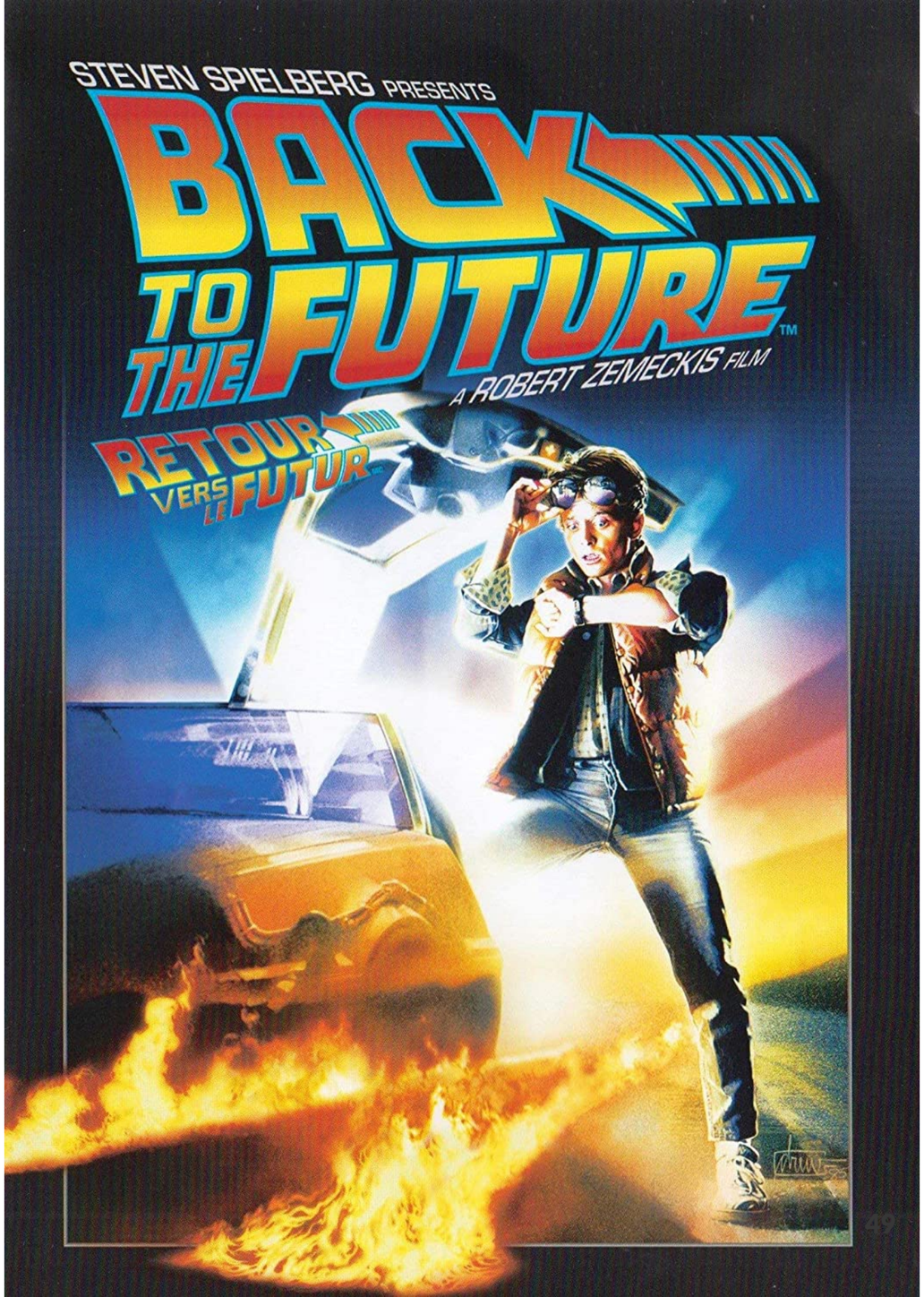
Backfilling

Often, we might desire to revisit the historical trends and movements. In such cases, we would need to compute metric and dimensions in the past,

Airflow has a recipe for Backfilling. You can call the command

```
backfill -s START_DATE -e
END_DATE dag_id
```

from the cli, and it will rerun any DAG with the specified dates, and that way you can very effortlessly satisfy your tech lead's needs.



Operators

DAGs describe **how** to run a data pipeline, operators describe **what** to do in a data pipeline.

