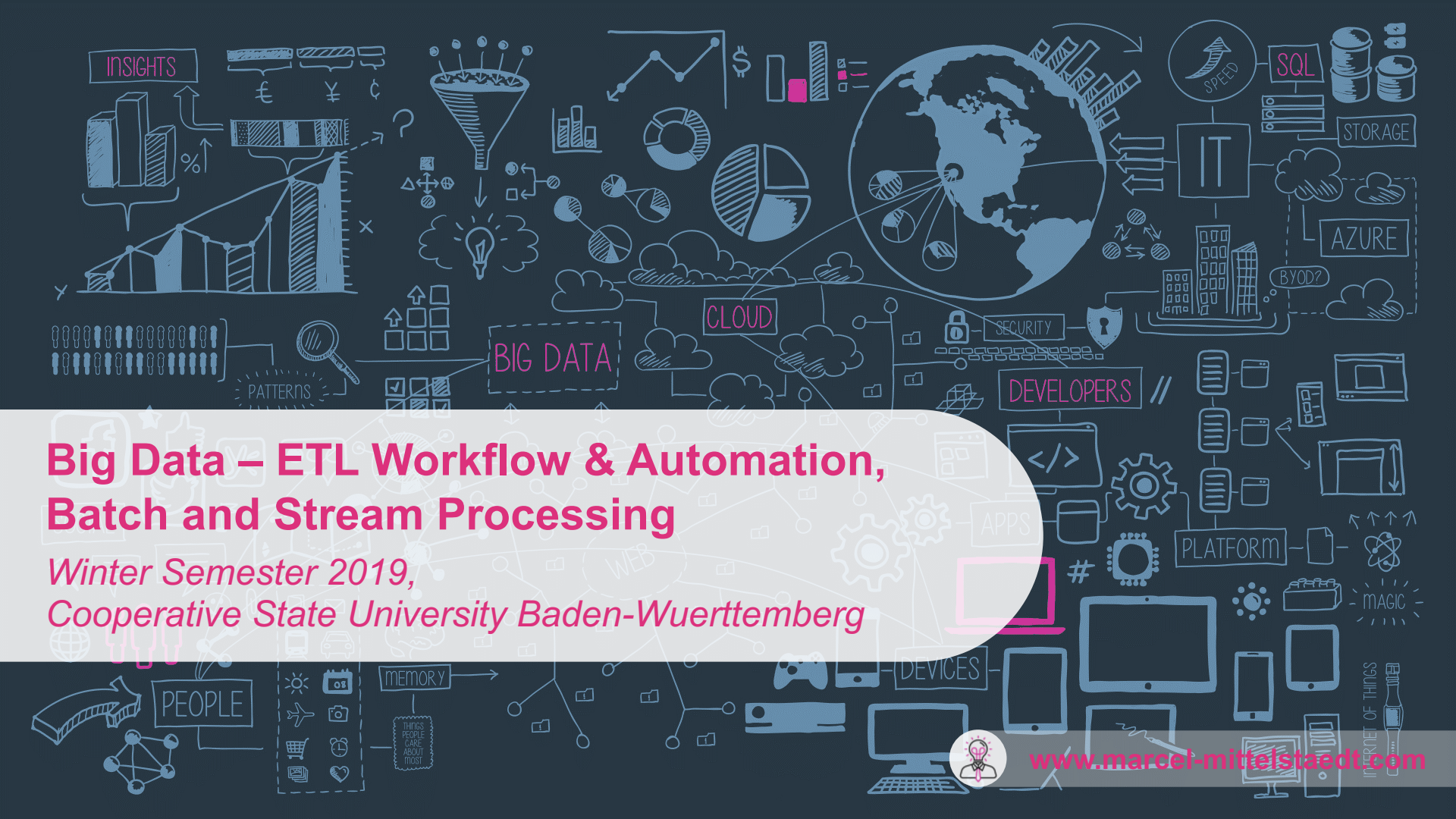


Big Data – ETL Workflow & Automation, Batch and Stream Processing

Winter Semester 2019,
Cooperative State University Baden-Wuerttemberg

www.marcel-mittelstaedt.com

Agenda – 04.11.2018

01

Presentation and Discussion: Exercise Of Last Lecture

Spark, PySpark and Jupyter

02

Batch and Stream Processing

A quick introduction to the principles, architectures and purposes of batch and stream processing in terms of big data.

03

Exercise – Working with PDI on Hadoop and Hive

Automate the process of downloading, importing, transforming and storing IMDb data within da Hadoop Cluster.

04

Exercise – Working with Apache Airflow on Hadoop and Hive

Automate the process of downloading, importing, transforming and storing IMDb data within da Hadoop Cluster.

Schedule

	Lecture Topic	*HandsOn*
14.10.2019 13:15-18:00 Ro. 1.18	About This Lecture, Introduction to Big Data, Setup Cloud Environment (Google Cloud)	HandsOn Hadoop, MapReduce and Hive(-QL)
21.10.2019 13:15-18:00 Ro. 1.18	(Non-)Functional Requirements Of Distributed Data-Systems, Data Models and Access	Partitioning with HDFS/Hive, HiveServer2
28.10.2019 13:15-18:00 Ro. 1.18	Challenges Of Distributed Data Systems: Replication and Partitioning	Spark, Scala and PySpark/Jupyter
04.11.2019 13:15-18:00 Ro. 1.18	**ETL Workflow and Automation, Batch and Stream Processing**	Pentaho Data Integration & Airflow
11.11.2019 13:15-18:00 Ro. 1.18	Practical Exam	Work On Practical Exam
18.11.2019 13:15-18:00 Ro. 1.18	Practical Exam Presentation	

Introduction to:
Batch and Stream Processing

A quick introduction to the principles, architectures and purposes of batch and stream processing in terms of big data.

Batch vs Stream Processing

	Batch Processing	Stream Processing
Kind of data:	large, historic	volatile, live, stream
Runtime:	minutes, hours, days	real-time/near-real-time
Re-Execution:	possible	„impossible“

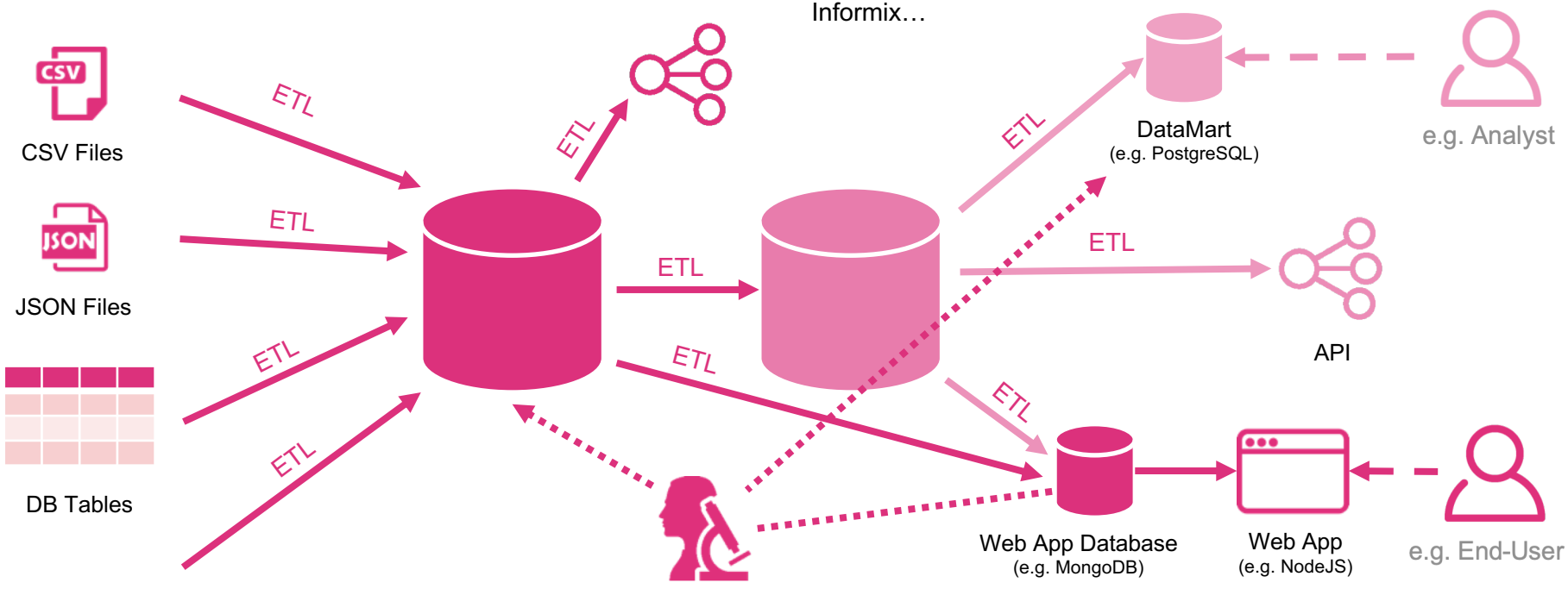
Batch Processing – Example Data Flow

Source Systems:
e.g. CRM, ERP, Webserver Logfiles, …

Data Lake:
e.g. Hadoop HDFS

Data Warehouse:
e.g. PostgreSQL, Oracle, MS SQL Server, DB2, Informix…

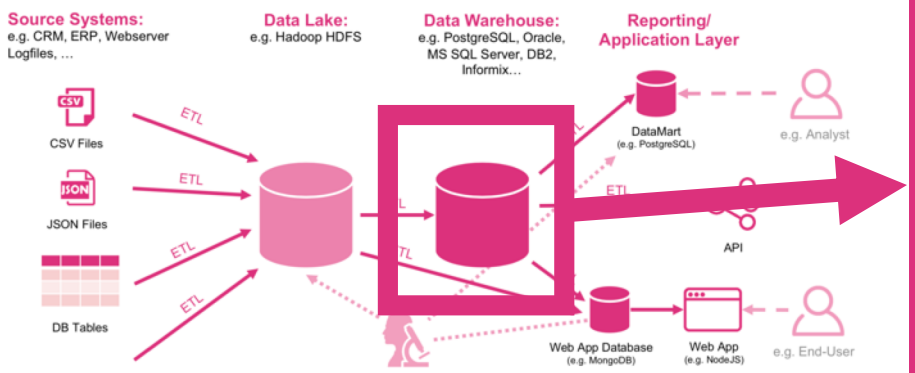
Reporting/ Application Layer

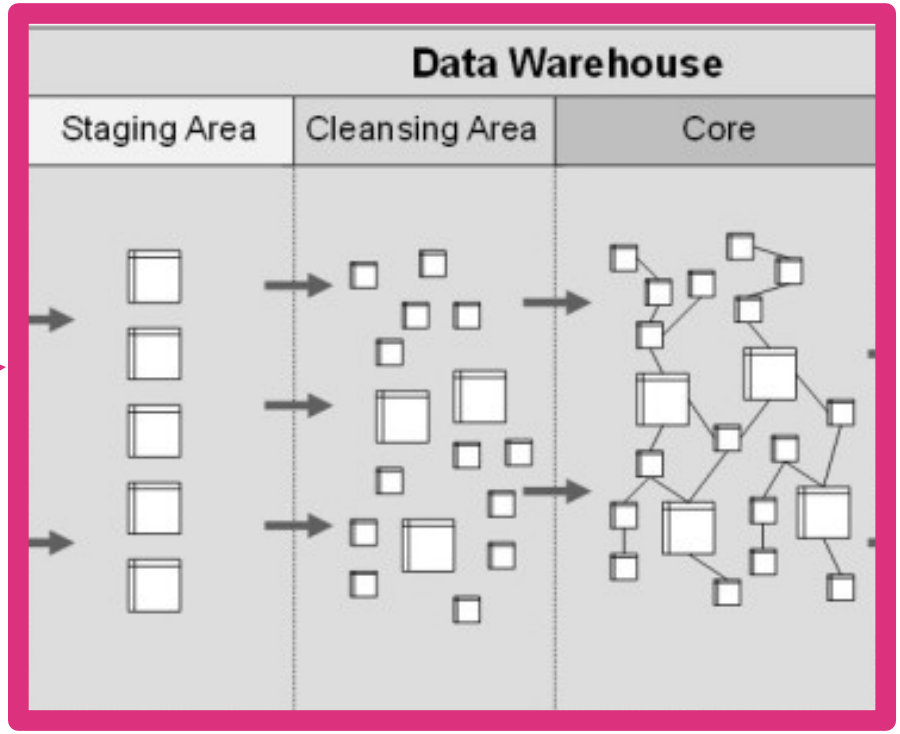


Batch Processing - ETL

ETL (Extract, Transform, Load) *is a basic pattern for data processing, commonly known in data warehousing. It's all about* ***extracting*** *data from a source,* ***transforming*** *the data (e.g. by applying business rules or changing structures) and at the end writing/****loading*** *everything to a target (e.g. Hadoop HDFS, Hive, Relational Database, Data Warehouse, Data Mart etc.).*

Batch Processing – Example Data Flow





Batch Processing – Dissociation Datawarehousing

- a Big Data data-system can be a part or source of a Data Warehouse, e.g.:
  - Data Lake or
  - Enterprise Data Hub

- A Data Warehouse is not Big Data

Data Warehouse

- handles mainly structured data
- suitable for small amounts of data
- focuses on analytical and reporting purposes
- 100% accuracy

Big Data

- handles data in any kind of structure
- serves broad variety of data-driven pur poses (e.g. analytical, data science, data-driven applications, …)
- usually not about 100% accuracy

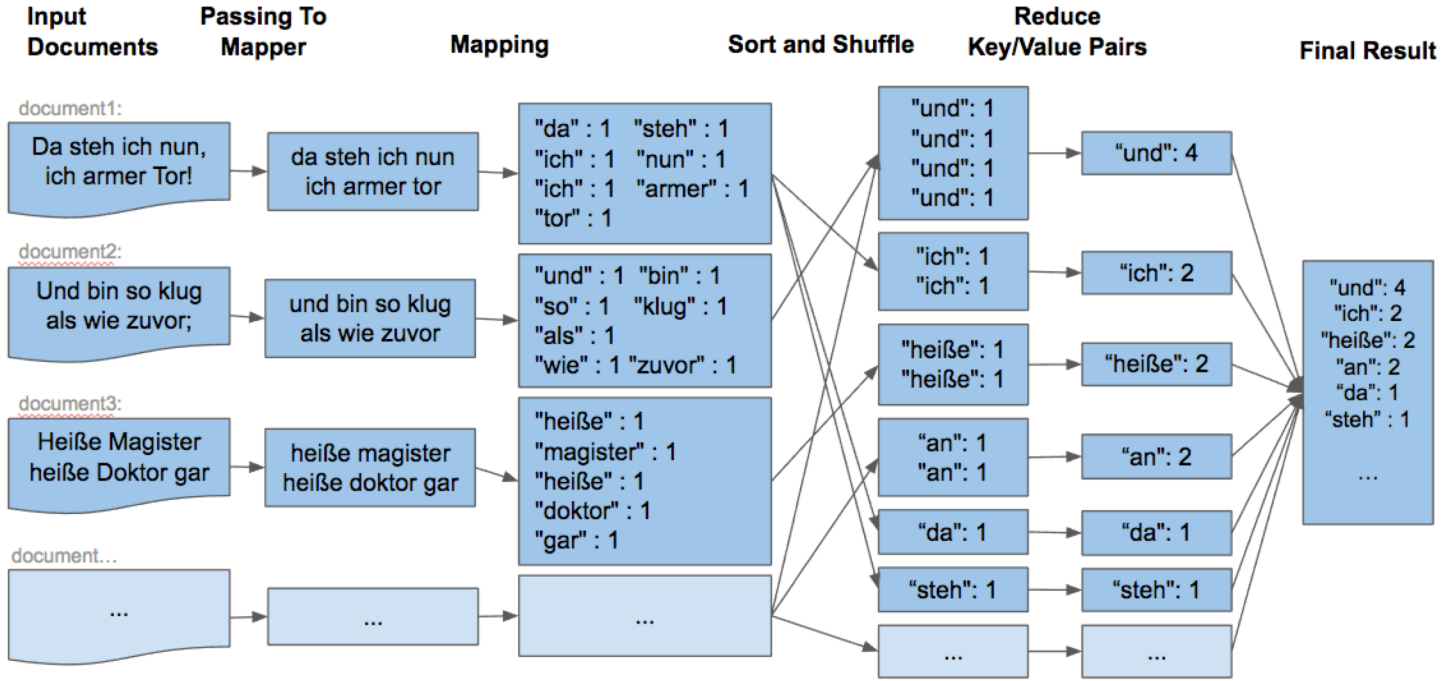
Distributed Batch Processing

Distributed Storage

Distributed Processing

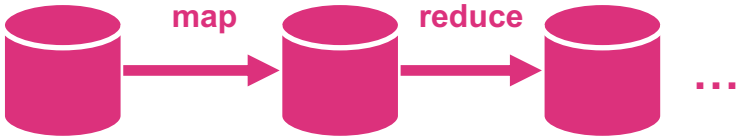
Batch Processing – MapReduce

- Programming paradigm for processing large datasets in parallel on a distributed cluster



