Databases

INTRODUCTION TO DATA ENGINEERING

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What are databases?

- Holds data
- Organizes data
- Retrieve/Search data through DBMS

> *A usually large collection of data organized especially for rapid search and retrieval.*

Databases and file storage

Databases

- Very organized
- Functionality like search, replication, ...

File systems

- Less organized
- Simple, less added functionality

Structured and unstructured data

Structured: database schema

- Relational database

Semi-structured

- JSON

```
{ "key": "value"}
```

Unstructured: schemaless, more like files

- Videos, photos

SQL and NoSQL

SQL

- Tables
- Database schema
- Relational databases

MySQL

PostgreSQL

NoSQL

- Non-relational databases
- Structured or unstructured
- Key-value stores (e.g. caching)
- Document DB (e.g. JSON objects)

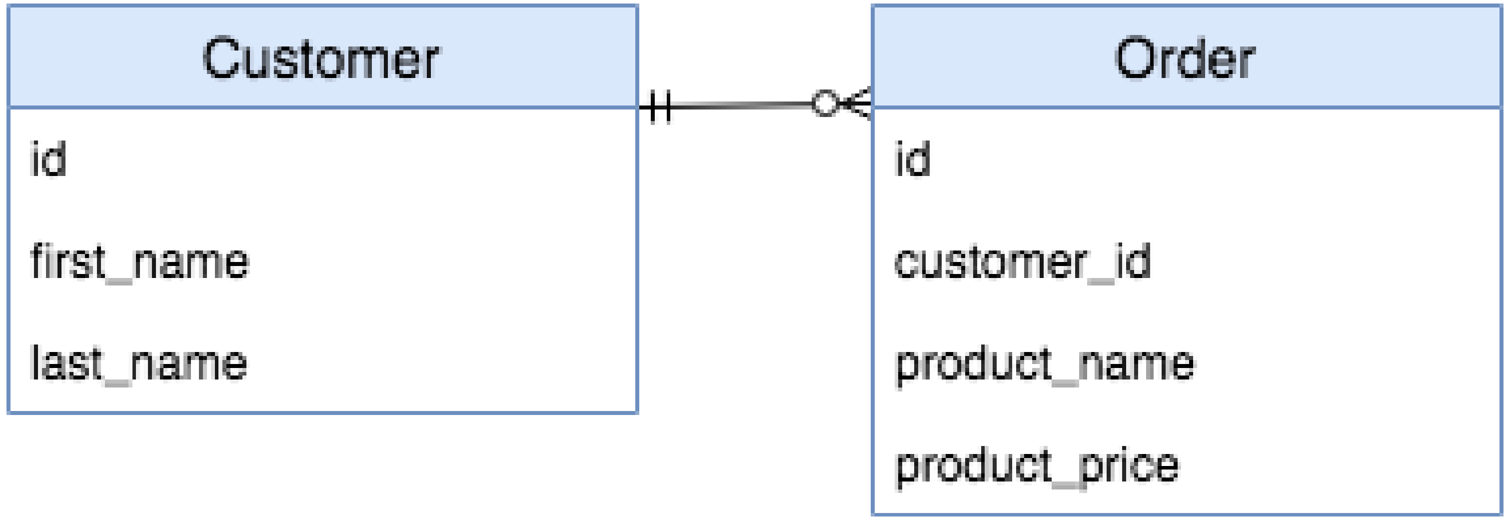
CACHING LAYER IN DISTRIBUTED WEB WERVER

redis mongoDB

SQL: The database schema

```sql
-- Create Customer Table
CREATE TABLE "Customer" (
  "id" SERIAL NOT NULL,
  "first_name" varchar,
  "last_name" varchar,
  PRIMARY KEY ("id")
);

-- Create Order Table
CREATE TABLE "Order" (
  "id" SERIAL NOT NULL,
  "customer_id" integer REFERENCES "Customer",
  "product_name" varchar,
  "product_price" integer,
  PRIMARY KEY ("id")
);
```

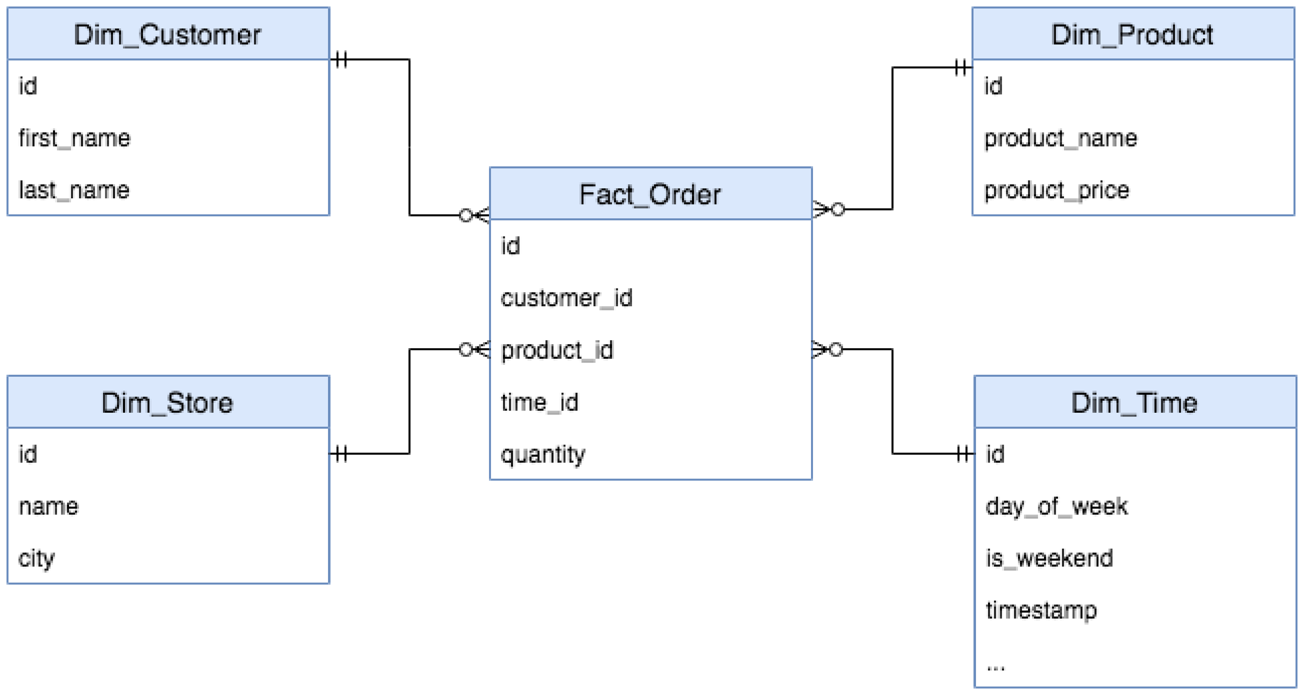



```sql
-- Join both tables on foreign key
SELECT * FROM "Customer"
INNER JOIN "Order"
ON "customer_id" = "Customer"."id";
```

```
id | first_name | ... | product_price
 1 | Vincent    | ... |            10
```

