Data Engineering

LTAT.02.007

Prof. Ahmed Awad

Ass. Prof Riccardo Tommasini

TAs: Kristo Raun, Fabiano Spiga, Mohamed Ragab

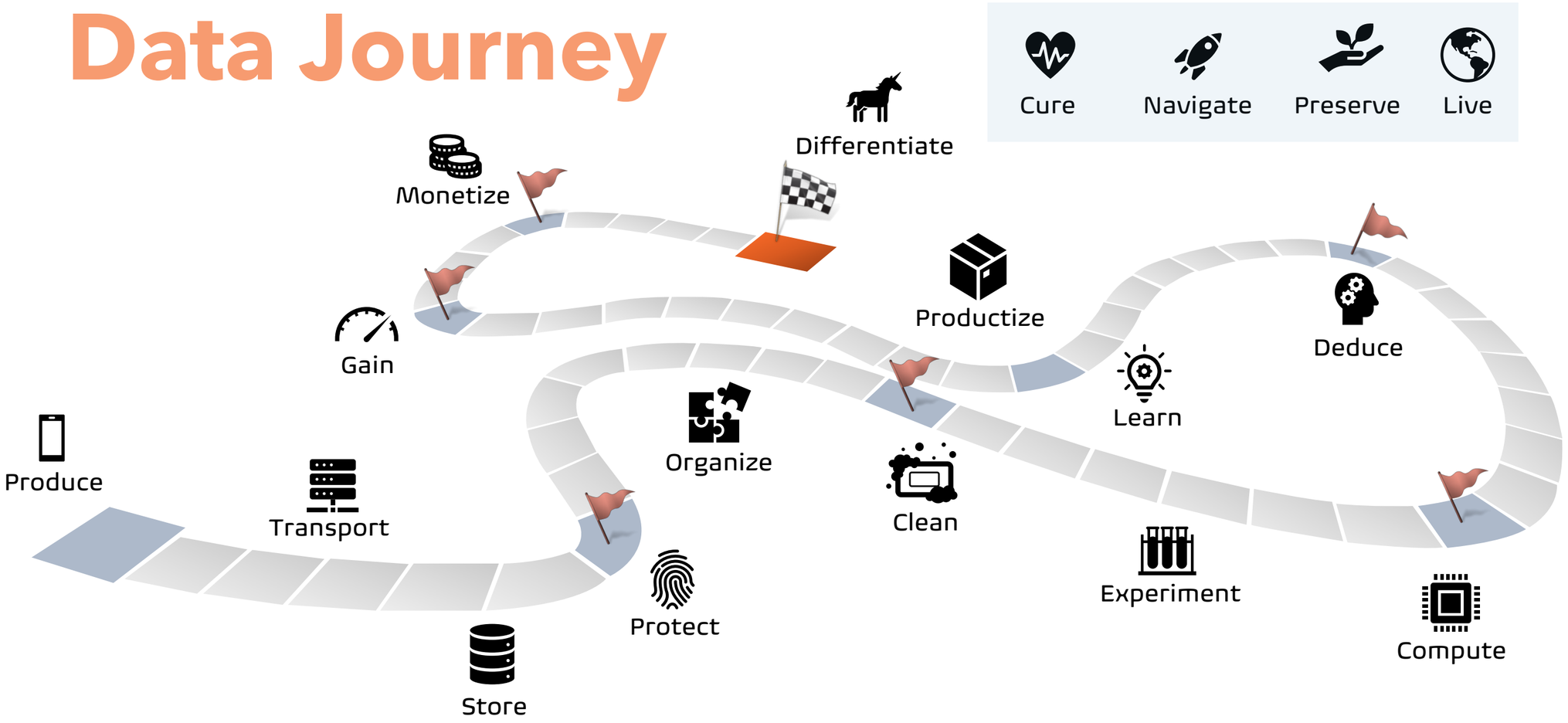
dataeng

Moodle

Data Lifecycle[dl1]