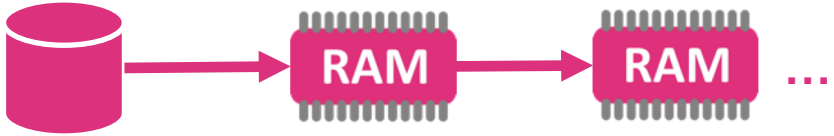
Batch Processing – MapReduce vs Spark

Hadoop MapReduce



- Good reliability
- Bad performance

Spark



- Bad reliability
- Good performance

Spark vs Flink

- **batch processing framework** that emulates stream processing
- **stream processing** = Execution of **micro batches**
- cuts event stream into micro batches and processes each batch
- **Latency:** (several) seconds
- **Maturity:** high, many libraries, huge community and developer base

- **stream processing framework** that emulates batch processing
- **batch processing** = bounded stream processing
- processes each event when it arrives
- **Latency:** milliseconds-seconds
- **Maturity:** medium, limited libraries, medium community and developer base

Spark vs Flink

- good choice for batch processing
- stream processing:

  if **reliabilty > latency**

- good choice for stream processing:

  if **latency > reliability**

Stream Processing – **Definition**

Data Stream:

- is data made available over time in an incemental way
- created by:
  - static data (e.g. file or database read line-wise)
  - dynamic data (e.g. logs, sensors, function calls, …)

Event:

- is an immutable record/item in a stream
- usually represented and encoded in e.g. JSON, XML, CSV or binary encoded
- pendants

Stream Processing – **Use Cases/Data Sources**

- User Interaction, e.g.:
  - webserver logfiles
  - tracking data like Google Analytics
  - recommendation systems (advertisement, personalization)
  - …
- Sensor data
- Any API serving data in a stream, e.g.:
  - Twitter Postings API,
  - Message Queue/Broking Systems (e.g. Kafka, ZeroMQ, RabbitMQ…)
  - IoT
- Location Tracking (e.g. DriveNow, Car2Go, Google Maps…)
- …

Message Broker/Queues

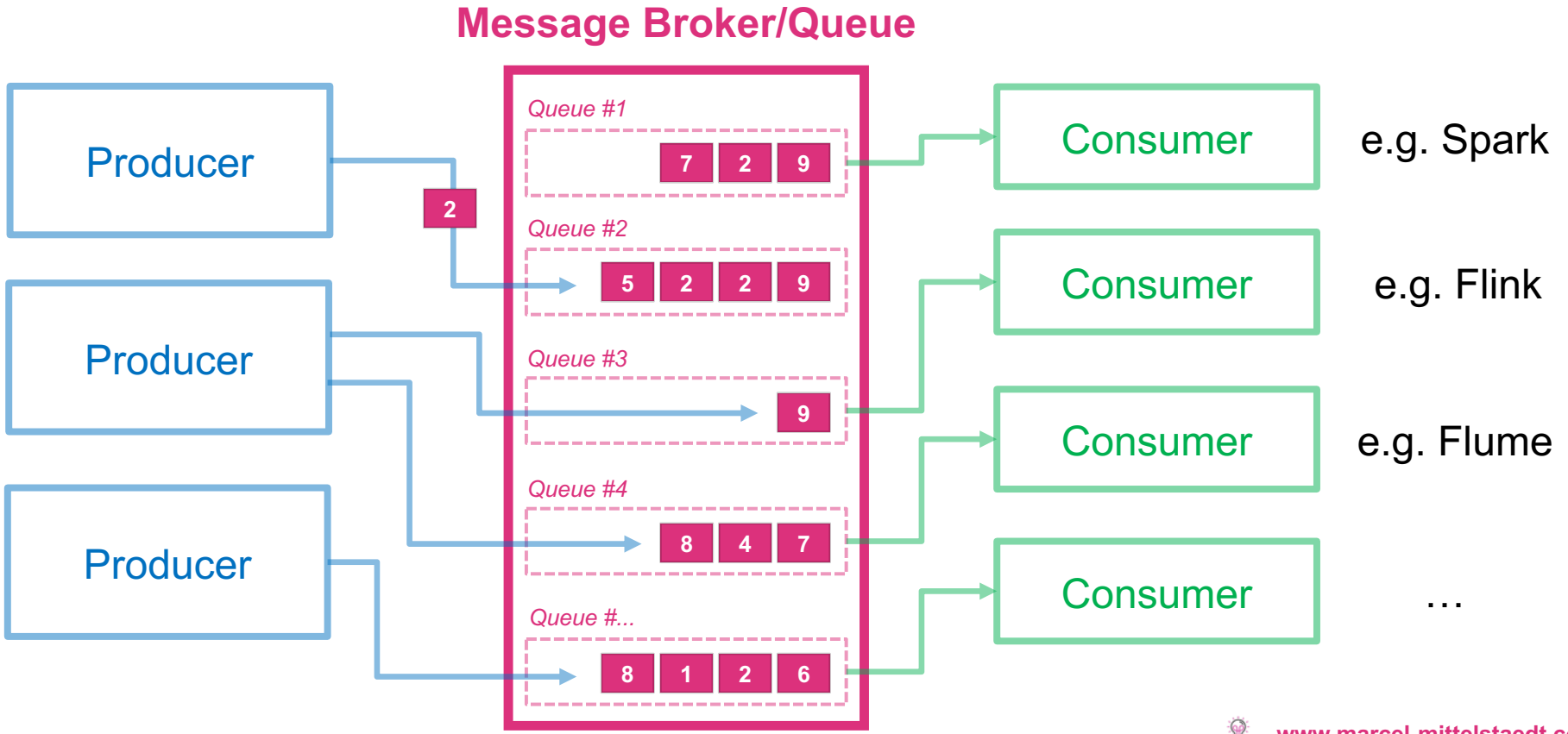
Why:

- decouples Producer and Receiver
- maintains queues for different topics
- temporarily persists messages
- Notifies subscribers on new messages
- Micro Services, IoT…

Examples:

- RabbitMQ,
- ZeroMQ,
- Kafka,
- ActiveMQ,
- Kestrel,
- …

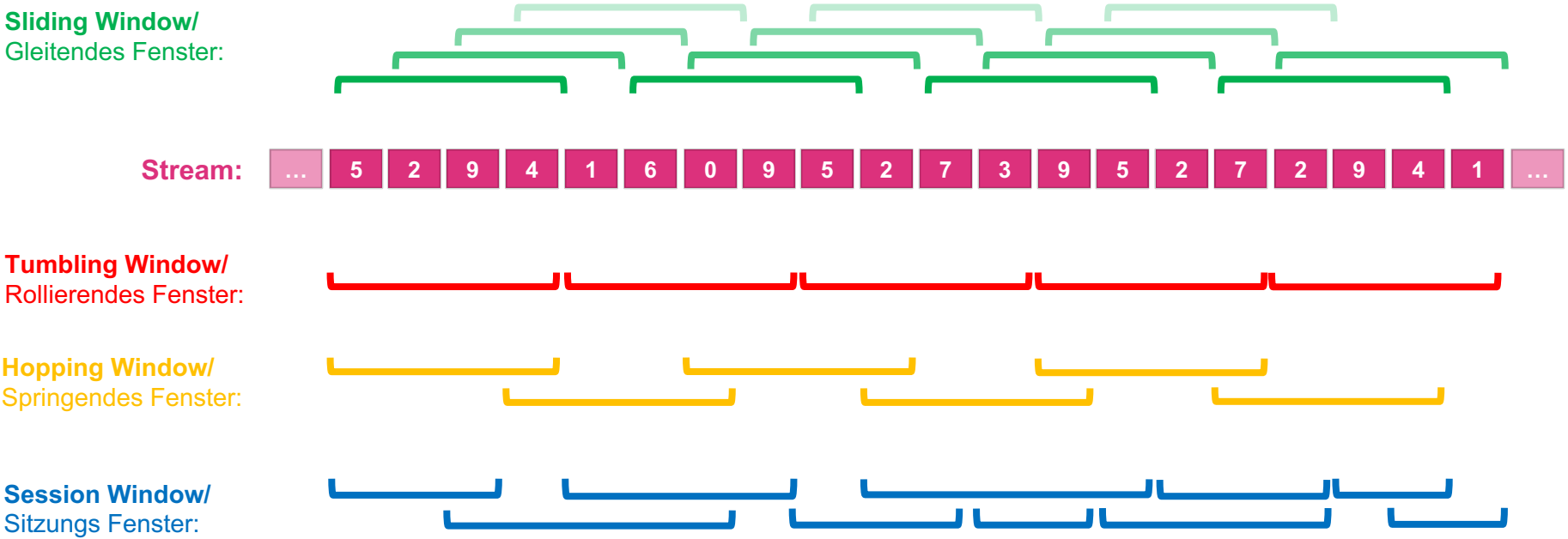
Message Broker/Queues



Message Broker/Queues vs Data-Systems

	Message Broker/Queue	Database
Persistence:	- **temporarily** (delete once transmitted or after a certain timeframe)	- **persistent**
Data Retrieval:	- **Subscription-based** (even if e.g. Kafka supports qu ery-based)	- **Query-based** (execute query to receive data)
Communi-cation:	- **Initiated by MB**	- **Initiated by clients**

Stream Processing – **Windows**

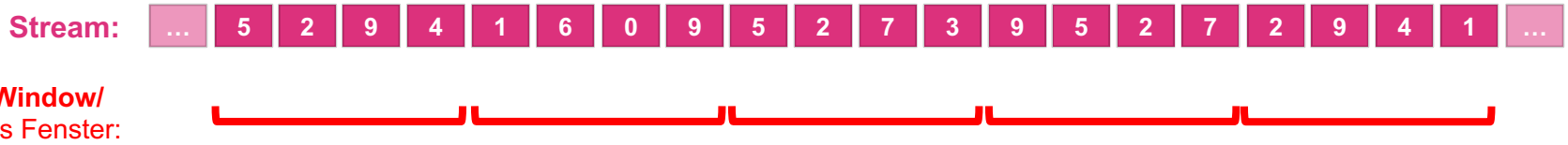


Stream Processing – Tumbling Windows

Data Stream:
- Fixed length
- Non-overlapping
- An event relates to exactly one window

Twitter Example:
- Calculate the count of tweets for every 4 seconds

```
SELECT count(*) as tweet_count FROM Twitter_Stream TIMESTAMP BY
CreationTime GROUP BY TumblingWindow(second, 4)
```

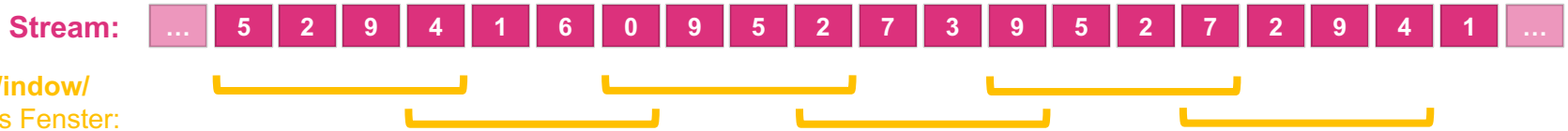


Stream Processing – Hopping Windows

Data Stream:
- Fixed length
- Overlapping (with fix steps)
- An event relates to more than one window

Twitter Example:
- Every 3 seconds calculate the count of tweets for last 4 seconds

```
SELECT count(*) as tweet_count FROM Twitter_Stream TIMESTAMP BY
CreationTime GROUP BY HoppingWindow(second, 4, 3)
```



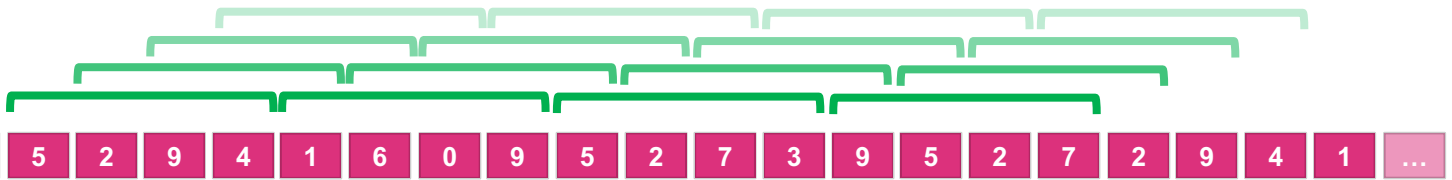
Stream Processing – Sliding Windows

Data Stream:
- Fixed length
- Overlapping (dependending on event)
- An event can relate to more than one window
- Event-based, every window contains at least one event and is continuesly slided forward

Twitter Example:
- Calculate count of tweets which have used a certain hashtag. Count number of tweets including hashtags, which were used more than 10 times within the last 4 seconds

```
SELECT HashTag, count(*) as tweet_count FROM Twitter_Stream TIMESTAMP BY
CreationTime GROUP BY Hashtag, SlidingWindow(second, 4)HAVING count(*) > 10
```

Sliding Window/
Gleitendes Fenster:

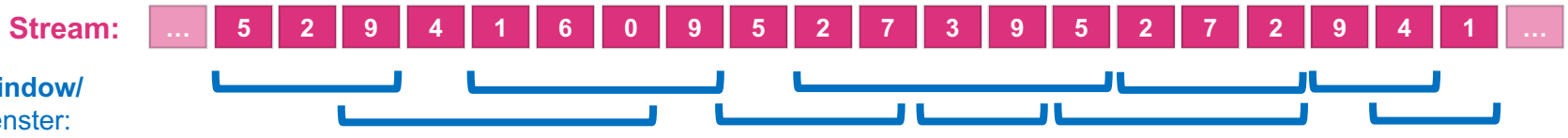


Stream Processing – Session Windows

Data Stream:
- Arbitrary-length
- Overlapping possible
- An event can relate to more than one window
- Windows containing no events are filtered out
- Fix start event (e.g. login) and end event (logout or timeout)
- Max size usually limited

Twitter Example:
- Calculate count of tweets for certain hashtags that occur within less than 5 minutes to each other

```
SELECT HashTag, count(*) as tweet_count FROM Twitter_Stream TIMESTAMP BY
CreationTime GROUP BY HashTag, SessionWindow(minute, 5)
```



Word Count on Stream – Apache Spark

```
// Initialize Spark Session
val spark = SparkSession
  .builder()
  .master("local")
  .appName("Socket_Streaming")
  .getOrCreate()

// Initialize Socket Stream
val socketStreamDf = spark.readStream
  .format("socket")
  .option("host", "localhost")
  .option("port", 4711)
  .load()

// parse, group, window and aggregate data
val words = socketStreamDf.as[String].flatMap(_.split(" "))
val wordCounts = words.groupBy("value").count()
val query = wordCounts.writeStream
  .outputMode("complete")
  .format("console")
  .start()

query.awaitTermination()
```