SQL: Star schema

> *The star schema consists of one or more fact tables referencing any number of dimension tables.*



- **Facts**: things that happened (eg. Product Orders)
- **Dimensions**: information on the world (eg. Customer Information)

[1] Wikipedia: https://en.wikipedia.org/wiki/Star_schema

Let's practice!

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What is parallel computing

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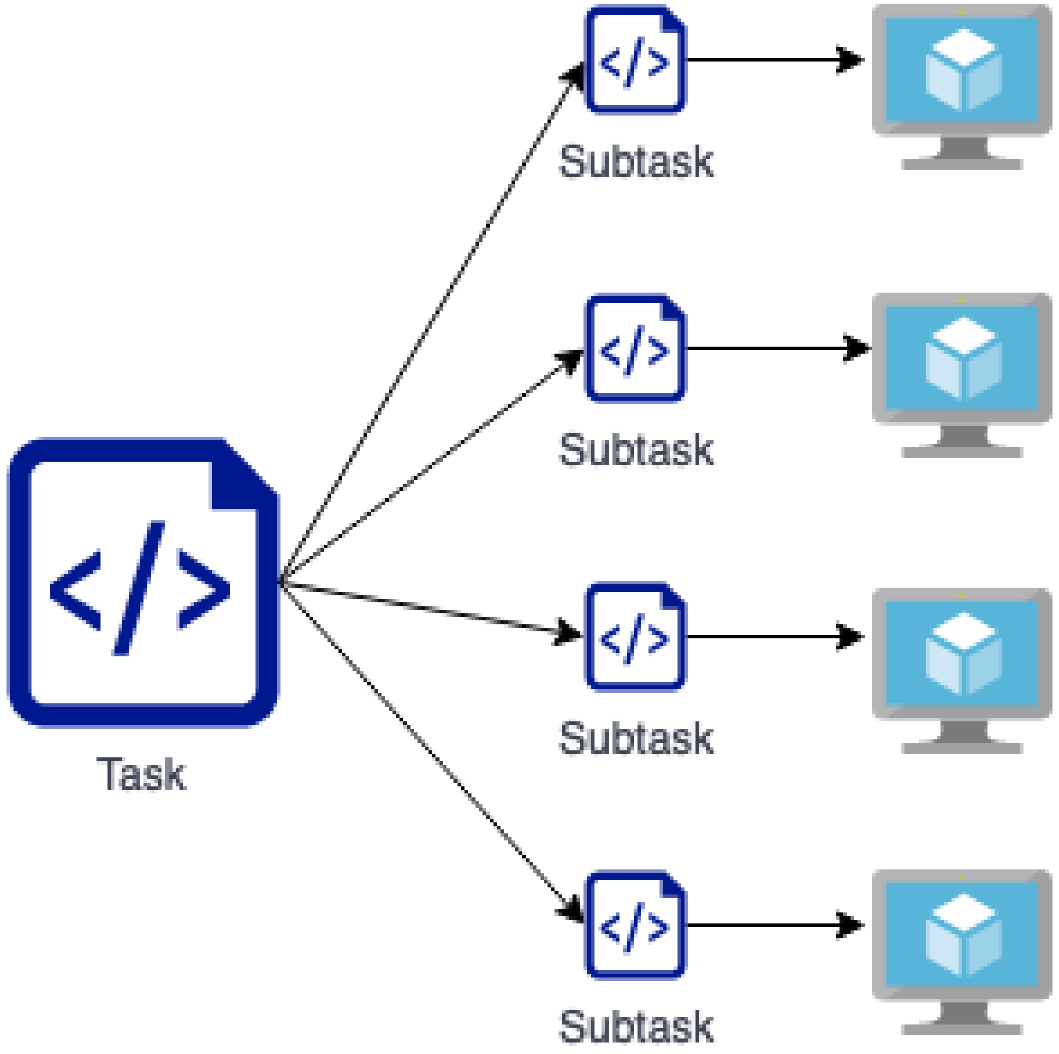
Idea behind parallel computing