Operators trigger data transformations, which corresponds to the **T**ransform step

Operators: Sensors, Operators, and Transfers

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- **Operators**: triggers a certain action (e.g. run a bash command, execute a python function, or execute a Hive query, etc)
- **Transfers**: moves data from one location to another

DummyOperator (1/2)

The simplest, yet not useless, operator that there is, is the dummy:

```
task_one = DummyOperator(
    task_id='get_spreadsheet',
    dag=first_dag,
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Operators are declared similarly as dags, and only require two arguments at first:

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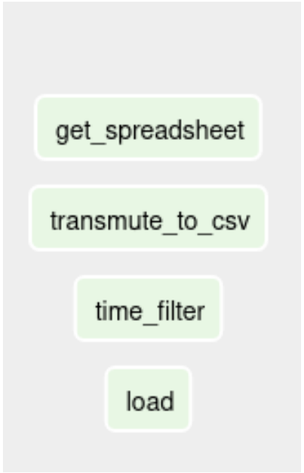
Operators are declared similarly as dags, and only require two arguments at first:

- `task_id` = unique id for the operator
- `dag` = which dag does does this operator belong to? Because there can be sub-dags, this needs to be declared explicitly.

DummyOperator (2/2)

In practice, the dummy operator does nothing, but it can be used to do two things:

More often than not we would like to visualize an ETL process in the least time-wasting manner as possible.



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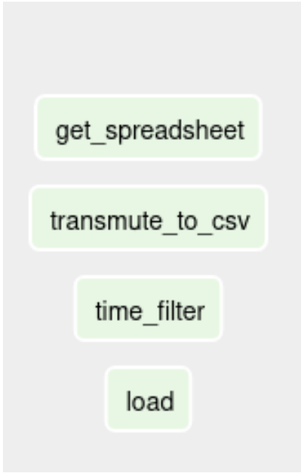
- sketching a dag out



More often than not we would like to visualize an ETL process in the least time-wasting manner as possible.

DummyOperator (2/2)

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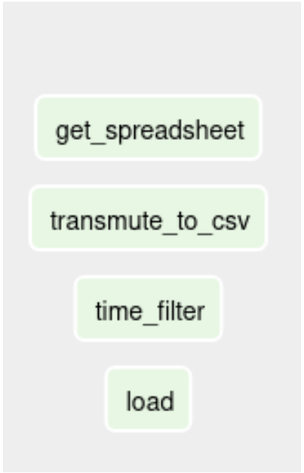

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- `PostgreSQL` allows you to communicate with postgres instances.
- `BashOperator` allows you to run shell scripts
- `PythonOperator` allows you to run Python code

BashOperator

Let us define a non-dummy operator, that runs a bash command:

```
task_one = BashOperator(
    task_id='get_spreadsheet',
    dag=first_dag,
    bash_command="curl http://www.gerbode.net/spreadsheet.xlsx --output /usr/local/airflow/data/{{ds_nodash}}.xlsx",
    trigger_rule='all_success',
    depends_on_past=False

)
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)
```

- `bash_command`- in case you know bash, you have already figured it out that this works almost exactly as typing `bash -c "some command"`
- `depends_on_past=False` means that if it failed during the previous dag run then it won't run this time. This is important because, as we've seen, airflow can have overlapping dag runs.

Python Operator

The last part we have to go over is both the briefest and most important, the Python Operator:

Very similar to the bash operator, having `task_id`, `dag`, `trigger_rule` and `depends_on_past`, as pretty much any other operator.

Python Operator takes a function as an input `python_callable`, that is where the python part of the python operator lies at. The callable's arguments are given by the `op_kwargs` dictionary, which also allows you to template these arguments.

```
task_one = PythonOperator(
    task_id='get_spreadsheet',
    dag=second_dag,
    python_callable=_get_spreadsheet,
    op_kwargs={
        "output_folder": "/usr/local/airflow/data",
        "epoch": "{{ execution_date.int_timestamp }}",
        "url": "http://www.gerbode.net/spreadsheet.xlsx"
    },
    trigger_rule='all_success',
    depends_on_past=False,
)
```

Task Relationships

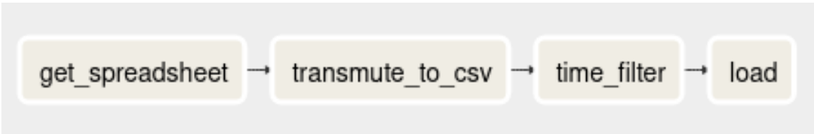
The directed relationships are given by the edges, and are very easily defined as follows, written at the end of the DAG file:

```
node_1 >> node_2 >> node_3 >> node_4
```

Looks like

Example

We want to show that the ETL process starts with `get_spreadsheet`, then its format is transmuted to a proper csv on `transmute_to_csv`, which is then filtered by time, `time_filter` to be loaded somewhere, `load`.