Input could also be **Kafka, Flume, Kinesis, Sockets, File, Custom Connectors…**

Output could also be **HDFS, Kafka, Kinesis, Console, …**

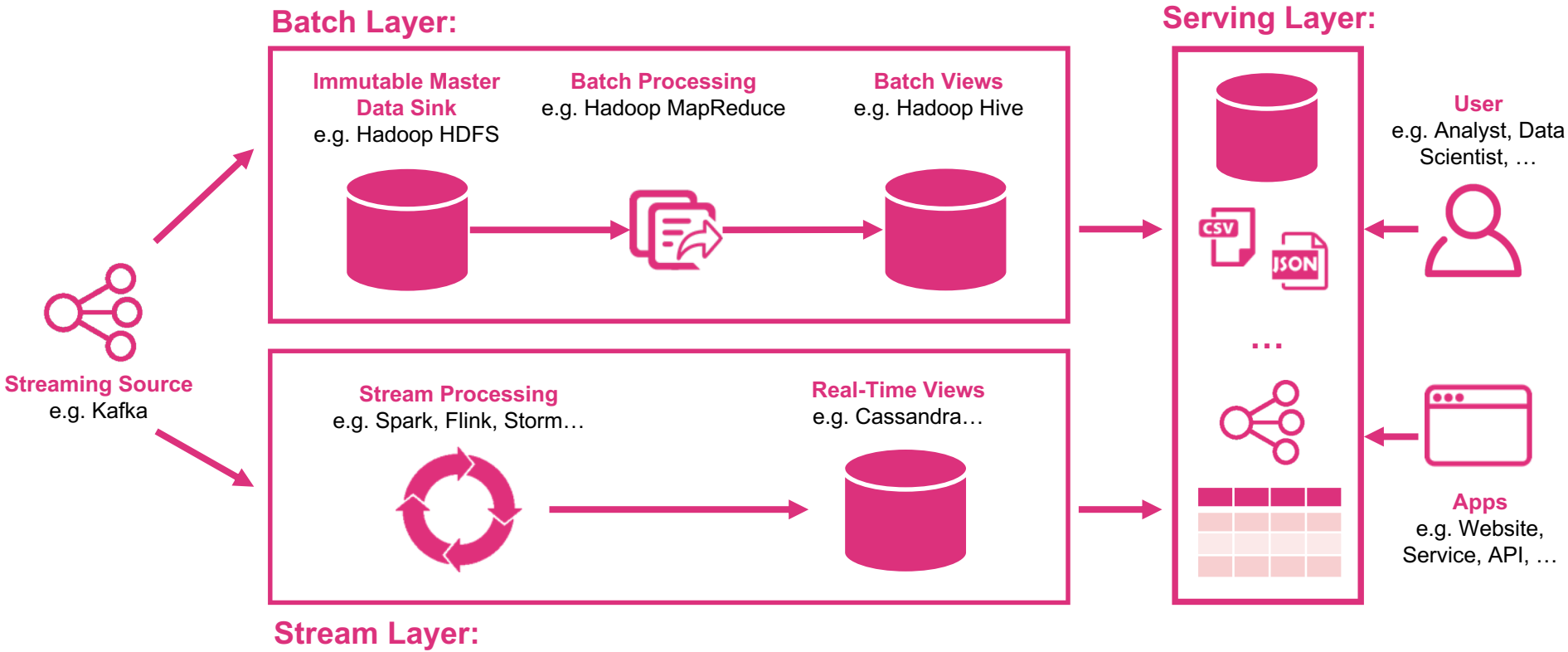
Word Count on Stream – Apache Flink

```
// Initiate Execution Environment
val env = StreamExecutionEnvironment.getExecutionEnvironment

// Read data from socket on localhost, port: 4711
val text = env.socketTextStream("localhost", 4711, '\n')

// parse, group, window and aggregate data
val word_counts = text
  // Split lines into 2-tuples: (word,1)
  .flatMap(_.toLowerCase.split("\\s"))
  .filter(_.nonEmpty)
  .map((_, 1))
  // group by word (tuple field "0")
  .keyBy(0)
  // sliding window: 5 second length, 1 second trigger interval
  .timeWindow(Time.seconds(5), Time.seconds(1))
  // sum up word count (tuple field "1")
  .sum(1)

// print result (single thread)
word_counts.print().setParallelism(1)
}

// Execute
env.execute("Streaming Example: WordCount")
```

Input Could also be **Kafka, Kinesis, RabbitMQ, NiFi, ActiveMQ, Socket, File, Netty, Custom Connectors…**

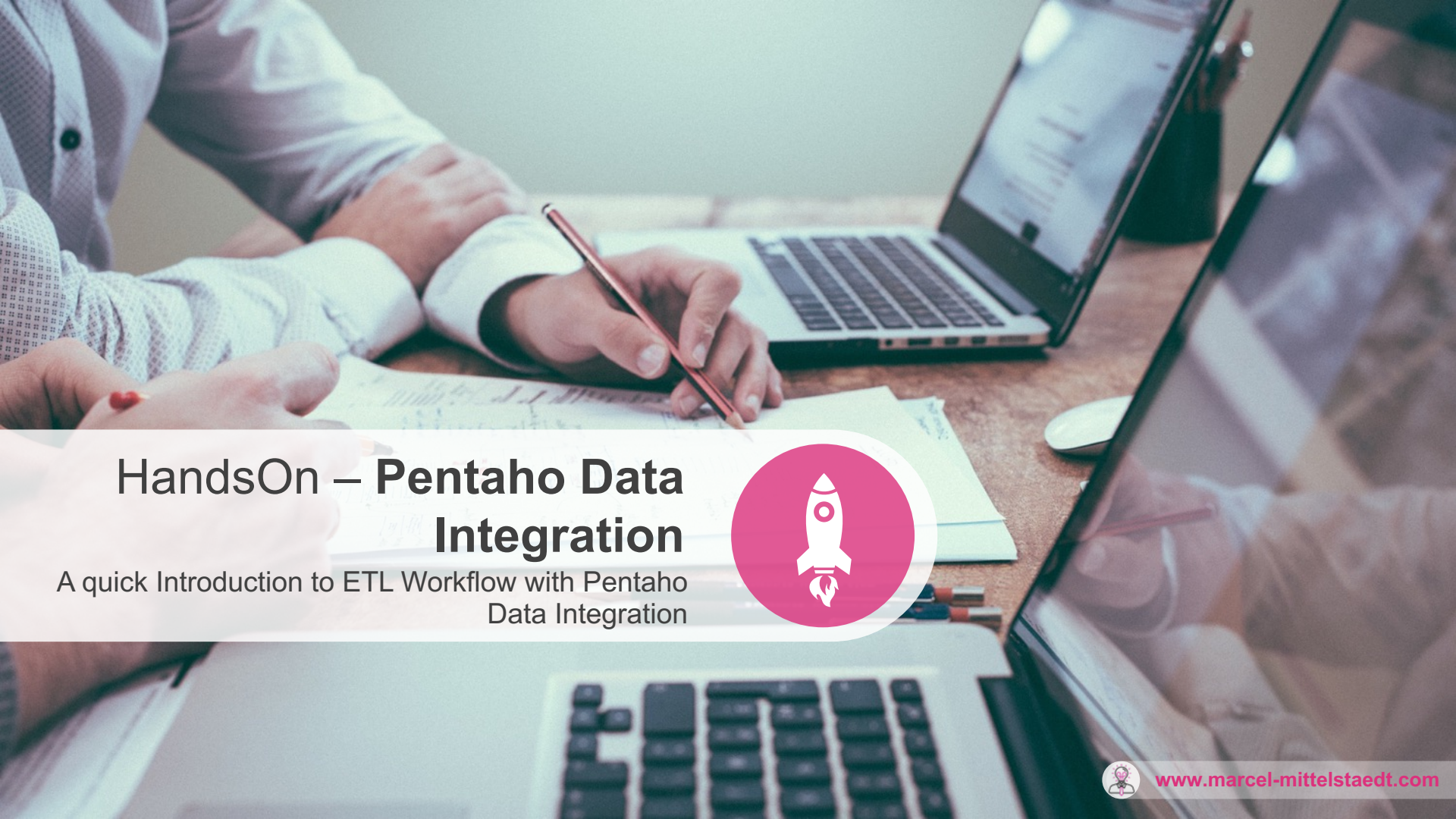
Output could also be **HDFS, Kafka, Elasticsearch, Kinesis, RabbitMQ, NiFi, Akka, Redis, Cassandra, Flume, ActiveMQ, Custom Connectors… …**

Batch&Stream Processing – Lambda Architecture



Break

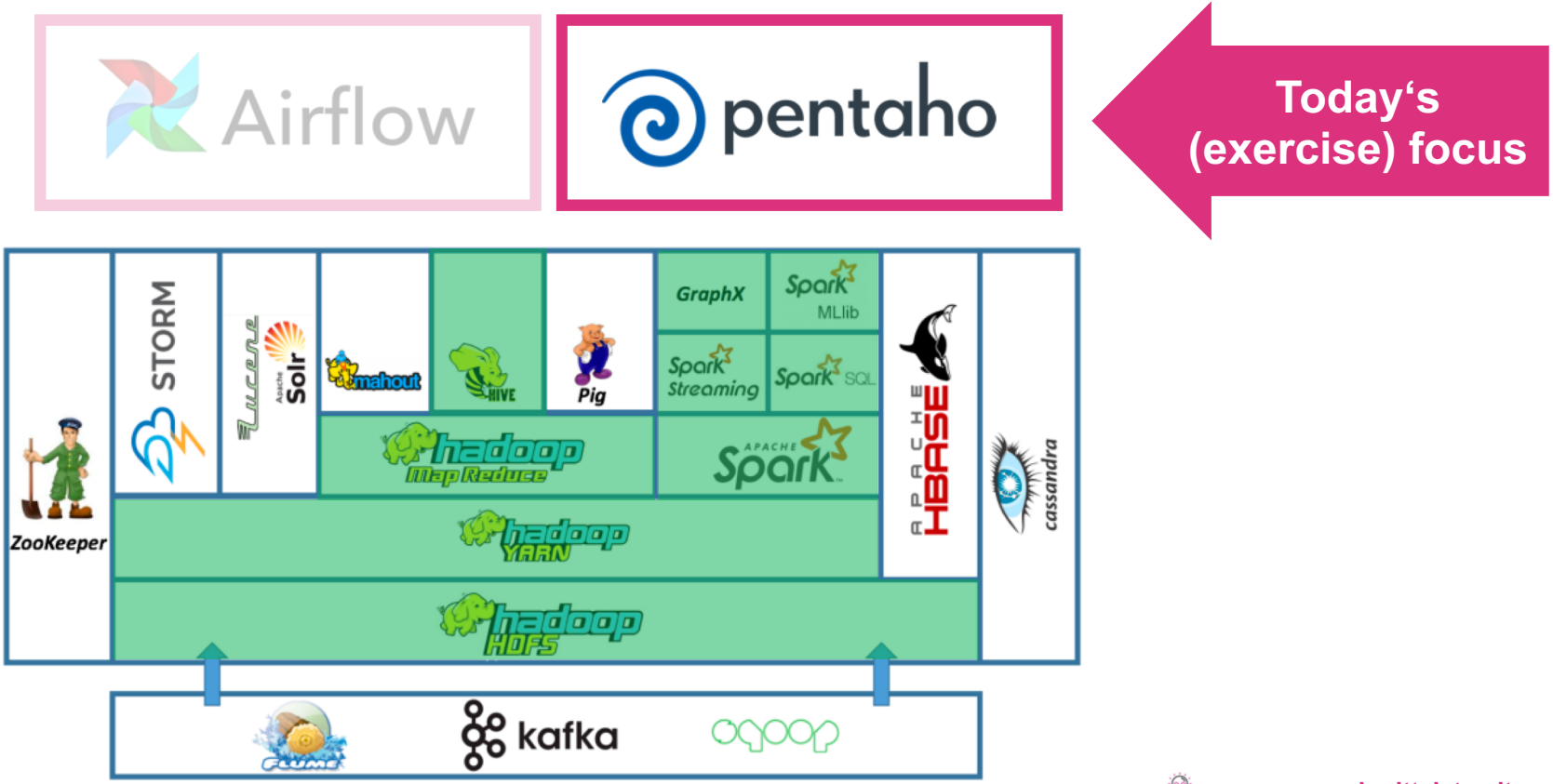
TIME FOR A BREAK



HandsOn – **Pentaho Data Integration**

A quick Introduction to ETL Workflow with Pentaho Data Integration

The Hadoop Ecosystem



Exercises Preparation I

Install and Setup Pentaho Data Integration
First Steps

Download And Install PDI

1. Download Pentaho Data Integration (8.0)

```
https://sourceforge.net/projects/pentaho/
```

2. Extract:

```
unzip pdi-ce-8.1.0.0-365.zip
```


Start PDI (Spoon)

3. Start Pentaho Data Integration

UNIX:

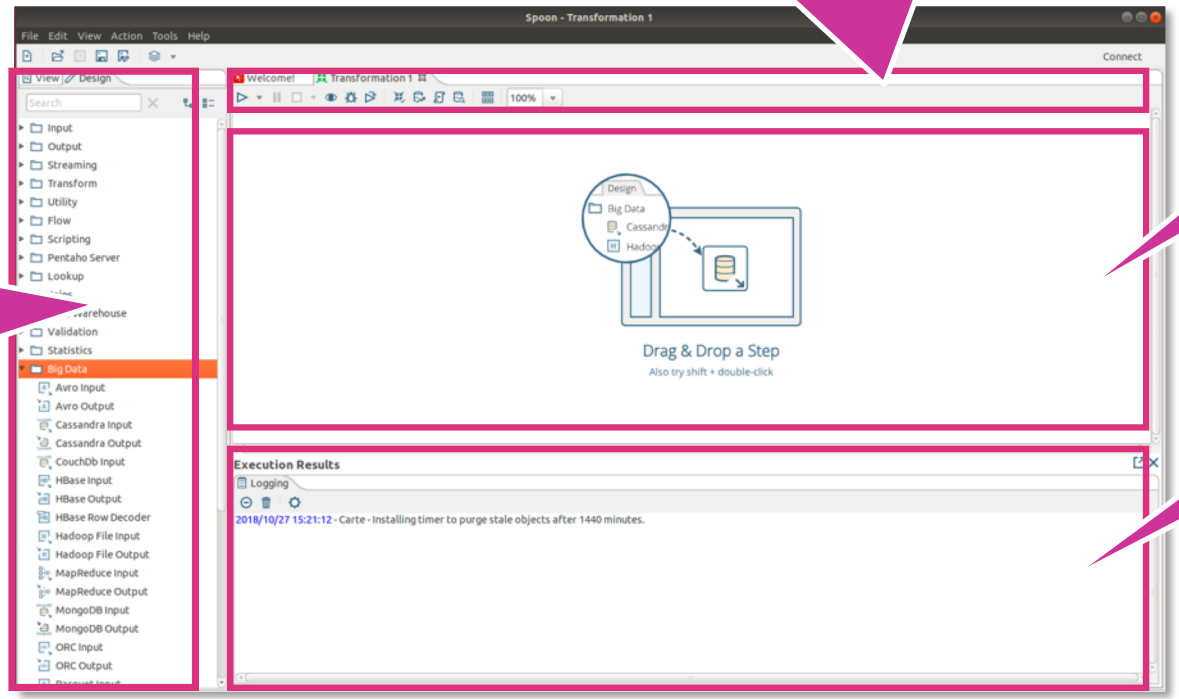
```
/your/pentaho/directory/spoon.sh
```