Basis of modern data processing tools

- Memory
- Processing power

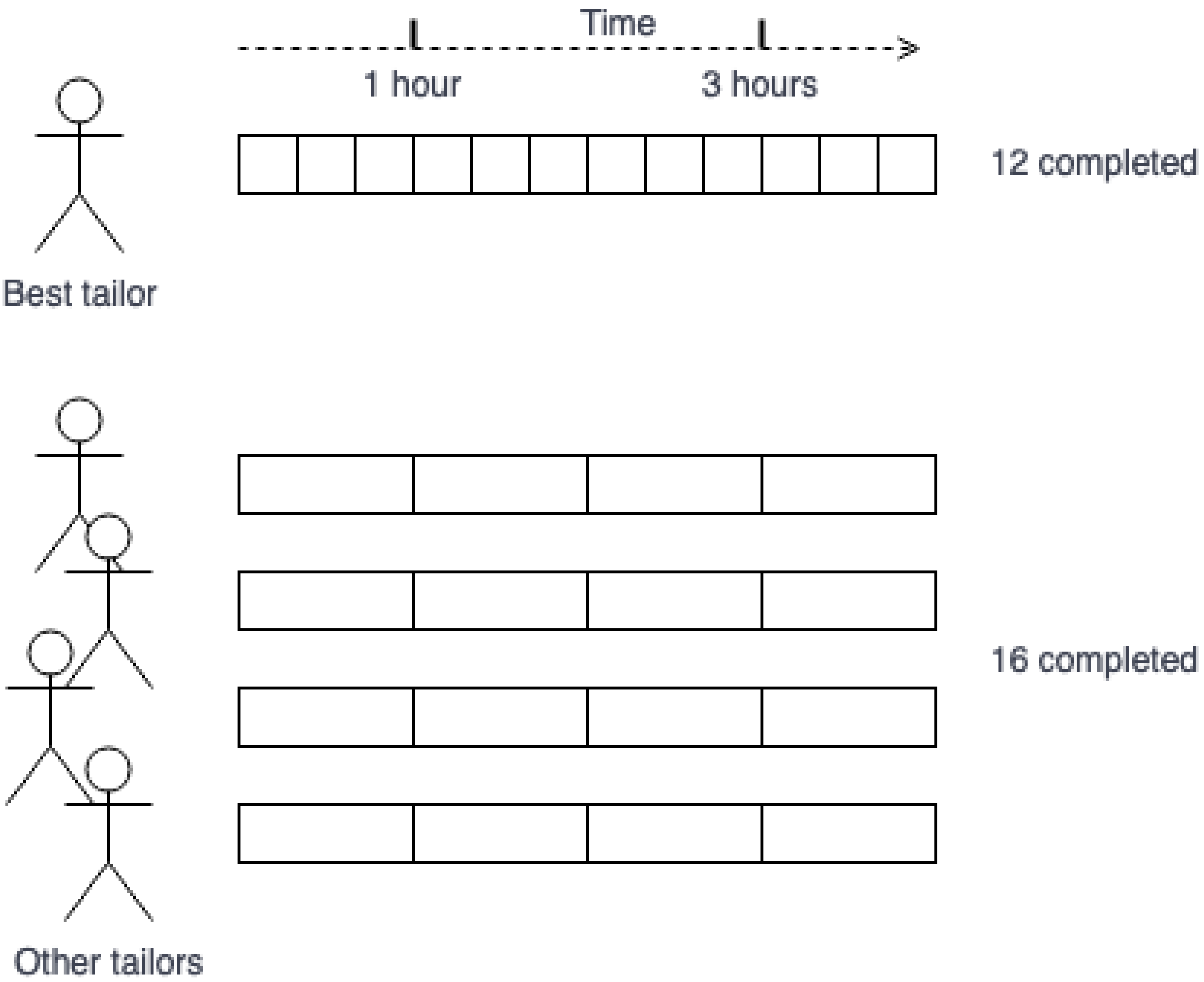
Idea

- Split task into subtasks
- Distribute subtasks over several computers
- Work together to finish task



Obs: You can't split every task successfully into subtasks.
Additionally, some tasks might be too small to benefit from parallel computing due to the communication overhead.

The tailor shop



Running a tailor shop

Goal: 100 shirts

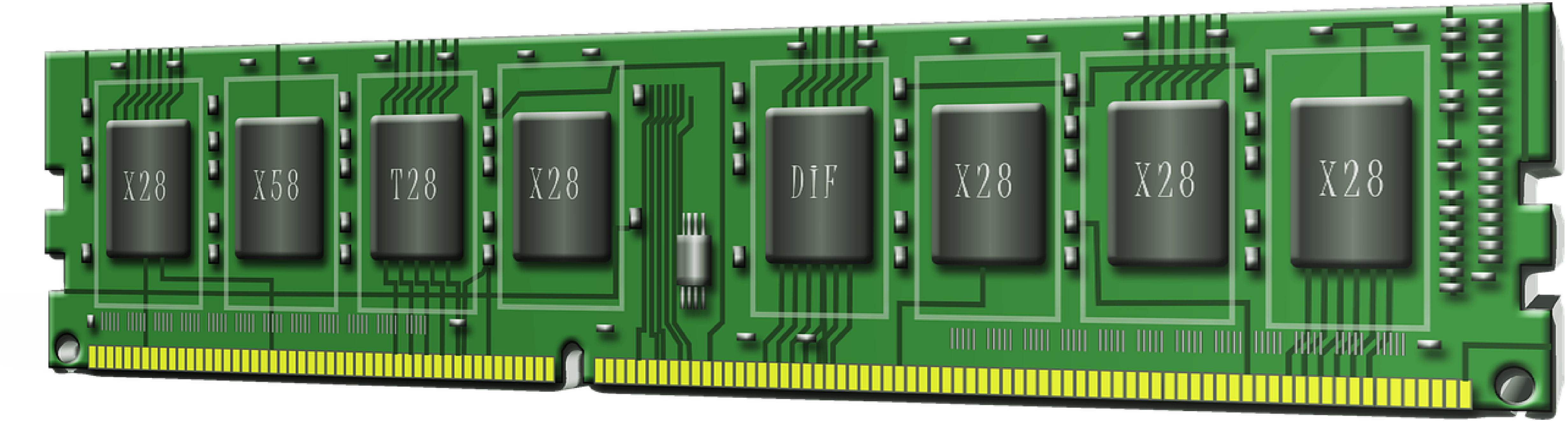
- Best tailor finishes shirt / 20 minutes
- Other tailors do shirt / 1 hour