```
get_spreadsheet >> transmute_to_csv >> time_filter >> load
```

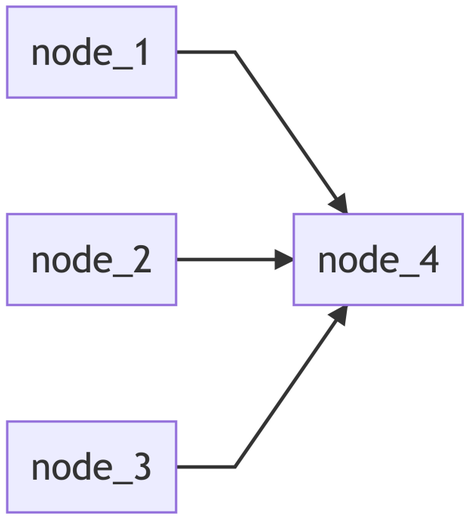
Will yield the following sequential configuration:

N-Ary Relationships

N-Ary are encoded as lists, so you can put to code that many nodes have an edge to one node as follows:

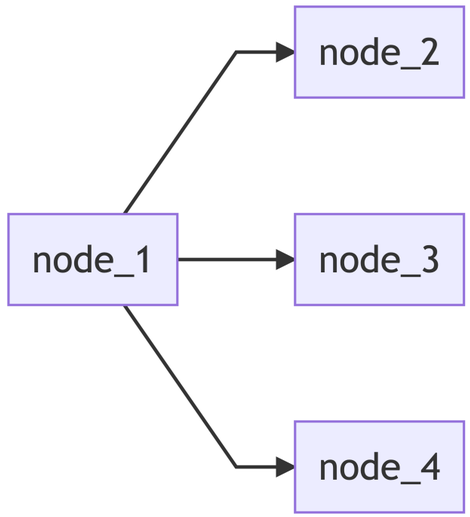
many-to-one

```
[node_1, node_2, node_3] >> node_4
```



one-to-many

```
node_1 >> [node_2, node_3, node_4]
```



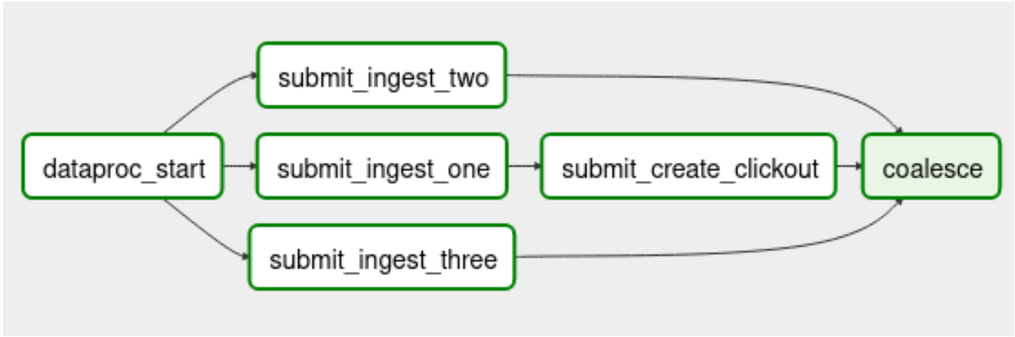
Example

Let's say that you have to create an ETL process entirely done in the cloud, and we define the following tasks:

We could define that with the following edge configuration:

```
dataproc_start >>
    [dataproc_ingest_one, dataproc_ingest_two, dataproc_ingest_three]
dataproc_ingest_one
    >> dataproc_create_clickout