Windows:

```
/your/pentaho/directory/spoon.bat
```


Spoon Interface

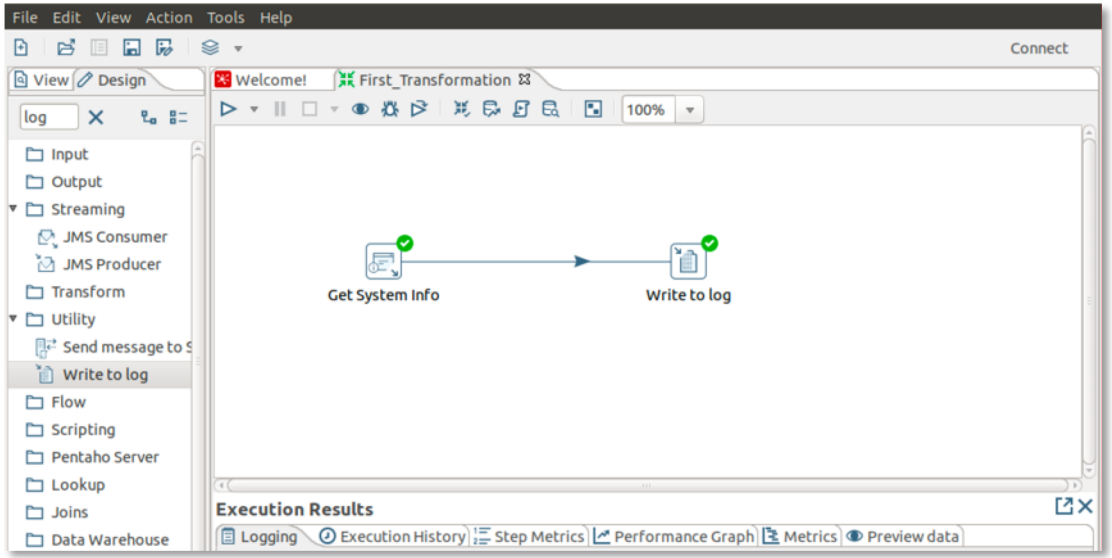
3. Start Pentaho Data Integration



PDI Basics/Examples – First Transformation

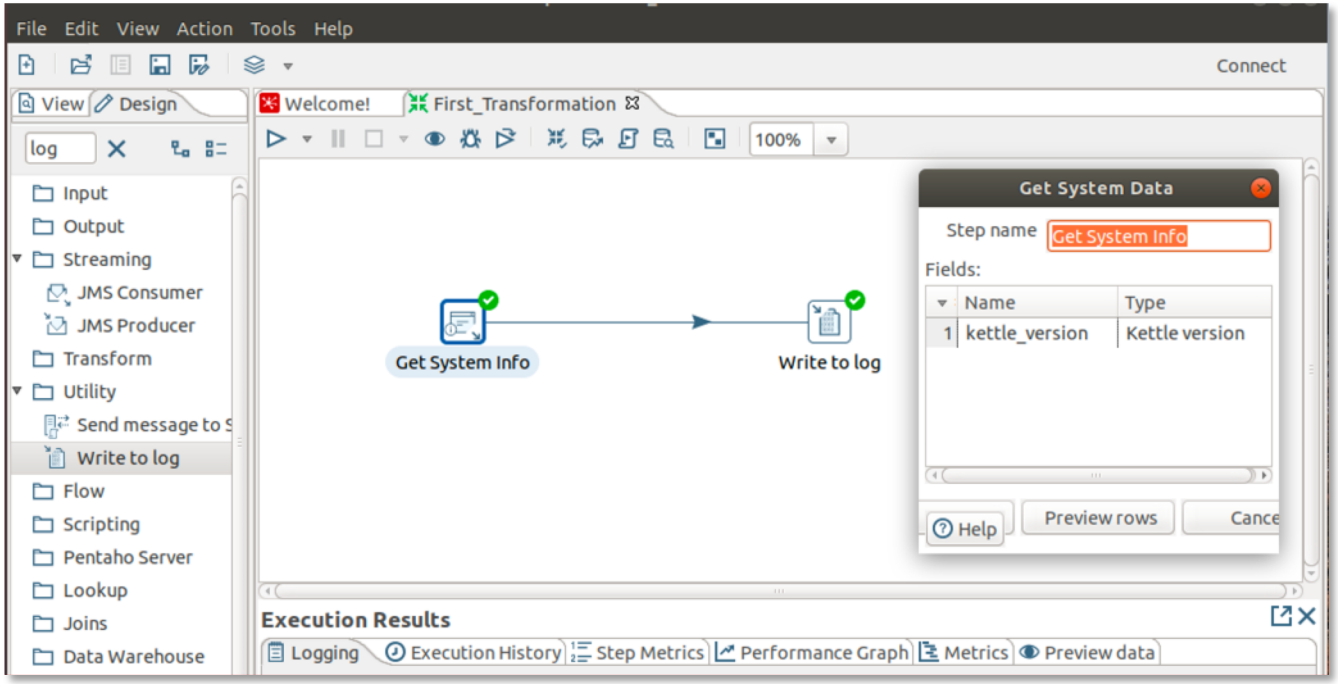
1. Create new **Transformation** (Click: *File → New → Transformation*)

2. Drag&Drop step „*Get System Info*“ and „*Write To Log*“ into Work/Design Area and connect both steps:



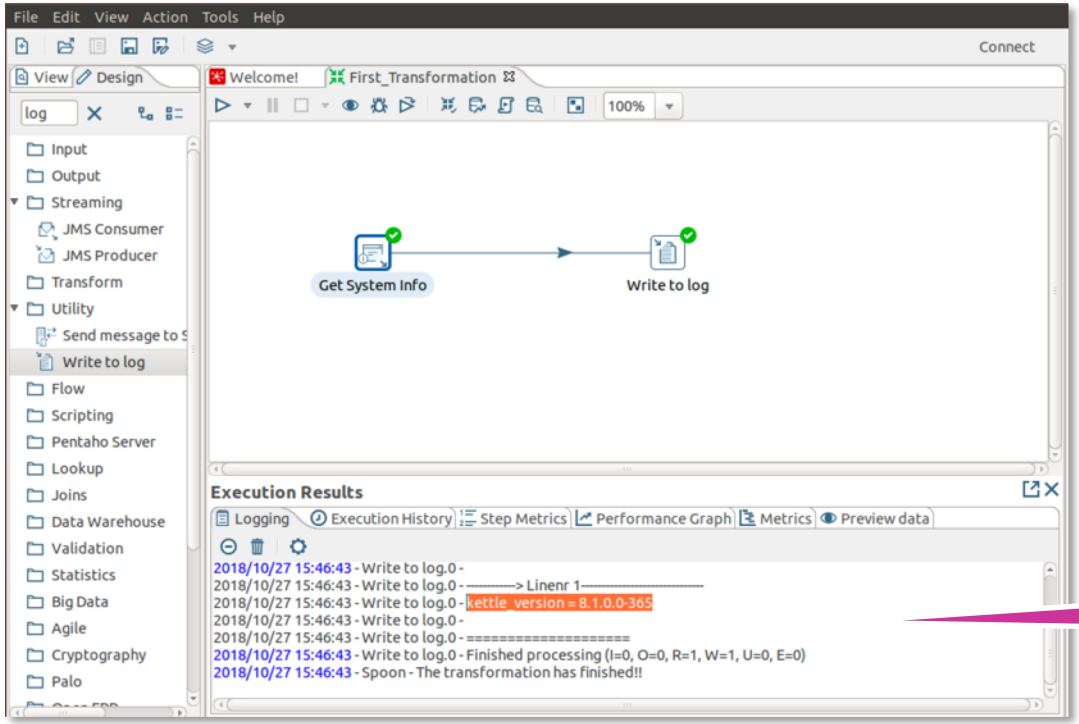
PDI Basics/Examples – First Transformation

3. Double Click „*Get System Info*“ step to configure step accordingly to kettle (PDI) version info:



PDI Basics/Examples – **First Transformation**

4. Save Transformation (*First_Transformation*). Press Run Button. See Results:



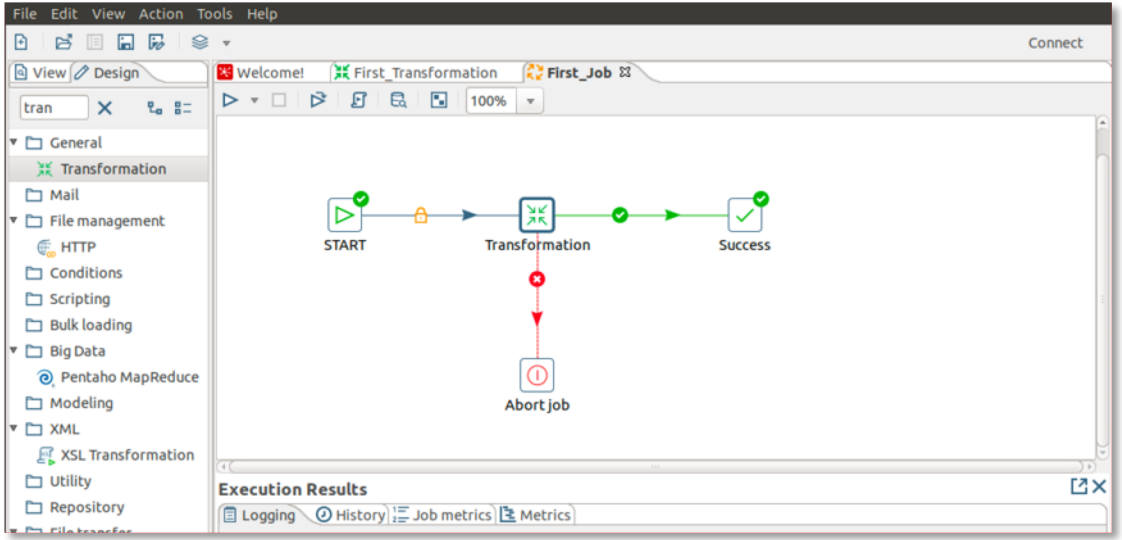
- results of „*Get System Info*“ step are redircected to „Write To Log“ step
- „Write to Log“ step will write results to execution log
- **transformations** are all about actual data transform ation and data flow

Results

PDI Basics/Examples – **First Job**

1. Create New **Job** (Click: *File* → *New* → *Job*)

2. Drag&Drop step „*START*“, „Transformation“, „Abort Job“ and „Success“ steps into Work/ Design Area and connect all steps accordingly:



- Start of each Job

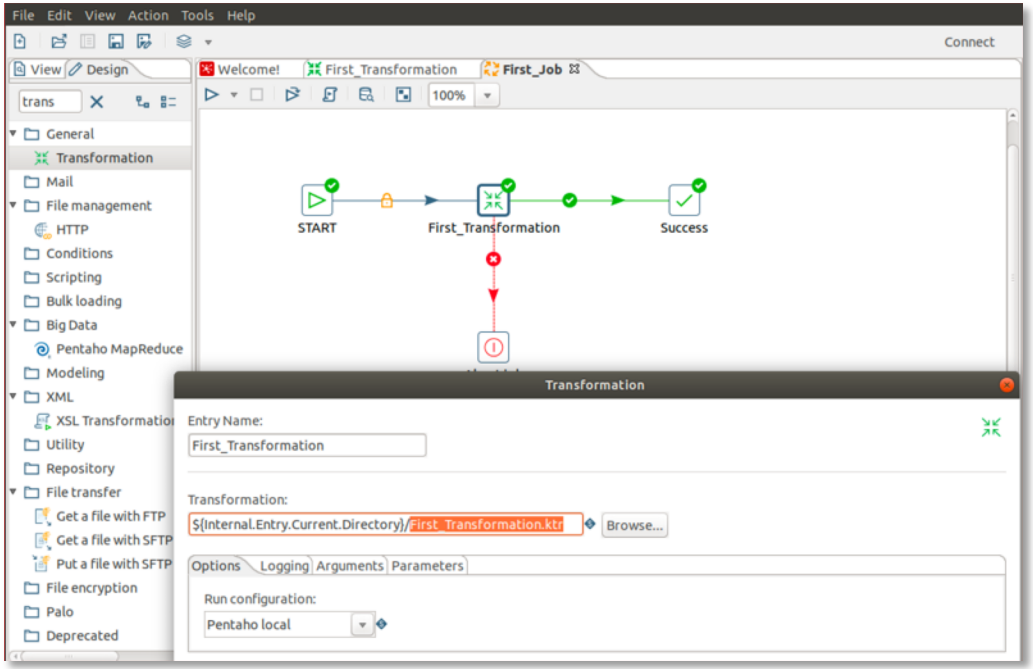
- End of a Job (if not successful)

- End of a Job (if successful)

- Includes a Transformation

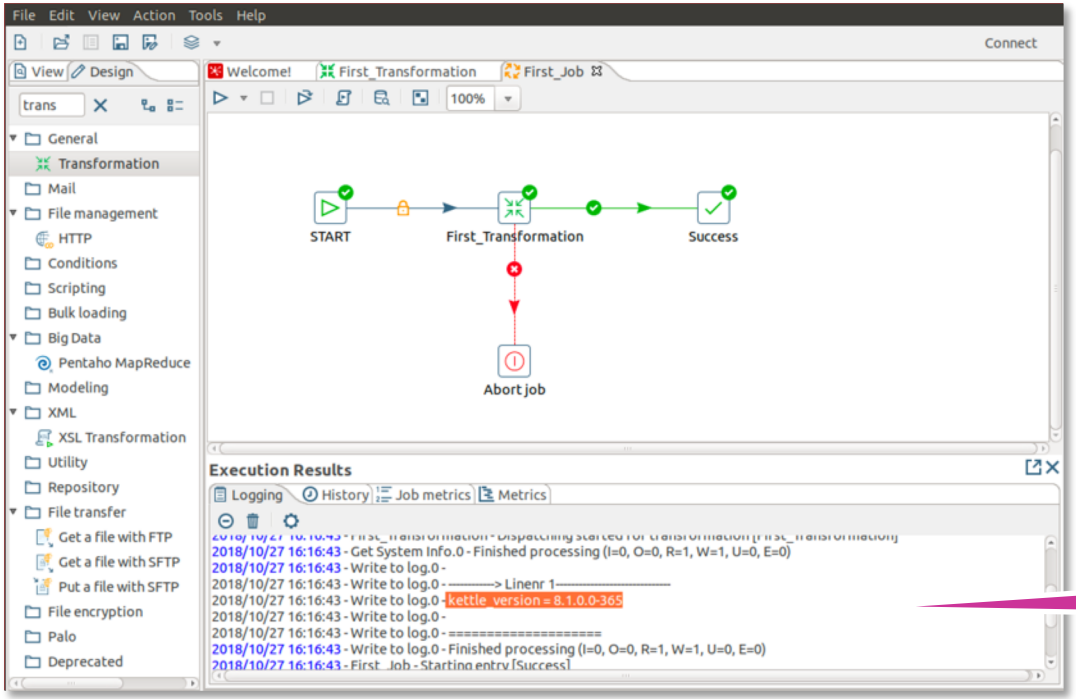
PDI Basics/Examples – **First Job**

3. Include previously created Transformation (First_Transformation) by double click on step „*Transformation*“ and including „*First_Transformation.ktr*“:



PDI Basics/Examples – **First Job**

4. Save Job (*First_Job*). Press Run Button. See Results:



- Job will execute previously created transformation (*First_Transformation.ktr*)
- Output of transformation will be appended to execution log of Job
- **jobs** are all about workflows of multiple transformations and jobs

Results

PDI Basics/Examples – **Execute Jobs Using Kitchen**

1. It‘s nice to run jobs locally during development, but how to run them on a remote server (e.g. in a productive manner)? This is easily achieved using kitchen.sh for Jobs:

```
/home/pentaho/pentaho/data-integration/pan.sh -file=/home/pentaho/pdi_jobs/First_Transformation.ktr

[...]
2019/11/03 19:47:59 - Kitchen - Finished!
2019/11/03 19:47:59 - Kitchen - Start=2019/11/03 19:47:34.003, Stop=2019/11/03 19:47:59.250
2019/11/03 19:47:59 - Kitchen - Processing ended after 25 seconds.
```

2. Or using pan.sh for Transformations:

```
/home/pentaho/pentaho/data-integration/kitchen.sh -file=/home/pentaho/pdi_jobs/First_Job.ktr

[...]
2019/11/03 19:45:47 - Pan - Start=2019/11/03 19:45:46.897, Stop=2019/11/03 19:45:47.023
2019/11/03 19:45:47 - Pan - Processing ended after 0 seconds.
2019/11/03 19:45:47 - First_Transformation -
2019/11/03 19:45:47 - First_Transformation - Step Get System Info.0 ended successfully, processed 1 lines. ( - lines/s)
2019/11/03 19:45:47 - First_Transformation - Step Write to log.0 ended successfully, processed 1 lines. ( - lines/s)
```