[dl1] Curtesy of Herminio Velazquez

Data Journey



Data Journey Master Class
Tartu, Estonia / November 19, 2020

UNIVERSITY OF TARTU

A 30000ft view

A 30000ft view

- Data Collection

A 30000ft view

- Data Collection
- Data Wrangling

A 30000ft view

- Data Collection
- Data Wrangling
  - Data Shaping

A 30000ft view

- Data Collection
- Data Wrangling
  - Data Shaping
  - Data Cleansing

A 30000ft view

- Data Collection
- Data Wrangling
  - Data Shaping
  - Data Cleansing
  - Data Augmenting

A 30000ft view

- Data Collection
- Data Wrangling
  - Data Shaping
  - Data Cleansing
  - Data Augmenting
- Data Analysis

Data Collection

Data Collection

- We call Data Collection (aka Acquisition) the process of finding and accessing new data sources

Data Collection

- We call Data Collection (aka Acquisition) the process of finding and accessing new data sources
- Happens **outside** the data warehouse/lake and may involve different organizations

Data Collection

- We call Data Collection (aka Acquisition) the process of finding and accessing new data sources
- Happens **outside** the data warehouse/lake and may involve different organizations
- Not to be confused with [[synonimns/Data Ingestion]], which is the process of filling our Data Warehouse/Lake with new data

Data Collection Examples

Data Collection Examples

- [[Reading Files]]

Data Collection Examples

- [[Reading Files]]
- [[Data Crawling]]

Data Collection Examples

- [[Reading Files]]
- [[Data Crawling]]
- [[Accessing Databases]]

Data Collection Examples

- [[Reading Files]]
- [[Data Crawling]]
- [[Accessing Databases]]
- [[Web API | Calling REST API]]

Data Collection Examples

- [[Reading Files]]
- [[Data Crawling]]
- [[Accessing Databases]]
- [[Web API | Calling REST API]]
- [[Consuming WebSockets]]

Not to be confused with [[Data Ingestion]]

Not to be confused with [[Data Ingestion]]

- Maintaining a [[Distributed File System]]

Not to be confused with [[Data Ingestion]]

- Maintaining a [[Distributed File System]]
- Using a [[Distributed Message Queue]]

Not to be confused with [[Data Ingestion]]

- Maintaining a [[Distributed File System]]
- Using a [[Distributed Message Queue]]
- Using a[[Publishing Subscribe System]]

Data Source Selection Criteria

Data Source Selection Criteria

- Credibility

Data Source Selection Criteria

- Credibility
- Completeness

Data Source Selection Criteria

- Credibility
- Completeness
- Accurateness

Data Source Selection Criteria

- Credibility
- Completeness
- Accurateness
- Verifiability

Data Source Selection Criteria

- Credibility
- Completeness
- Accurateness
- Verifiability
- Currency

Data Source Selection Criteria

- Credibility
- Completeness
- Accurateness
- Verifiability
- Currency
- Accessibility

Data Source Selection Criteria

- Credibility
- Completeness
- Accurateness
- Verifiability
- Currency
- Accessibility

Data Source Selection Criteria

- Credibility
- Completeness
- Accurateness
- Verifiability
- Currency
- Accessibility
- Compliance

Data Source Selection Criteria

- Credibility
- Completeness
- Accurateness
- Verifiability
- Currency
- Accessibility
- Compliance
- Cost

Data Source Selection Criteria

- Credibility
- Completeness
- Accurateness
- Verifiability
- Currency
- Accessibility
- Compliance
- Cost
- Legal issues

Data Source Selection Criteria

- Credibility
- Completeness
- Accurateness
- Verifiability
- Currency
- Accessibility
- Compliance
- Cost
- Legal issues
- Security

Data Source Selection Criteria

- Credibility
- Completeness
- Accurateness
- Verifiability
- Currency
- Accessibility
- Compliance
- Cost
- Legal issues
- Security
- Storage

Data Source Selection Criteria

- Credibility
- Completeness
- Accurateness
- Verifiability
- Currency
- Accessibility
- Compliance
- Cost
- Legal issues
- Security
- Storage
- Provenance

Data Wrangling

The process of transforming “raw” data into data that can be analyzed to generate valid actionable insights

Data scientists spend more time preparing data than analyzing them.

Isn’t data science sexy?