Multiple tailors working together > best tailor

Benefits of parallel computing

- Processing power
- Memory: partition the dataset

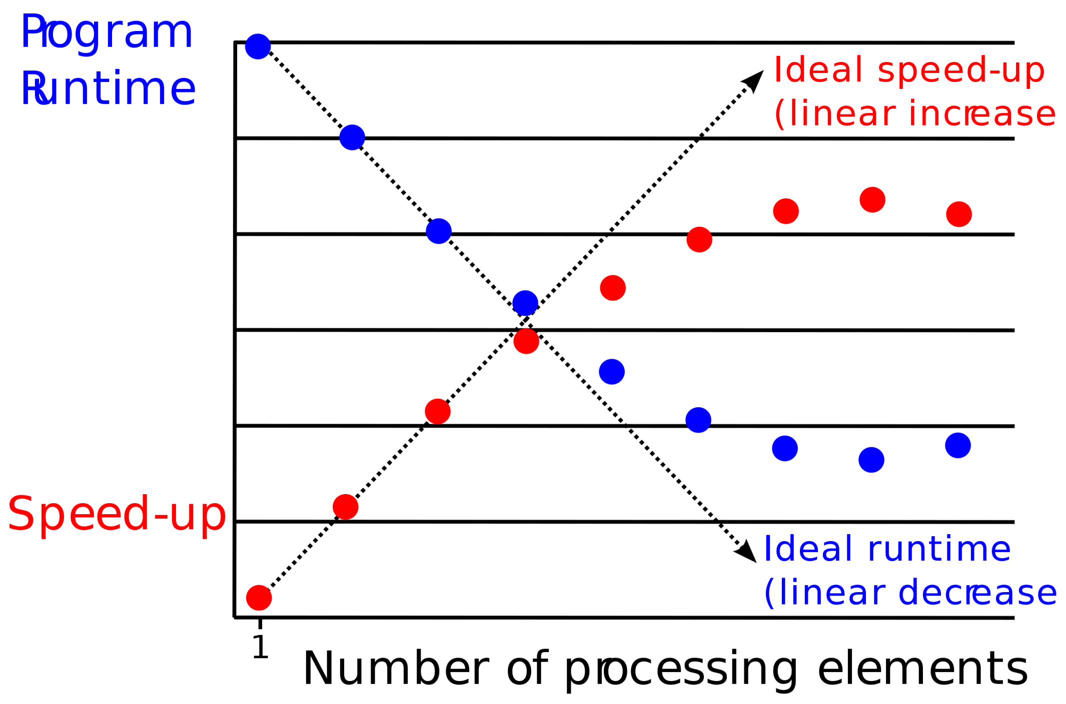
RAM memory chip:



Risks of parallel computing

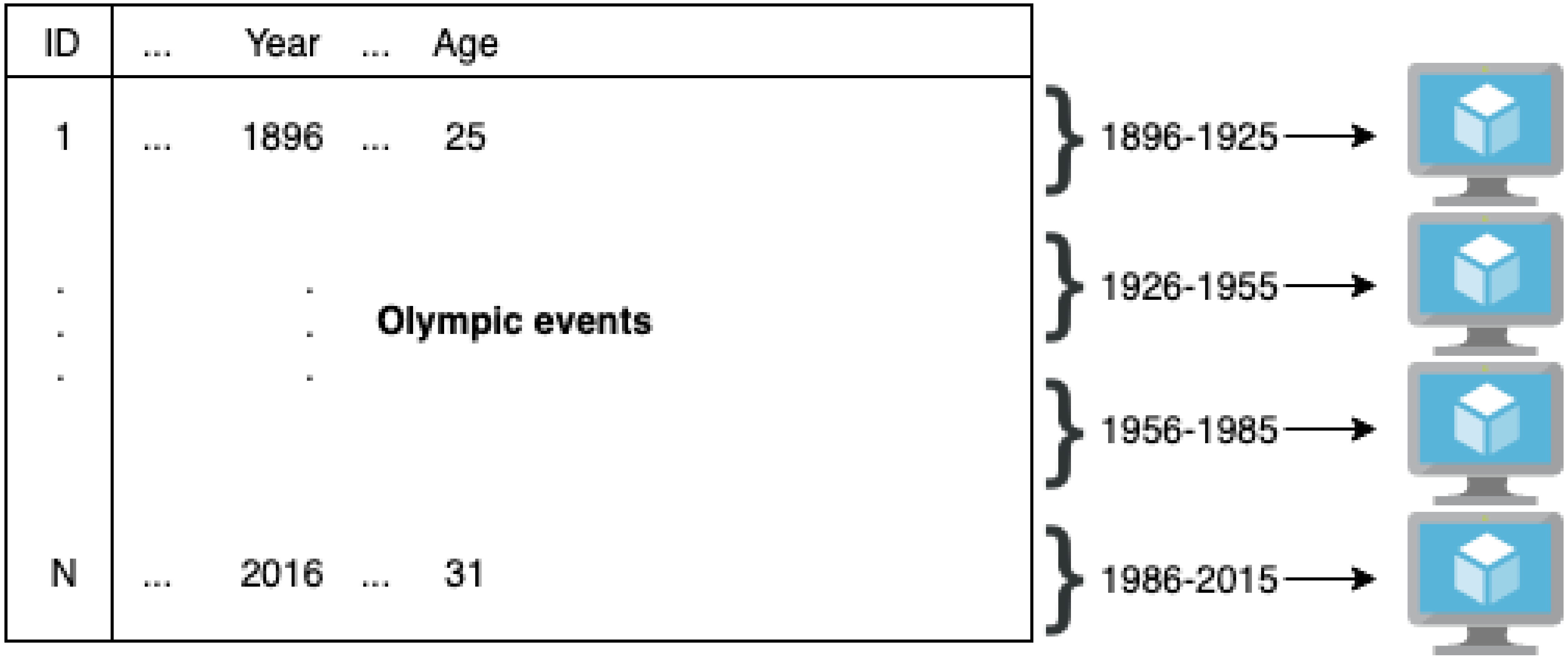
Overhead due to communication

Parallel slowdown:



- Task needs to be large
- Need several processing units

An example



ID
...
Year
...
Age
1
...
1896
...
25
Olympic events
N
...
2016
...
31
1896-1925
1926-1955
1956-1985
1986-2015

`multiprocessing.Pool`

```
from multiprocessing import Pool

def take_mean_age(year_and_group):
    year, group = year_and_group
    return pd.DataFrame({"Age": group["Age"].mean()}, index=[year])


with Pool(4) as p:
    results = p.map(take_mean_age, athlete_events.groupby("Year"))


result_df = pd.concat(results)
```

dask

```
import dask.dataframe as dd

# Partition dataframe into 4
athlete_events_dask = dd.from_pandas(athlete_events, npartitions = 4)

# Run parallel computations on each partition
result_df = athlete_events_dask.groupby('Year').Age.mean().compute()
```

Let's practice!

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Parallel computation frameworks