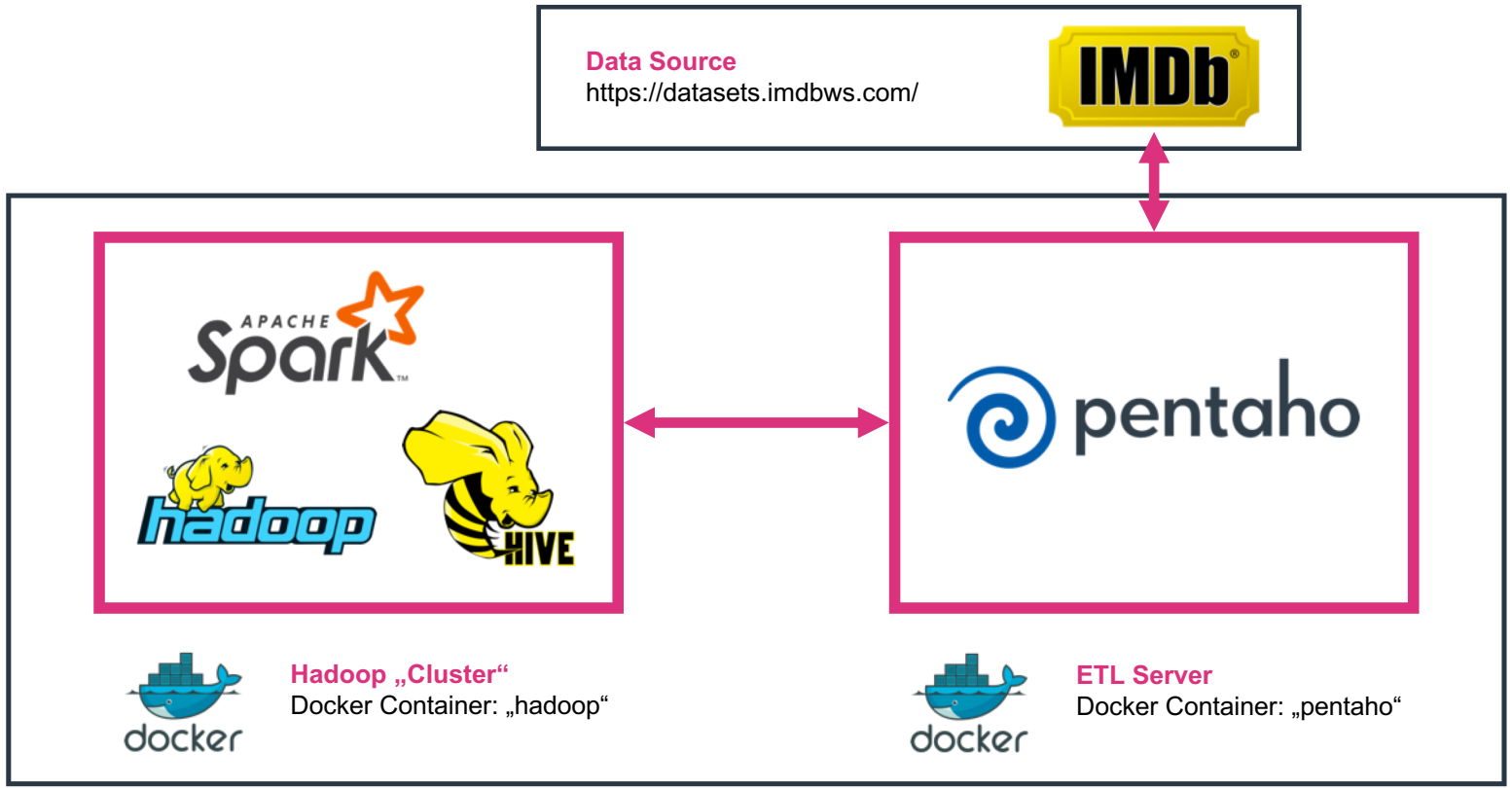
Break

TIME FOR A BREAK

Exercises Preparation II

Start Hadoop/Hive/Spark Docker Image and a Pentaho Data Integration Docker Image

What do we want to do?



Start Gcloud VM and Connect

1. Start Gcloud Instance:

```
gcloud compute instances start big-data
```

2. Connect to Gcloud instance via SSH (on Windows using Putty):

```
ssh hans.wurst@XXX.XXX.XXX.XXX
```


Start Hadoop/Hive/Spark Docker Container

1. Pull Docker Image:

```
docker pull marcelmittelstaedt/spark_base:latest
```

2. Start Docker Image:

```
docker run -dit --name hadoop \
          -p 8088:8088 -p 9870:9870 -p 9864:9864 -p 10000:10000 \
          -p 8032:8032 -p 8030:8030 -p 8031:8031 -p 9000:9000 \
          -p 8888:8888 --net bigdatanet \
          marcelmittelstaedt/spark_base:latest
```

3. Wait till first Container Initialization finished:

```
docker logs hadoop

[…]
Stopping nodemanagers
Stopping resourcemanager
Container Startup finished.
```


Start Hadoop/Hive/Spark Docker Container

4. Get into Docker container:

```
docker exec -it hadoop bash
```

5. Switch to hadoop user:

```
sudo su hadoop
```

```
cd
```

6. Start Hadoop Cluster:

```
start-all.sh
```

7. Start HiveServer2:

```
hiveserver2
```


Start Hadoop/Hive/Spark Docker Container

8. Start HiveServer2:

```
hive/bin/hiveserver2

2018-10-02 16:19:08: Starting HiveServer2
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/home/hadoop/hive/lib/log4j-slf4j-impl-2.10.0.jar!/org/slf4
j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/home/hadoop/hadoop/share/hadoop/common/lib/slf4j-log4j12-1
.7.25.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.apache.logging.slf4j.Log4jLoggerFactory]
Hive Session ID = b8d1efb3-fc8c-4ec8-bdf0-6a9a41e2ddaa
Hive Session ID = 32503981-a5fd-497e-b887-faf3ec1e686e
Hive Session ID = 00f7eab4-5a29-4ce4-ad97-e90904d9206f
Hive Session ID = 100e54c5-14c6-4acc-b398-040152b08ebf
[…]
```


Start ETL (Pentaho) Docker Container

1. Pull Docker Image:

```
docker pull marcelmittelstaedt/pentaho:latest
```

2. Start Docker Image:

```
docker run -dit --name pentaho \
          --net bigdatanet \
          marcelmittelstaedt/pentaho:latest
```

3. Wait till first Container Initialization finished:

```
docker logs pentaho

[…]
Resolving deltas: 100% (692/692), done.
Checking out files: 100% (216/216), done.
Container Startup finished.
```


Start ETL (Pentaho) Docker Container

4. Get into Docker container:

```
docker exec -it pentaho bash
```

5. Switch to pentaho user:

```
sudo su pentaho
```

```
cd
```


Execute Transformations using pan.sh

1. Run first Transformation on ETL Server:

```
/home/pentaho/pentaho/data-integration/pan.sh -file=/home/pentaho/pdi_jobs/First_Transformation.ktr

[...]
2019/11/03 19:45:46 - Pan - Start of run.
2019/11/03 19:45:46 - First_Transformation - Dispatching started for transformation [First_Transformation]
2019/11/03 19:45:47 - Get System Info.0 - Finished processing (I=0, O=0, R=1, W=1, U=0, E=0)
2019/11/03 19:45:47 - Write to log.0 -
2019/11/03 19:45:47 - Write to log.0 - ------------> Linenr 1------------------------------
2019/11/03 19:45:47 - Write to log.0 - ketle_version = 8.0.0.0-28
2019/11/03 19:45:47 - Write to log.0 -
2019/11/03 19:45:47 - Write to log.0 - ====================
2019/11/03 19:45:47 - Write to log.0 - Finished processing (I=0, O=0, R=1, W=1, U=0, E=0)
2019/11/03 19:45:47 - Pan - Finished!
2019/11/03 19:45:47 - Pan - Start=2019/11/03 19:45:46.897, Stop=2019/11/03 19:45:47.023
2019/11/03 19:45:47 - Pan - Processing ended after 0 seconds.
2019/11/03 19:45:47 - First_Transformation -
2019/11/03 19:45:47 - First_Transformation - Step Get System Info.0 ended successfully, processed 1 lines. ( - lines/s)
2019/11/03 19:45:47 - First_Transformation - Step Write to log.0 ended successfully, processed 1 lines. ( - lines/s)
```

Execute Transformations using kitchen.sh

1. Run first Job on ETL Server:

```
/home/pentaho/pentaho/data-integration/kitchen.sh -file=/home/pentaho/pdi_jobs/First_Job.ktr

[...]
2019/11/03 19:47:59 - First_Job - Start of job execution
2019/11/03 19:47:59 - First_Job - Starting entry [Transformation]
2019/11/03 19:47:59 - Transformation - Loading transformation from XML file [file:///home/pentaho/pdi_jobs/First_Transformation.k
tr]
2019/11/03 19:47:59 - Transformation - Using run configuration [Pentaho local]
2019/11/03 19:47:59 - Transformation - Using legacy execution engine
2019/11/03 19:47:59 - First_Transformation - Dispatching started for transformation [First_Transformation]
2019/11/03 19:47:59 - Get System Info.0 - Finished processing (I=0, O=0, R=1, W=1, U=0, E=0)
2019/11/03 19:47:59 - Write to log.0 -
2019/11/03 19:47:59 - Write to log.0 - ------------> Linenr 1------------------------------
2019/11/03 19:47:59 - Write to log.0 - ketle_version = 8.0.0.0-28
2019/11/03 19:47:59 - Write to log.0 -
2019/11/03 19:47:59 - Write to log.0 - ====================
2019/11/03 19:47:59 - Write to log.0 - Finished processing (I=0, O=0, R=1, W=1, U=0, E=0)
2019/11/03 19:47:59 - First_Job - Starting entry [Success]
2019/11/03 19:47:59 - First_Job - Finished job entry [Success] (result=[true])
2019/11/03 19:47:59 - First_Job - Finished job entry [Transformation] (result=[true])
2019/11/03 19:47:59 - First_Job - Job execution finished
2019/11/03 19:47:59 - Kitchen - Finished!
2019/11/03 19:47:59 - Kitchen - Start=2019/11/03 19:47:34.003, Stop=2019/11/03 19:47:59.250
2019/11/03 19:47:59 - Kitchen - Processing ended after 25 seconds.
```

Exercises Preparation III

A simple ETL examples of how to use an ETL Workflow tool (PDI) to integrate IMDb data

PDI IMDb Import

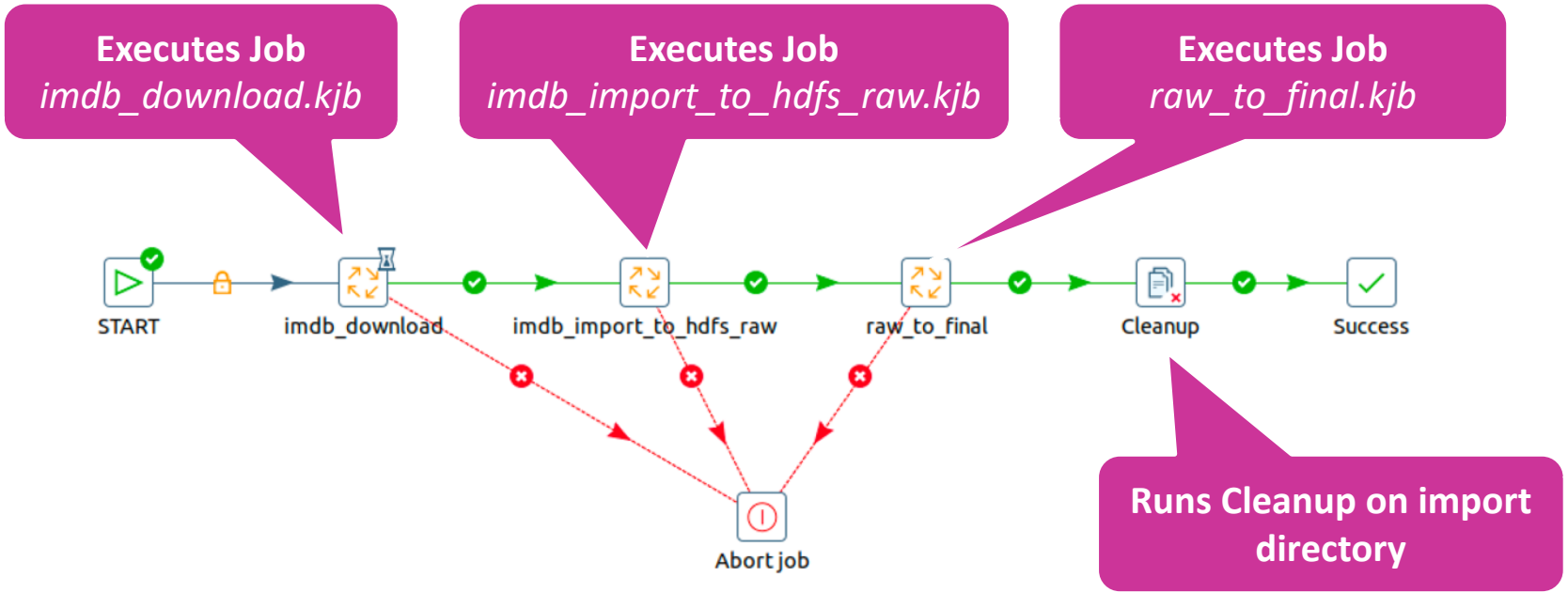
Now let‘s take a look at a real world example: **IMDB data**

https://github.com/marcelmittelstaedt/BigData/tree/master/exercises/winter_semester_2019-2020/06_pentaho

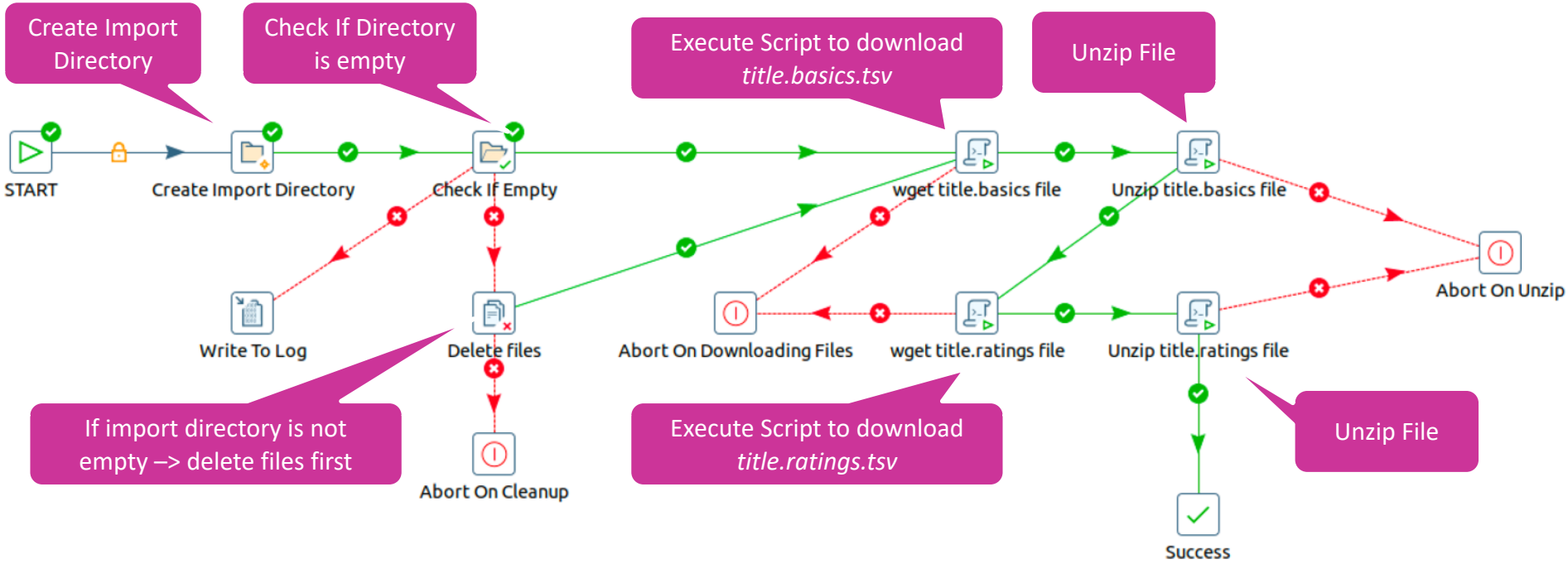
A very simple and naive ETL workflow which is able to run each day:

- **Download of IMDb data** to local filesystem
- Move Data to HDFS (raw directory/layer)
- Create Hive tables for **Raw Layer**
- Create and fill **Final Layer** (Hive tables) by raw layer tables, applying business rules and using dynamic partitioning