Data Wrangling: an Iterative process

Data Wrangling: an Iterative process

- Understand

Data Wrangling: an Iterative process

- Understand
- Explore

Data Wrangling: an Iterative process

- Understand
- Explore
- Transform

Data Wrangling: an Iterative process

- Understand
- Explore
- Transform
- Augment

Data Wrangling: an Iterative process

- Understand
- Explore
- Transform
- Augment
- Visualize

Data Processing

Pre

Post

Data Processing

Pre **Post**

- [[Data Cleansing]]

Data Processing

Pre **Post**

- [[Data Cleansing]]
- Data Integration

Data Processing

Pre **Post**

- [[Data Cleansing]]
- Data Integration
- Data Reduction

Data Processing

Pre **Post**

- [[Data Cleansing]]
- Data Integration
- Data Reduction

Data Processing

Pre

- [[Data Cleansing]]
- Data Integration
- Data Reduction

Post

- Transformation

Data Processing

Pre

- [[Data Cleansing]]
- Data Integration
- Data Reduction

Post

- Transformation
- Erinchment

Data Processing

Pre

- [[Data Cleansing]]
- Data Integration
- Data Reduction

Post

- Transformation
- Erinchment
- Summarization

Data Cleansing

Data cleansing or ** data scrubbing** is the act of **detecting and correcting (or removing corrupt or inaccurate records)** from a dataset.

The term refers to identifying incomplete, incorrect, inaccurate, partial or irrelevant parts of the data and then replacing, modifying, filling in or deleting this dirty data.

Why is Data “Dirty” ?

Why is Data “Dirty” ?

- Dummy Values

Why is Data “Dirty” ?

- Dummy Values
- Absence of Data

Why is Data “Dirty” ?

- Dummy Values
- Absence of Data
- Multipurpose Fields

Why is Data “Dirty” ?

- Dummy Values
- Absence of Data
- Multipurpose Fields
- Cryptic Data

Why is Data “Dirty” ?

- Dummy Values
- Absence of Data
- Multipurpose Fields
- Cryptic Data
- Contradicting Data

Why is Data “Dirty” ?

- Dummy Values
- Absence of Data
- Multipurpose Fields
- Cryptic Data
- Contradicting Data

Why is Data “Dirty” ?

- Dummy Values
- Absence of Data
- Multipurpose Fields
- Cryptic Data
- Contradicting Data
- Shared Field Usage

Why is Data “Dirty” ?

- Dummy Values
- Absence of Data
- Multipurpose Fields
- Cryptic Data
- Contradicting Data
- Shared Field Usage
- Inappropriate Use of Fields

Why is Data “Dirty” ?

- Dummy Values
- Absence of Data
- Multipurpose Fields
- Cryptic Data
- Contradicting Data
- Shared Field Usage
- Inappropriate Use of Fields
- Violation of Business Rules

Why is Data “Dirty” ?

- Dummy Values
- Absence of Data
- Multipurpose Fields
- Cryptic Data
- Contradicting Data
- Shared Field Usage
- Inappropriate Use of Fields
- Violation of Business Rules
- Non-Unique Identifiers

Why is Data “Dirty” ?

- Dummy Values
- Absence of Data
- Multipurpose Fields
- Cryptic Data
- Contradicting Data
- Shared Field Usage
- Inappropriate Use of Fields
- Violation of Business Rules
- Non-Unique Identifiers
- Data Integration Problems

[[Data Integration]]

Data integration systems aims at providing a uniform access to a set of heterogeneous data sources.

Why data needs to be integrated?

Data sources can differ on the data model (relational, hierarchical, semi-structured), on the schema level, or on the query-processing capabilities.

In a data integration architecture, these sources are queried by using a global schema, also called mediated schema, which provides a virtual view of the underlying sources.

Mapping Lav and gav

Data Reduction

Obtain a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) analytical results

Why data reduction?

A database/data warehouse may store terabytes of data. Complex data analysis may take a very long time to run on the complete data set.