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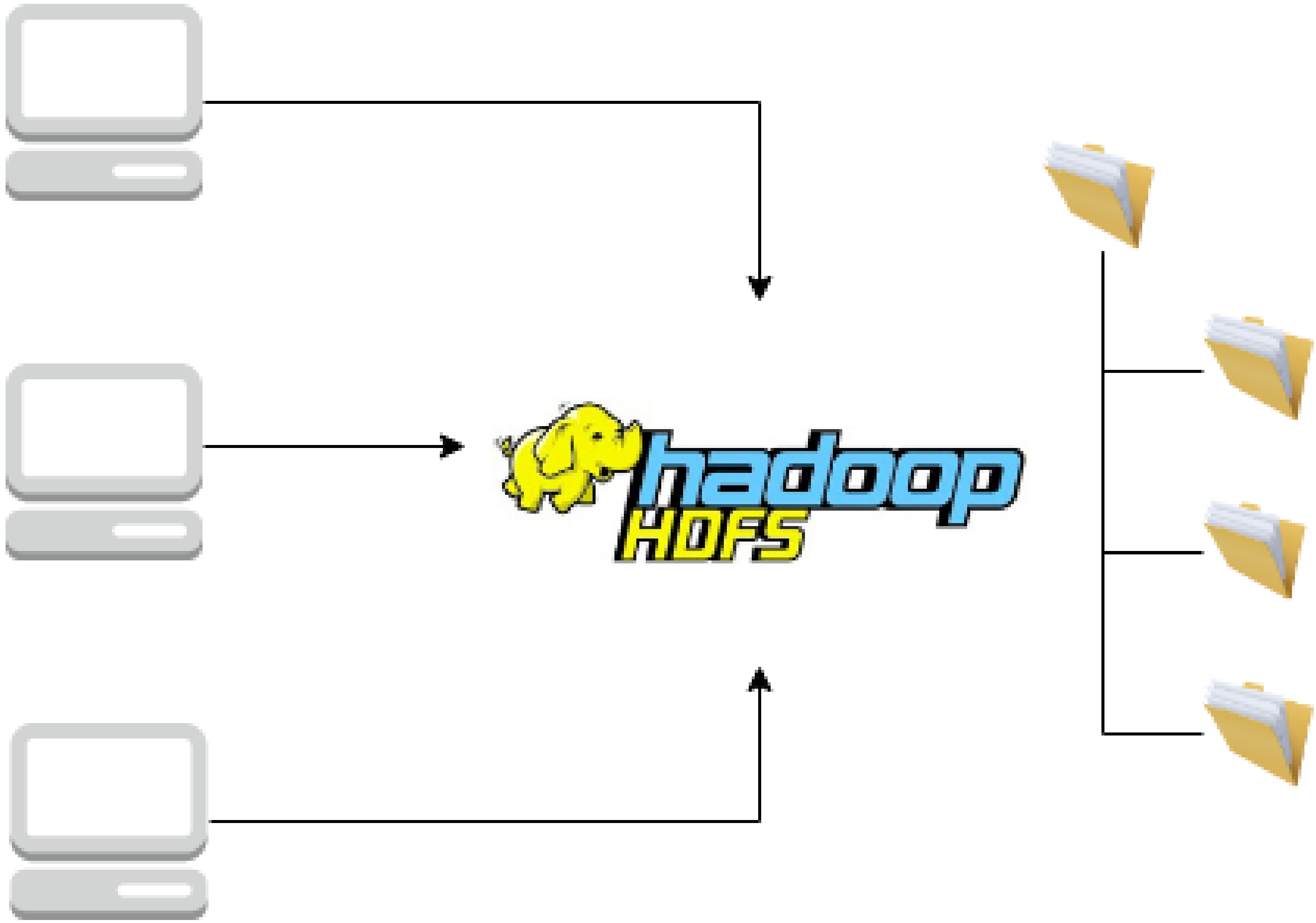
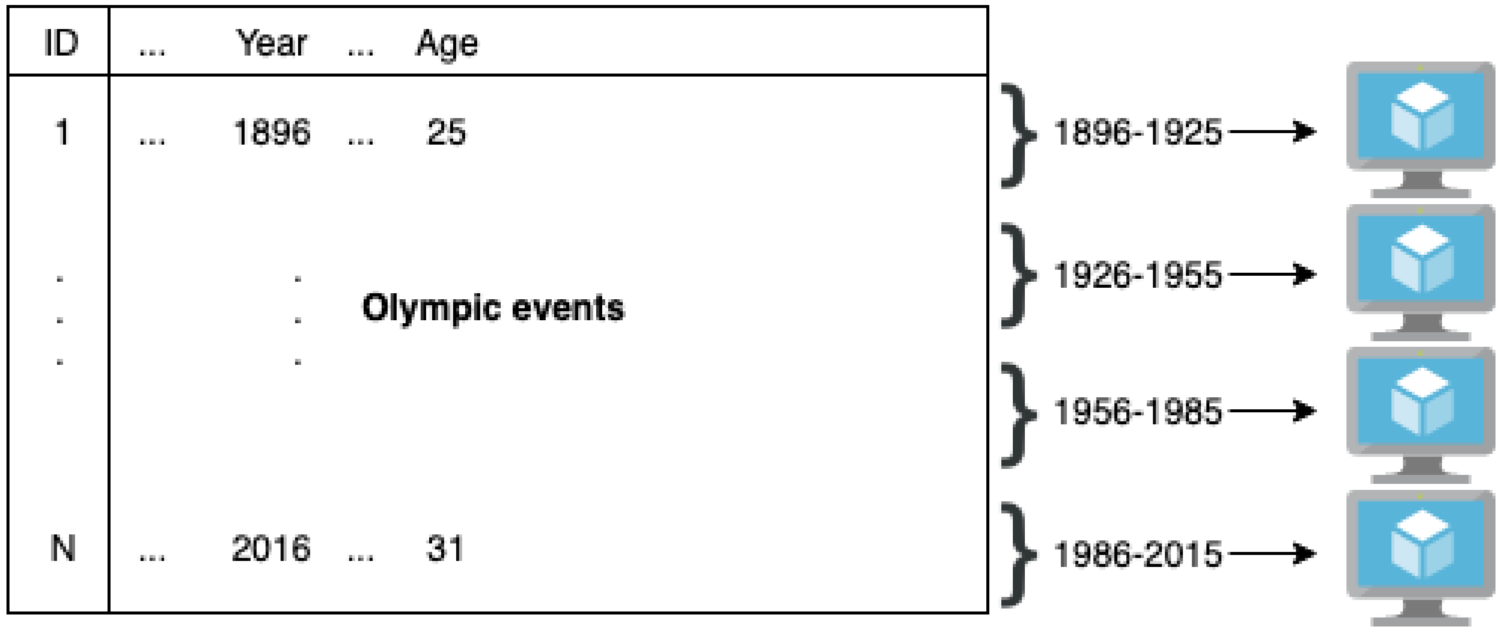
Collection of Open Source packages for Big Data

HDFS



MapReduce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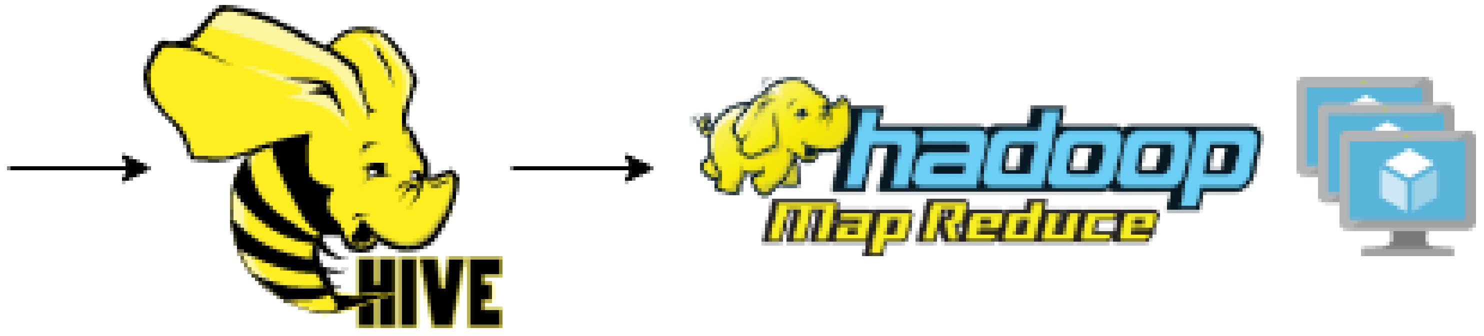
Hive