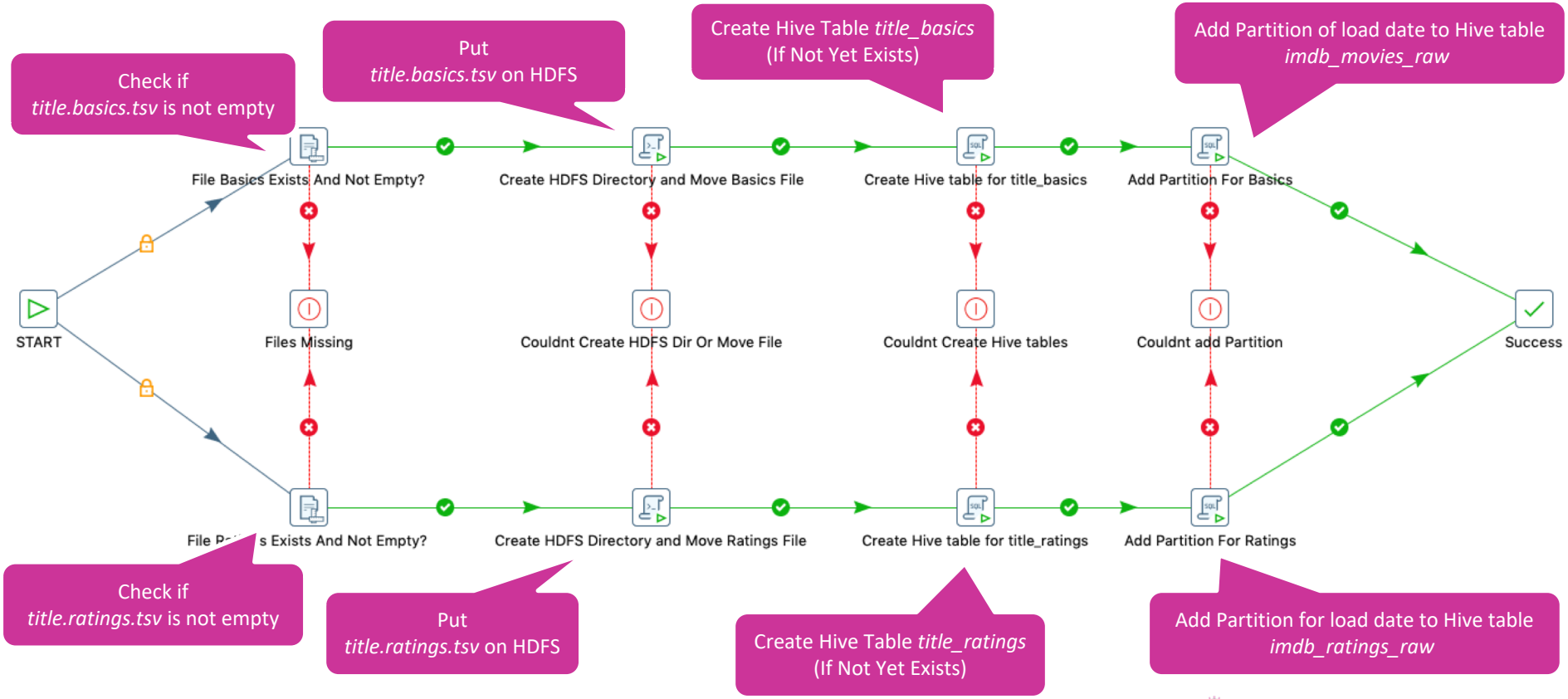
PDI IMDb Import – **Main Job** *(imdb_main.kjb)*



PDI IMDb Import – *imdb_download.kjb*



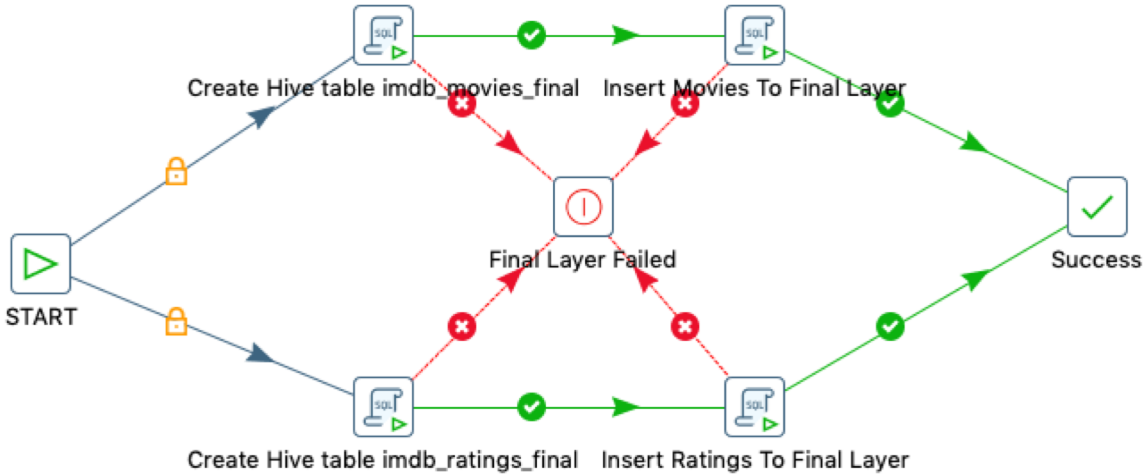
PDI IMDb Import – *imdb_import_to_hdfs_raw.kjb*



PDI IMDb Import – *raw_to_final.kjb*

Create Hive Table *imdb_movies*
(If Not Yet Exists)

Fill table ***imdb_movies*** by using:
- raw layer table ***title_basics*** and
- **Dynamic** partitioning



Create Hive Table *imdb_ratings*
(If Not Yet Exists)

Fill table ***imdb_ratings*** by using:
- raw layer table ***title_ratings*** and
- **Static** partitioning

PDI IMDb Import – **Execution**

1. Execute using kitchen.sh on ETL Server:

```
/home/pentaho/pentaho/data-integration/kitchen.sh -file=/home/pentaho/pdi_jobs/imdb_main.kjb
-param:load_year=2019 -param:load_month=11 -param:load_day=3
```

A Job like this could be scheduled e.g. by `cron` to run on a daily basis, receiving parameters:

- load_day
- load_month
- load_year

… from crontab job to run every day 06:30 a.m. in the morning and logging everything:

```
30 6 * * *   /home/pentaho/pentaho/data-integration/kitchen.sh -file=/home/pentaho/pdi_jobs/imdb_main.kjb
-param:load_year=`date --date=-1days +\%Y` -param:load_month=`date --date=-1days +\%m`
-param:load_day=`date --date=-1days +\%d` >> ~/log/imdb_log_$(date +\%Y\%m\%d).log
```


Exercises I

Use Pentaho Data Integration to solve exercises based on IMDb data

Pentaho Data Integration Exercises – **IMDB**

1. Execute Tasks of previous HandsOn Slides

2. Use PDI and previous Jobs&Transformations to do following changes:

   a) **Extend job** *imdb_download.kjb* to also download ***name.basics.tsv.gz***

   b) **Extend job** *imdb_import_to_hdfs_raw.kjb* to also import ***name.basics.tsv*** to HDFS raw layer.

   c) **Create Hive table *name_basics*** for ***name.basics.tsv*** in raw layer.
   Table should be partitioned by year, month and day of load date like the other tables.

   d) **Create table *imdb_actors*** and **extend job *raw_to_final.kjb*** to also fill table *imdb_actors_final* using:
      - data of table *name_basics* and
      - **partition table** by column *partition_is_alive* containing „alive“ or „dead“, whether the actor is alive or dead.

Pentaho Data Integration Exercises – **IMDB**

3. Run main workflow job **imdb_main.kjb** using:

```
 /home/pentaho/pentaho/data-integration/kitchen.sh -file=/home/pentaho/pdi_jobs/imdb_main.kjb
-param:load_year=2019 -param:load_month=11 -param:load_day=3
```

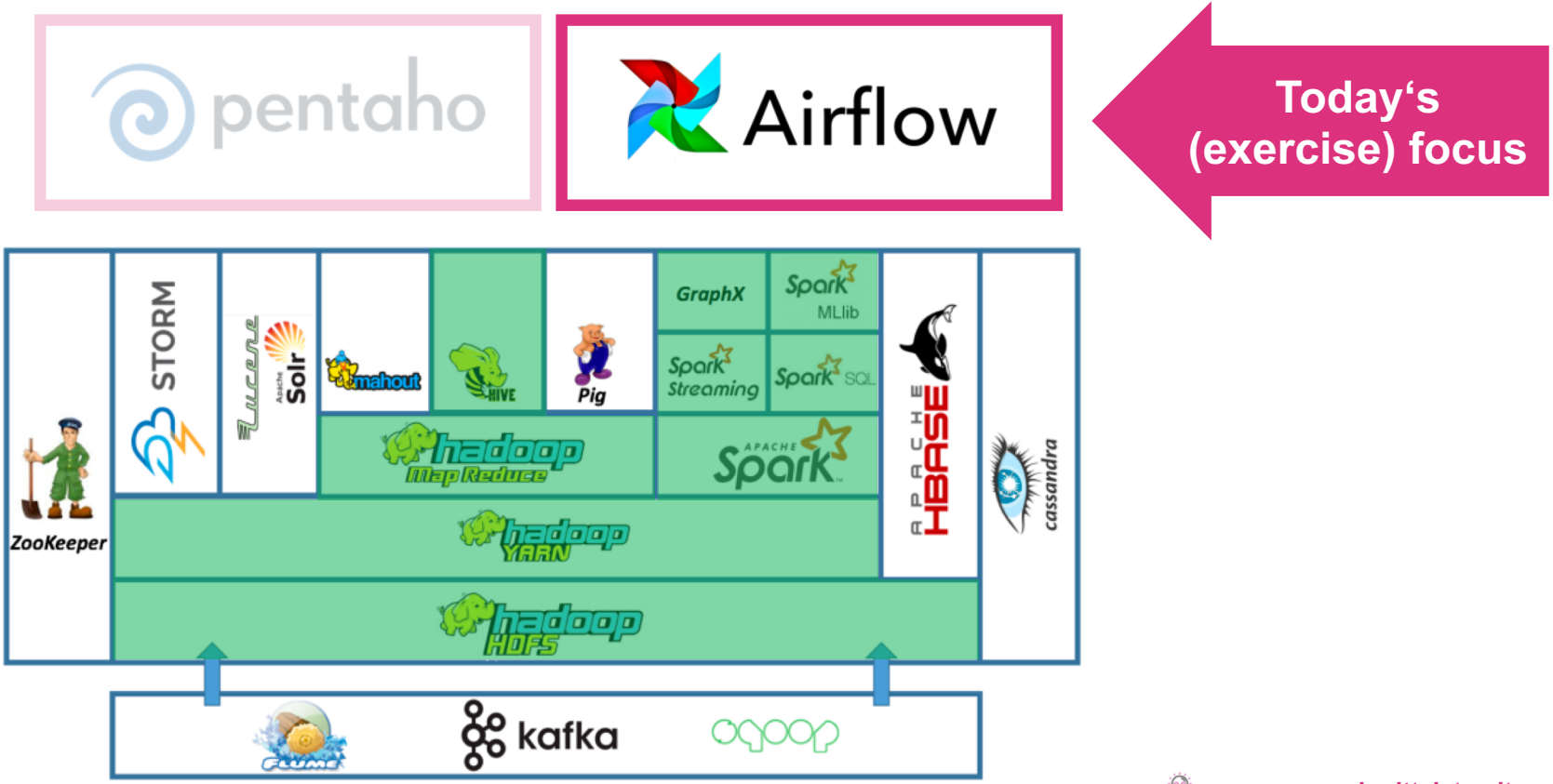

Break

TIME FOR A BREAK

HandsOn – **Apache Airflow**

A quick Introduction to ETL Workflow with Apache Airflow

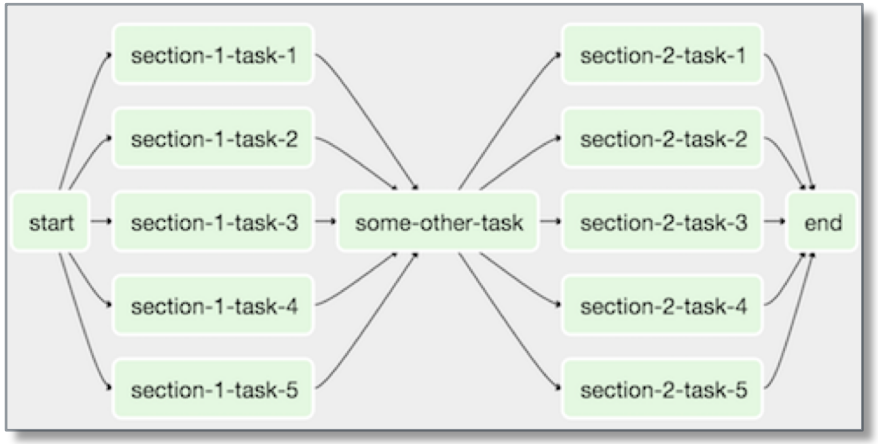
The Hadoop Ecosystem



Airflow

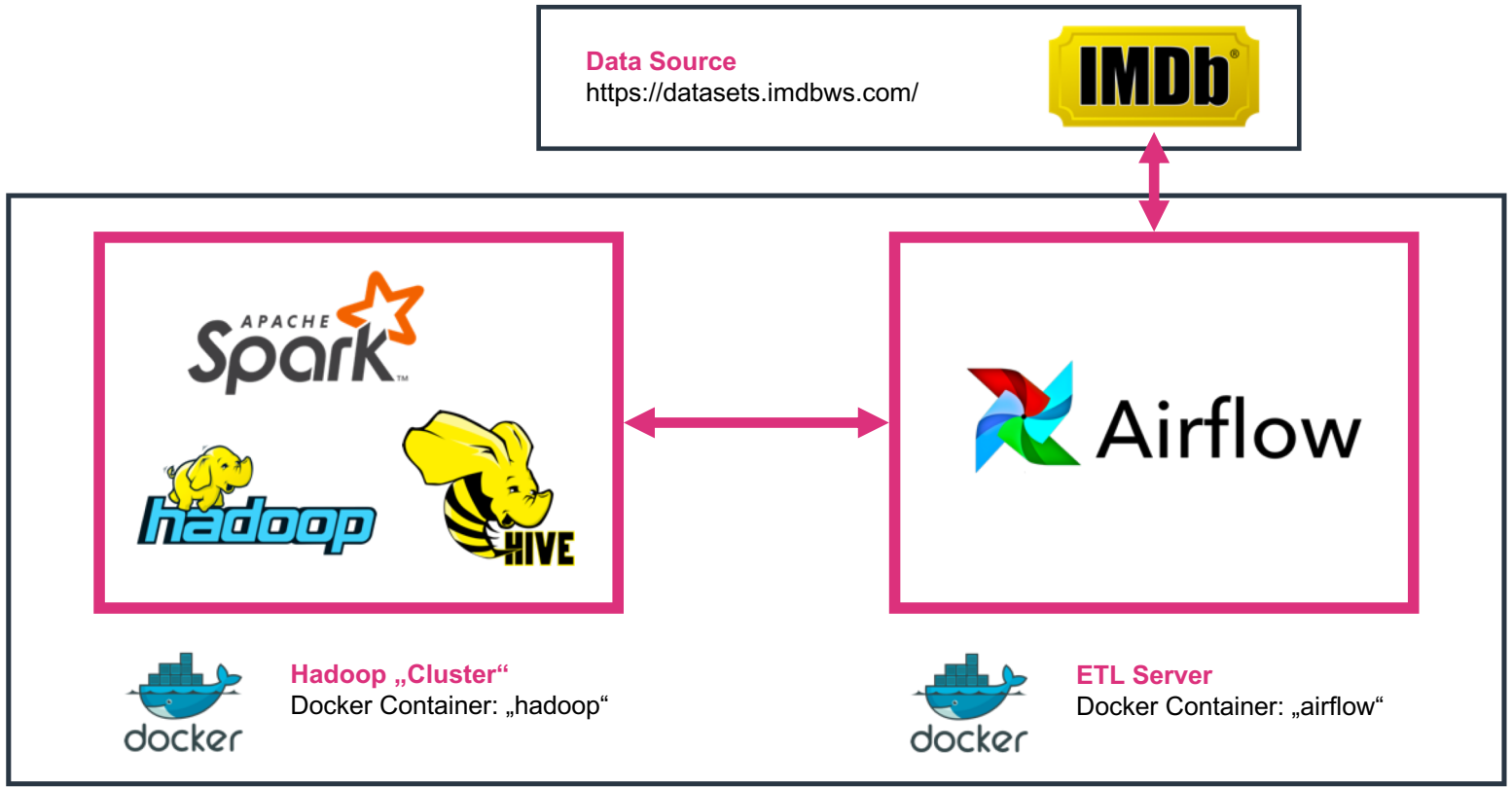
- Apache Open Source Project
- Model Task (e.g. ETL) Workflows
- Python Code Base
- Scheduling, Queues and Pools
- Cluster Ready
- Web UI

- DAG = **Directed Acyclic Graph**



→ a collection of all the tasks you want to run, organized in a way that reflects their relationships and dependencies.