Data reduction strategies

Data reduction strategies

- Dimensionality reduction, e.g., remove unimportant attributes

Data reduction strategies

- Dimensionality reduction, e.g., remove unimportant attributes
  - Wavelet transforms

Data reduction strategies

- Dimensionality reduction, e.g., remove unimportant attributes
  - Wavelet transforms
  - Principal Components Analysis (PCA)

Data reduction strategies

- Dimensionality reduction, e.g., remove unimportant attributes
  - Wavelet transforms
  - Principal Components Analysis (PCA)
  - Feature subset selection, feature creation

Data reduction strategies

- Dimensionality reduction, e.g., remove unimportant attributes
  - Wavelet transforms
  - Principal Components Analysis (PCA)
  - Feature subset selection, feature creation
- Numerosity reduction (some simply call it: Data Reduction)

Data reduction strategies

- Dimensionality reduction, e.g., remove unimportant attributes
  - Wavelet transforms
  - Principal Components Analysis (PCA)
  - Feature subset selection, feature creation
- Numerosity reduction (some simply call it: Data Reduction)
  - Regression

Data reduction strategies

- Dimensionality reduction, e.g., remove unimportant attributes
  - Wavelet transforms
  - Principal Components Analysis (PCA)
  - Feature subset selection, feature creation
- Numerosity reduction (some simply call it: Data Reduction)
  - Regression
  - Histograms, clustering, sampling

Data reduction strategies

- Dimensionality reduction, e.g., remove unimportant attributes
  - Wavelet transforms
  - Principal Components Analysis (PCA)
  - Feature subset selection, feature creation
- Numerosity reduction (some simply call it: Data Reduction)
  - Regression
  - Histograms, clustering, sampling
  - Data cube aggregation

[[Data Enrichment]]/[[Data Agumentation]]

Data enrichment refers to the process of appending or otherwise enhancing collected data with relevant context obtained from additional sources.

Data agumentation in data analysis are techniques used to increase the amount of data by adding slightly modified copies of already existing data or newly created synthetic data from existing data.

Why we need Data Enrichment/Augumentation

Data analytics tasks are often data or knowledge intensive.

Data intensive analytical tasks require to increase the amount of available data, e.g., for boosting the model training

Knowledge intensive tasks require contextual domain knowledge to increase the accuracy of the result.

Data Transformation

Data Transformation refers to the process changing the shape of the data, typically for migrating data from one data system to another

Data transformation is the process of converting data from one format or structure into another format or structure. It is a fundamental aspect of most data integration[1] and data management tasks such as data wrangling, data warehousing, data integration and application integration.

Why we need Data Transformation

Different analytical tasks (e.g., queries) result either simpler to write or more efficient to run once executed within highly specialized systems.

Data transformation is often used to reshape data into forms that are more convenient.

Strategies for Data Transformation

Strategies for Data Transformation

- Batch

Strategies for Data Transformation

- Batch
- Streaming

Data Summarization/Visualization

Data Summarization refers to the process of aggregating data to reach an higher level of abstraction. DS is tightly coupled with **Data Visualization**, i.e., the process of representing data in a form that is more easy to understand for the data scientist.

Data Analysis

Data Analysis

- Statistical

Data Analysis

- Statistical
- Machine Learning

Data Analysis

- Statistical
- Machine Learning
- Query Based

Data Pipelines

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

Data pipelines are used to shape, organizes, and moves data to a destination for storage, insights, and analysis.

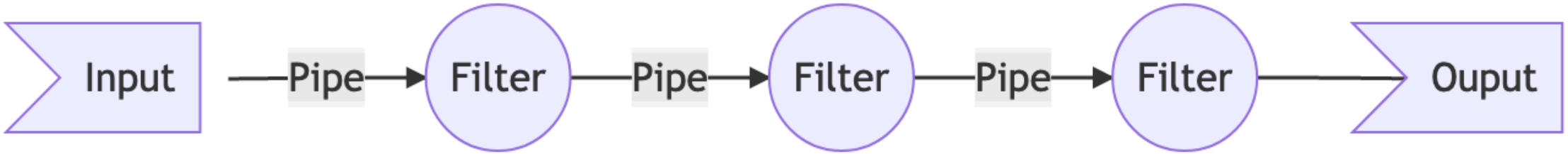
Modern data pipeline generalize the notion of ETL (extract, transform, load) to include data ingestion, integration, and movement across any cloud architecture and add additional layers of resiliency against failure.

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.

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.