Is built from the need to use structured queries for parallel processing

- Runs on Hadoop
- Structured Query Language: Hive SQL
- Initially MapReduce, now other tools

Hive: an example

```sql
SELECT year, AVG(age)
FROM views.athlete_events
GROUP BY year
```



- Avoid disk writes
- Maintained by Apache Software Foundation

Resilient distributed datasets (RDD)

- Spark relies on them
- Similar to list of tuples
- Transformations: `.map()` or `.filter()`
- Actions: `.count()` or `.first()`

PySpark

- Python interface to Spark
- DataFrame abstraction
- Looks similar to Pandas

PySpark: an example

```python
# Load the dataset into athlete_events_spark first

(athlete_events_spark
  .groupBy('Year')
  .mean('Age')
  .show())
```

```sql
SELECT year, AVG(age)
FROM views.athlete_events
GROUP BY year
```

```python
# Print the type of athlete_events_spark
print(type(athlete_events_spark))

# Print the schema of athlete_events_spark
print(athlete_events_spark.printSchema())

# Group by the Year, and find the mean Age
print(athlete_events_spark.groupBy('Year').mean('Age'))

# Group by the Year, and find the mean Age
print(athlete_events_spark.groupBy('Year').mean('Age').show())
```

Let's practice!

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Workflow scheduling frameworks

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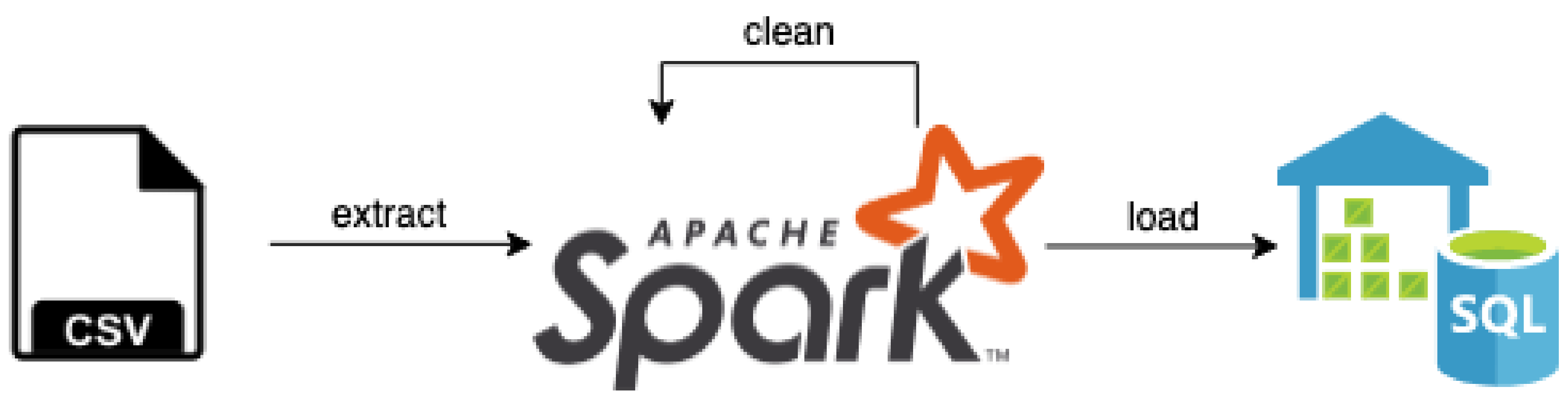
An example pipeline



How to schedule?

- Manually
- `cron` scheduling tool
- What about dependencies?