What do we want to do?



Remove Previously created Docker Container

1. Stop and Remove Images:

(This will delete all files you created within previous exercise.
Save them somewhere outside the docker container, if you haven‘t done yet.)

```
docker stop hadoop
docker rm hadoop
```

```
docker stop pentaho
docker rm pentaho
```


Start Hadoop/Hive/Spark Docker Container

1. Pull Docker Image:

```
docker pull marcelmittelstaedt/spark_base:latest
```

2. Start Docker Image:

```
docker run -dit --name hadoop \
          -p 8088:8088 -p 9870:9870 -p 9864:9864 -p 10000:10000 \
          -p 8032:8032 -p 8030:8030 -p 8031:8031 -p 9000:9000 \
          -p 8888:8888 --net bigdatanet \
          marcelmittelstaedt/spark_base:latest
```

3. Wait till first Container Initialization finished:

```
docker logs hadoop

[…]
Stopping nodemanagers
Stopping resourcemanager
Container Startup finished.
```


Start Hadoop/Hive/Spark Docker Container

4. Get into Docker container:

```
docker exec -it hadoop bash
```

5. Switch to hadoop user:

```
sudo su hadoop
```

```
cd
```

6. Start Hadoop Cluster:

```
start-all.sh
```

7. Start HiveServer2:

```
hiveserver2
```


Start Hadoop/Hive/Spark Docker Container

8. Start HiveServer2:

```
hive/bin/hiveserver2

2018-10-02 16:19:08: Starting HiveServer2
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/home/hadoop/hive/lib/log4j-slf4j-impl-2.10.0.jar!/org/slf4
j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/home/hadoop/hadoop/share/hadoop/common/lib/slf4j-log4j12-1
.7.25.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.apache.logging.slf4j.Log4jLoggerFactory]
Hive Session ID = b8d1efb3-fc8c-4ec8-bdf0-6a9a41e2ddaa
Hive Session ID = 32503981-a5fd-497e-b887-faf3ec1e686e
Hive Session ID = 00f7eab4-5a29-4ce4-ad97-e90904d9206f
Hive Session ID = 100e54c5-14c6-4acc-b398-040152b08ebf
[…]
```


Start ETL (Airflow) Docker Container

1. Pull Docker Image:

```
docker pull marcelmittelstaedt/airflow:latest
```

2. Start Docker Image:

```
docker run -dit --name airflow \
           -p 8080:8080 \
           --net bigdatanet \
           marcelmittelstaedt/airflow:latest
```

3. Wait till first Container Initialization finished:

```
docker logs airflow

[…]
Successfully added `conn_id`=spark : spark://:@yarn:

Container Startup finished.
```


Start ETL (Airflow) Docker Container

4. Get into Docker container:

```
docker exec -it airflow bash
```

5. Switch to airflow user:

```
sudo su airflow
```

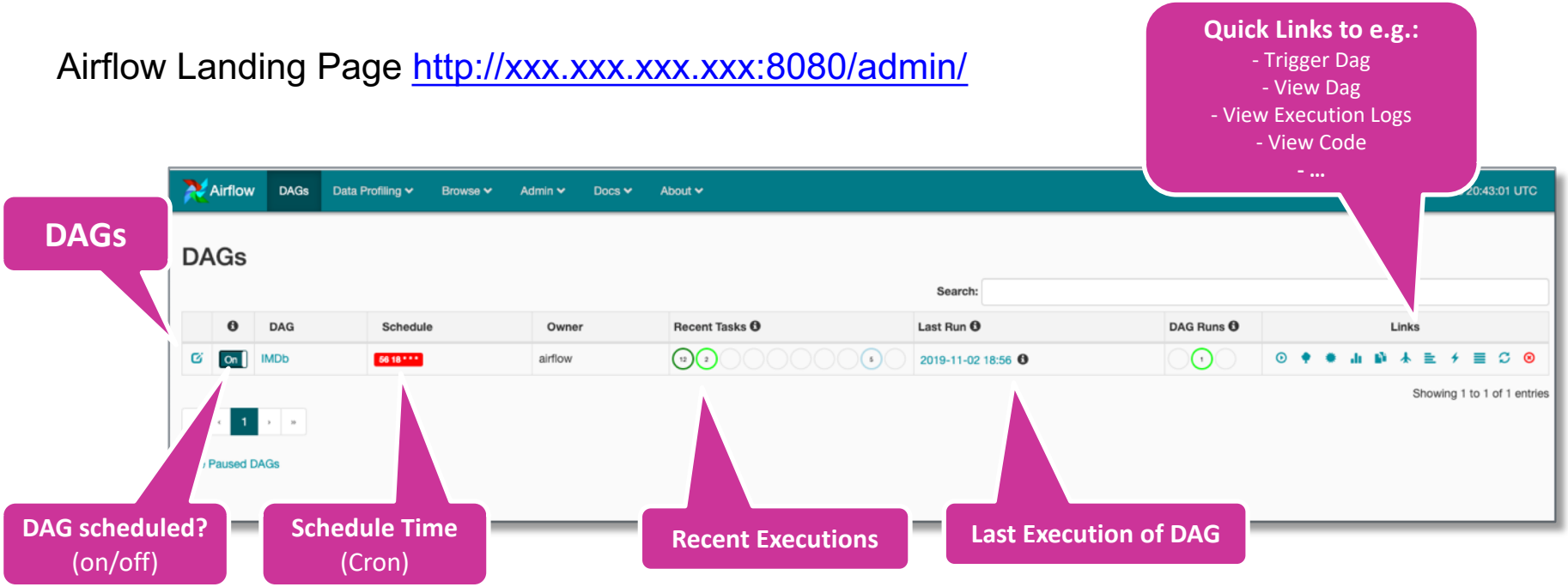
```
cd
```


Exercises Preparation II

Airflow First Steps/Dag

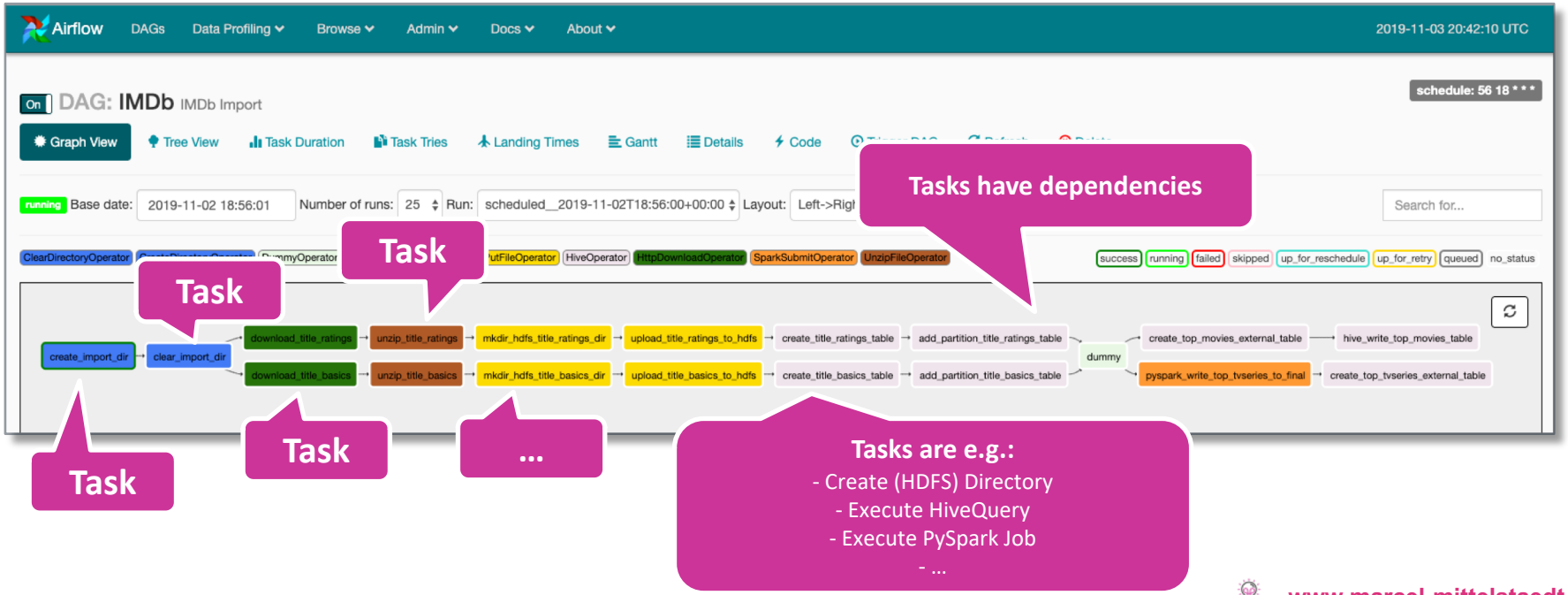
Spoon Interface

Airflow Landing Page http://xxx.xxx.xxx.xxx:8080/admin/



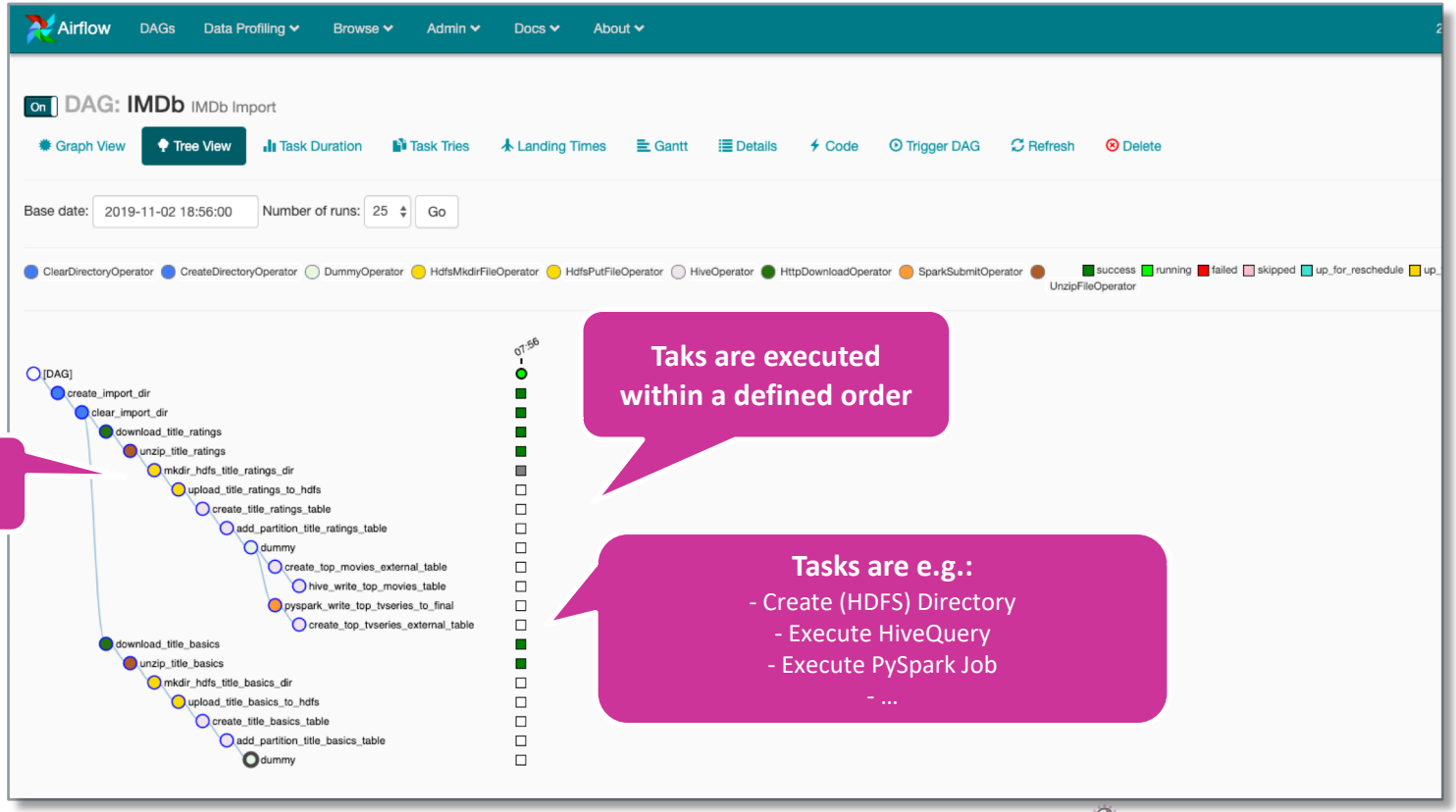
Spoon Interface

Graph View:



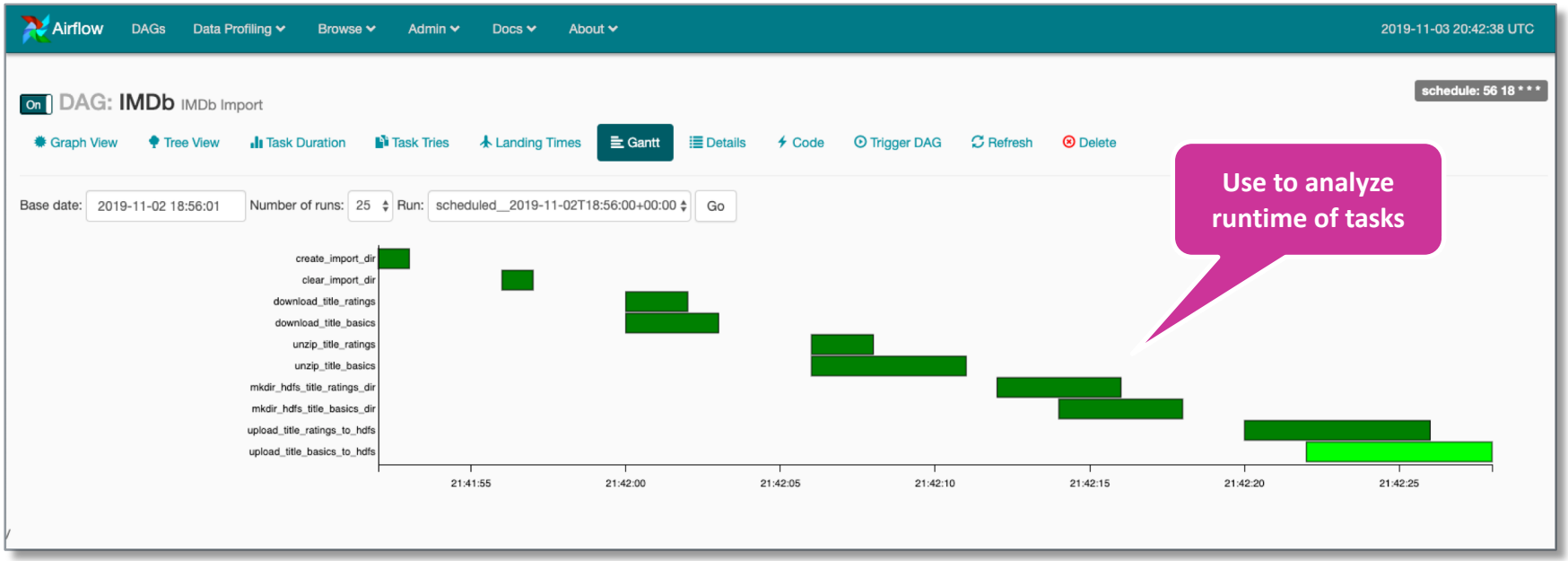
Spoon Interface

Tree View:



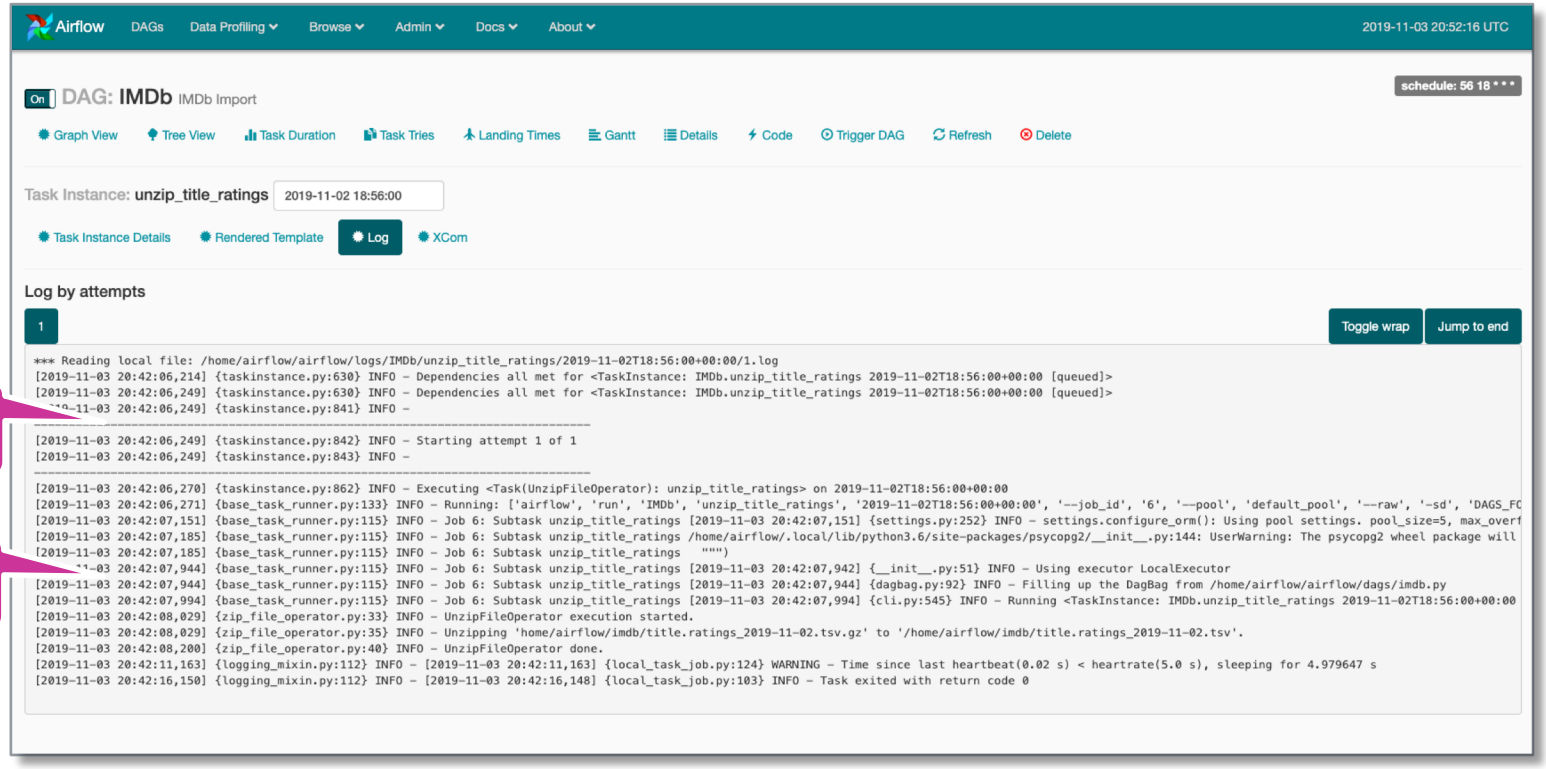
Spoon Interface

Gantt View:



Spoon Interface

Logs View:



Use for Debugging

Each Task has it's own Log

Create Simple Example DAG

1. Open Dag File:

```
vi /home/airflow/airflow/dags/example_dag.py
```

```
from airflow import DAG
from airflow.operators.bash_operator import BashOperator
from datetime import datetime, timedelta

args = {
    'owner': 'airflow'
}

dag = DAG('ExampleDAG', default_args=args, description='Simple Example DAG',
          schedule_interval='56 18 * * *',
          start_date=datetime(2019, 10, 16), catchup=False, max_active_runs=1)

task_1 = BashOperator(
    task_id='print_date',
    bash_command='date',
    dag=dag)

task_2 = BashOperator(
    task_id='sleep',
    bash_command='sleep 5',
    retries=3,
    dag=dag)

task_1 >> task_2
```

DAG Definition, e.g.
- Name
- Schedule Interval (Cron)
- Description
- Start date
- …

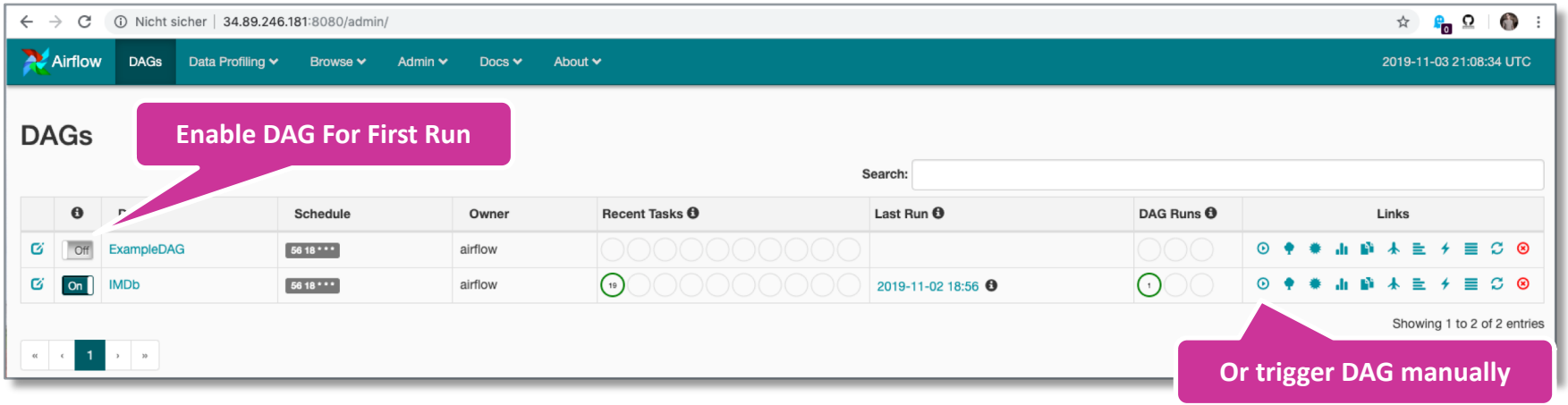
Task 1

Task 2

Task Execution Order
task_2 is dependent on **task_1**

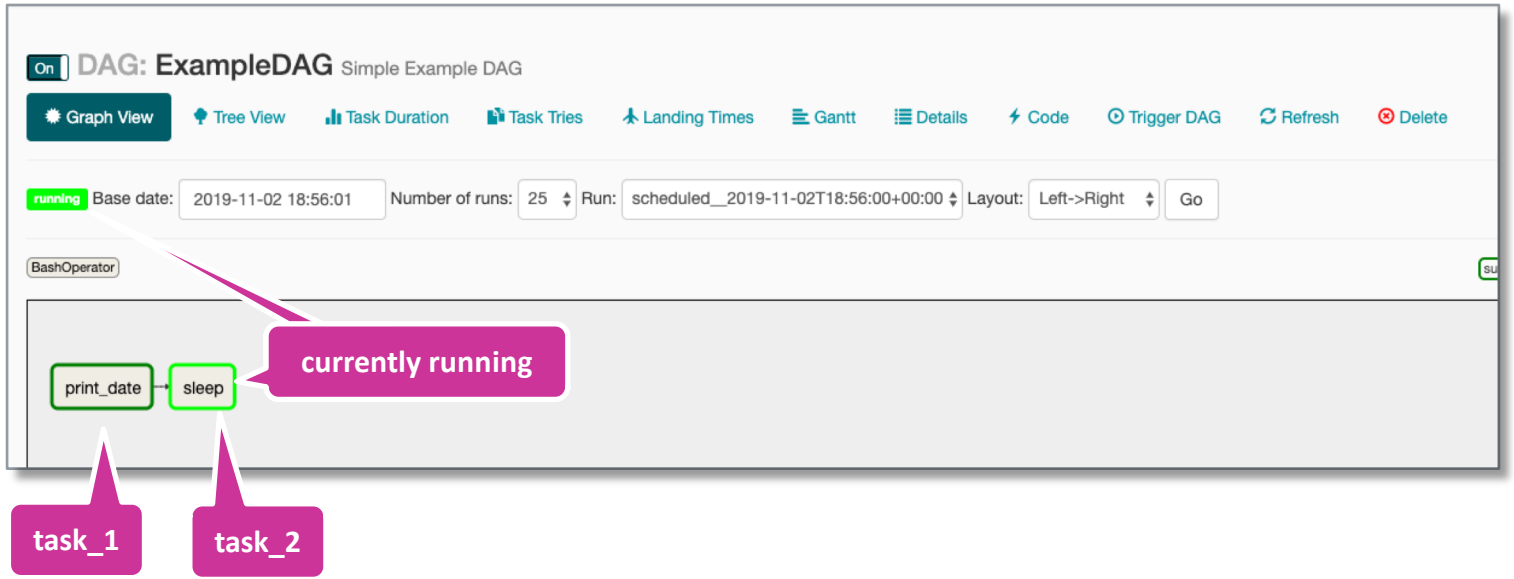
Spoon Interface

Execute DAG:



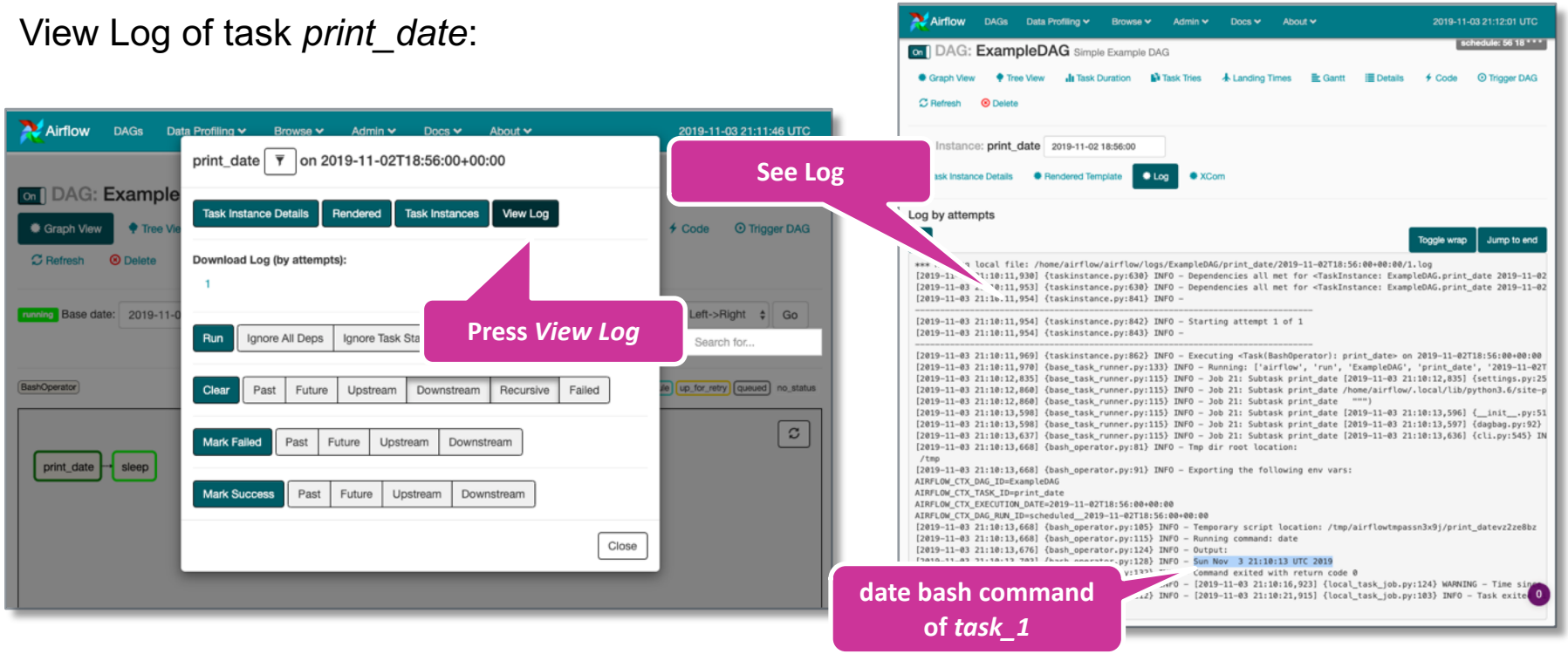
Spoon Interface

See executing DAG:



Spoon Interface

View Log of task *print_date*:

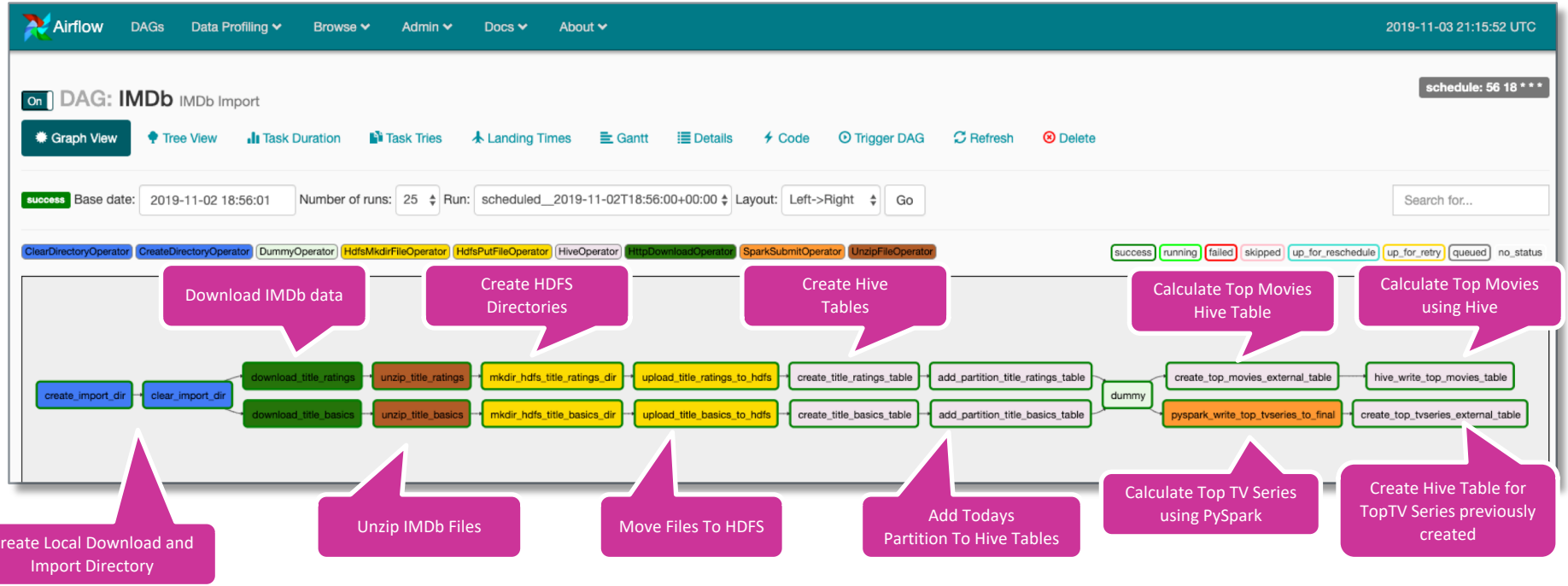


Exercises II

Use Apache Airflow to solve exercises based on IMDb data

Spoon Interface

See executing DAG:



Pentaho Data Integration Exercises – **IMDB**

1. Execute IMDb DAG

2. Use Airflow and previous IMDb DAG to do following changes (`vi /home/airflow/airflow/dags/imdb.py`):

    a) **Extend Airflow IMDb DAG** to also download ***name.basics.tsv.gz***

    b) **Extend Airflow IMDb DAG** to also import ***name.basics.tsv*** to HDFS raw layer.

    c) **Create Hive table *name_basics*** for ***name.basics.tsv*** in raw layer within DAG. Table should be partitioned by year, month and day of load date like the other tables.

    d) **Create table *actors*** and **extend IMDb Airflow DAG** to fill table using Hive or PySpark:
        - make use of all columns within table name_basics
        - add column ***alive*** which contains alive if actor is alive or dead if actor is dead
        - add column ***age*** which contains current age of actor (calculated by using birth and death year)

    e) Run DAG

Well Done

WE'RE DONE FOR ...TODAY