Basic Operations of Data Pipelines

Basic Operations of Data Pipelines

- access information of different data sources

Basic Operations of Data Pipelines

- access information of different data sources
- extract discrete data elements of the source data

Basic Operations of Data Pipelines

- access information of different data sources
- extract discrete data elements of the source data
- copy extracted data from a data source to another

Basic Operations of Data Pipelines

- access information of different data sources
- extract discrete data elements of the source data
- copy extracted data from a data source to another
- transform data

Basic Operations of Data Pipelines

- access information of different data sources
- extract discrete data elements of the source data
- copy extracted data from a data source to another
- transform data
  - correct errors in data elements extracted from source data

Basic Operations of Data Pipelines

- access information of different data sources
- extract discrete data elements of the source data
- copy extracted data from a data source to another
- transform data
  - correct errors in data elements extracted from source data
  - standardize data in data elements based on field type

Basic Operations of Data Pipelines

- access information of different data sources
- extract discrete data elements of the source data
- copy extracted data from a data source to another
- transform data
  - correct errors in data elements extracted from source data
  - standardize data in data elements based on field type
- join or merge (in a rule-driven way) with other data sources

Big Data Pipeline[1]

The big data world brings additional challenges, i.e., volume, variety and velocity, which forced a paradigm shift in data architectures.

[1] henceforth referred as data pipelines only

Big Data Pipeline - Batch

[[MapReduce]]

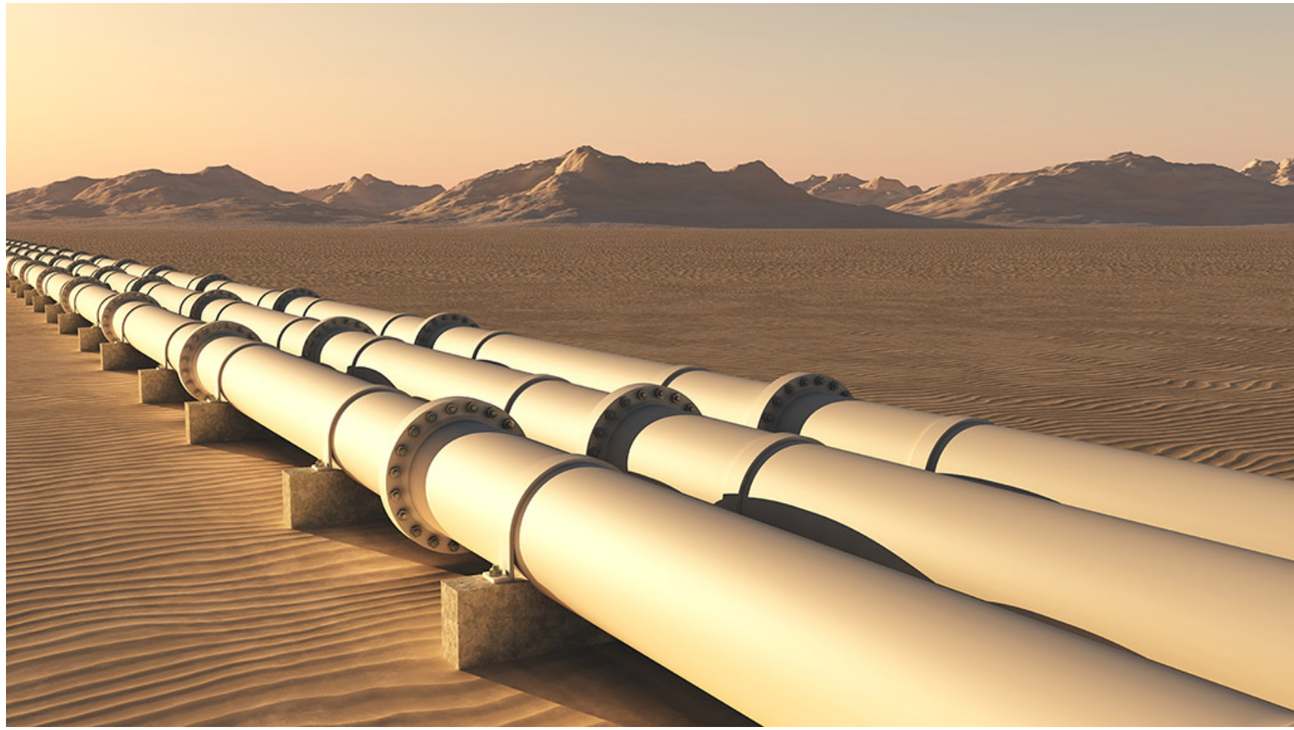
[[FlumeJava]]

[[Apache Airflow]]

Big Data Pipeline - Streaming

Typically represented as Direct Acyclic Graphs (DAG)

Data pipelines open up the possibility of creating "workflows" which can help reuse, modularize and componentize data flows.