[dataproc_create_clickout,
    dataproc_ingest_two,
        dataproc_ingest_three] >> end
```



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- `dataproc_start` - we use the google CreateDataProc operator in order to start a dataproc cluster that will be used to run pyspark scripts.

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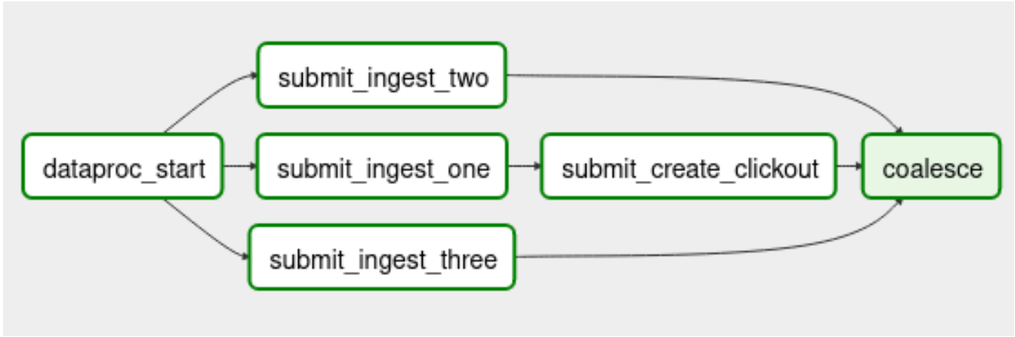

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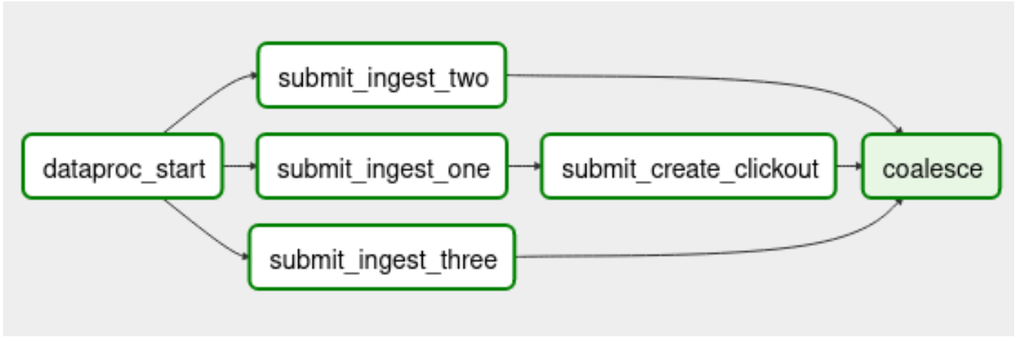

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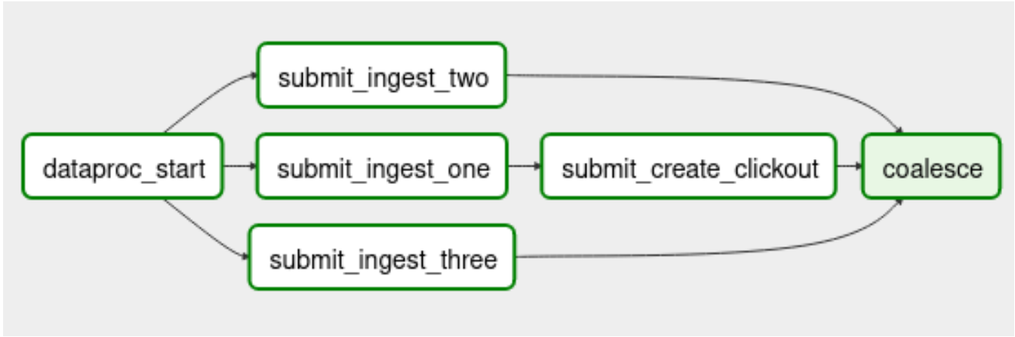

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- `submit_ingest_two, submit_ingest_three` - the same as `submit_ingest_one` except no other process depends on it
- `coalesce` - after all tasks have finished their execution, we would like to turn off the cluster.

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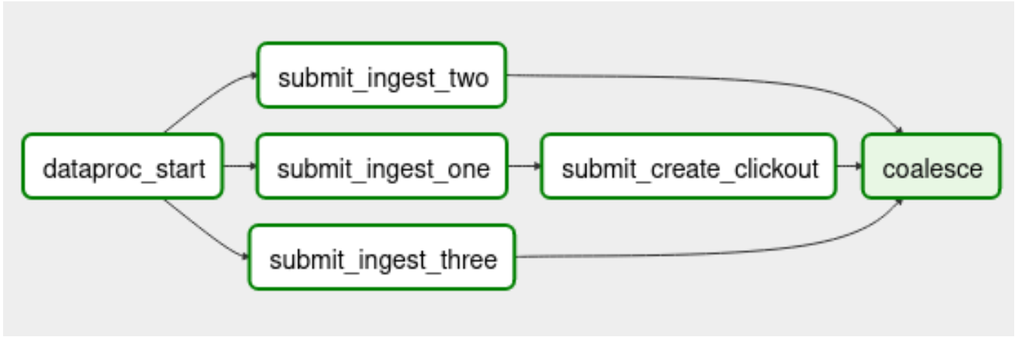

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- `all_failed` - ~~pair this one up with a callback so you can notify yourself of getting fired~~