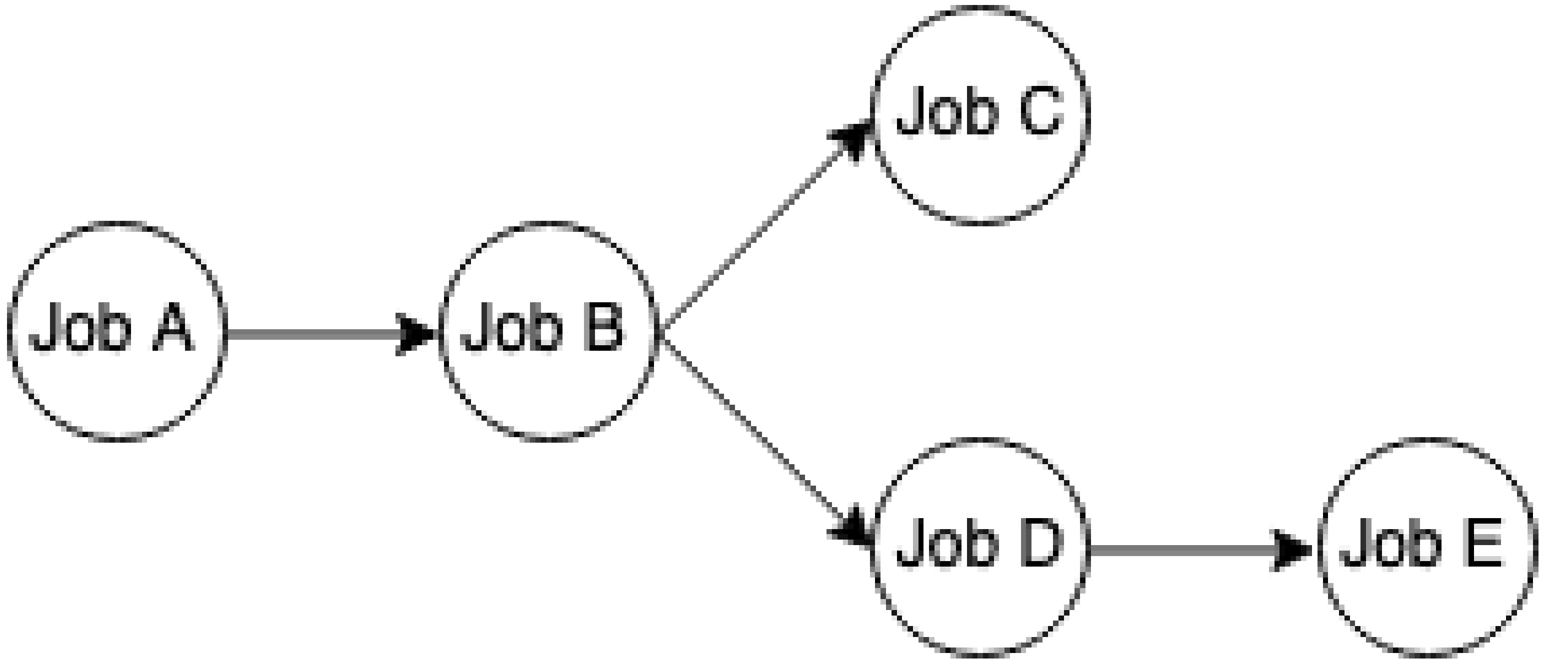
DAGs

Directed Acyclic Graph

- Set of nodes
- Directed edges
- No cycles

The nodes of the graph represent tasks that are executed.
The directed connections between nodes represent dependencies between the tasks.

Representing a data pipeline as a DAG makes much sense, as some tasks need to finish before others can start.
You could compare this to an assembly line in a car factory.
The tasks build up, and each task can depend on previous tasks being finished.



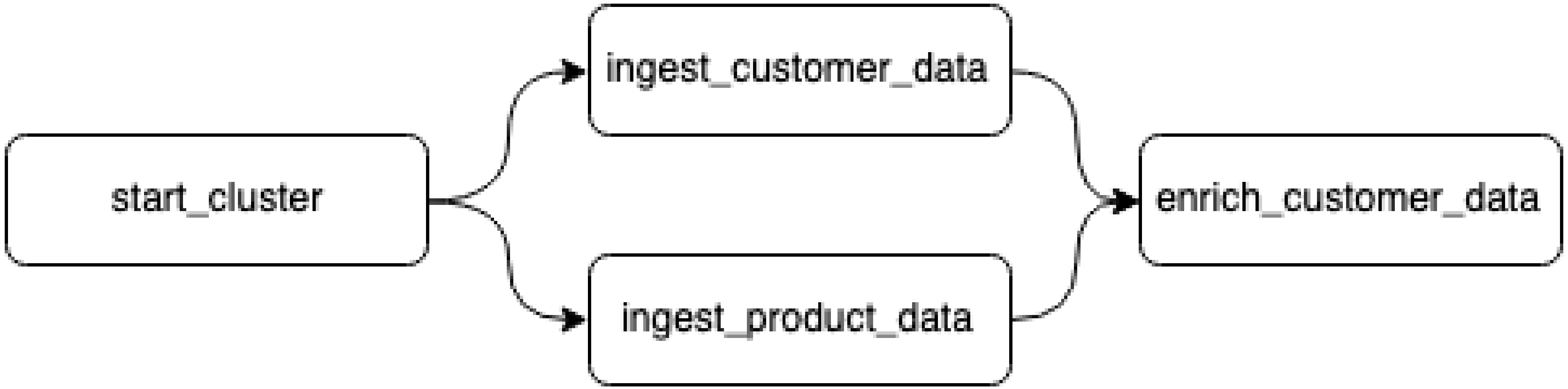
The tools for the job

- Linux's `cron`
- Spotify's Luigi
- Apache Airflow

You have exact control over the time at which jobs run. (like cron)

- Created at Airbnb
- DAGs
- Python

Airflow: an example DAG



Airflow: an example in code

```
# Create the DAG object
dag = DAG(dag_id="example_dag", ..., schedule_interval="0 * * * *")

# Define operations
start_cluster = StartClusterOperator(task_id="start_cluster", dag=dag)
ingest_customer_data = SparkJobOperator(task_id="ingest_customer_data", dag=dag)
ingest_product_data = SparkJobOperator(task_id="ingest_product_data", dag=dag)
enrich_customer_data = PythonOperator(task_id="enrich_customer_data", ..., dag = dag)

# Set up dependency flow
start_cluster.set_downstream(ingest_customer_data)
ingest_customer_data.set_downstream(enrich_customer_data)
ingest_product_data.set_downstream(enrich_customer_data)
```

```
# Create the DAG object
dag = DAG(dag_id="car_factory_simulation",
          default_args={"owner": "airflow","start_date": airflow.utils.dates.days_ago(2)},
          schedule_interval="0 * * * *")

# Task definitions
assemble_frame = BashOperator(task_id="assemble_frame", bash_command='echo "Assembling frame"', dag=dag)
place_tires = BashOperator(task_id="place_tires", bash_command='echo "Placing tires"', dag=dag)
assemble_body = BashOperator(task_id="assemble_body", bash_command='echo "Assembling body"', dag=dag)
apply_paint = BashOperator(task_id="apply_paint", bash_command='echo "Applying paint"', dag=dag)

# Complete the downstream flow
assemble_frame.set_downstream(place_tires)
assemble_frame.set_downstream(assemble_body)
assemble_body.set_downstream(apply_paint)
```

Let's practice!

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