Data pipeline components

Data pipeline components

- **Storage and Ingestion Layers**, e.g., HDFS

Data pipeline components

- **Storage and Ingestion Layers**, e.g., HDFS
  - Storage layers nowadays typically support [[polyglot persistence]].

Data pipeline components

- **Storage and Ingestion Layers**, e.g., HDFS
  - Storage layers nowadays typically support [[polyglot persistence]].
  - Message Buses that help move chunks of data (sometimes at blazing speeds) from one system to another, e.g., Kafka, RabbitMQ, Kinesis

Data pipeline components

- **Storage and Ingestion Layers**, e.g., HDFS
  - Storage layers nowadays typically support [[polyglot persistence]].
  - Message Buses that help move chunks of data (sometimes at blazing speeds) from one system to another, e.g., Kafka, RabbitMQ, Kinesis
  - Serialization Frameworks, e.g., Protocol Buffers, Avro,

Data pipeline components

- **Storage and Ingestion Layers**, e.g., HDFS
  - Storage layers nowadays typically support [[polyglot persistence]].
  - Message Buses that help move chunks of data (sometimes at blazing speeds) from one system to another, e.g., Kafka, RabbitMQ, Kinesis
  - Serialization Frameworks, e.g., Protocol Buffers, Avro,
- **(Event Stream) Processing frameworks**, e.g., Kafka Streams, Flink

Data pipeline components

- **Storage and Ingestion Layers**, e.g., HDFS
  - Storage layers nowadays typically support [[polyglot persistence]].
  - Message Buses that help move chunks of data (sometimes at blazing speeds) from one system to another, e.g., Kafka, RabbitMQ, Kinesis
  - Serialization Frameworks, e.g., Protocol Buffers, Avro,
- **(Event Stream) Processing frameworks**, e.g., Kafka Streams, Flink
  - JVM Based

Data pipeline components

- **Storage and Ingestion Layers**, e.g., HDFS
  - Storage layers nowadays typically support [[polyglot persistence]].
  - Message Buses that help move chunks of data (sometimes at blazing speeds) from one system to another, e.g., Kafka, RabbitMQ, Kinesis
  - Serialization Frameworks, e.g., Protocol Buffers, Avro,
- **(Event Stream) Processing frameworks**, e.g., Kafka Streams, Flink
  - JVM Based
  - SQL Based

Data pipeline components

- **Storage and Ingestion Layers**, e.g., HDFS
  - Storage layers nowadays typically support [[polyglot persistence]].
  - Message Buses that help move chunks of data (sometimes at blazing speeds) from one system to another, e.g., Kafka, RabbitMQ, Kinesis
  - Serialization Frameworks, e.g., Protocol Buffers, Avro,
- **(Event Stream) Processing frameworks**, e.g., Kafka Streams, Flink
  - JVM Based
  - SQL Based
- **Workflow Management Tools** that supervise the processes which run inside your data pipelines, e.g., Airflow, Luigi, Dagster

Data pipeline components

- **Storage and Ingestion Layers**, e.g., HDFS
  - Storage layers nowadays typically support [[polyglot persistence]].
  - Message Buses that help move chunks of data (sometimes at blazing speeds) from one system to another, e.g., Kafka, RabbitMQ, Kinesis
  - Serialization Frameworks, e.g., Protocol Buffers, Avro,
- **(Event Stream) Processing frameworks**, e.g., Kafka Streams, Flink
  - JVM Based
  - SQL Based
- **Workflow Management Tools** that supervise the processes which run inside your data pipelines, e.g., Airflow, Luigi, Dagster
  - "orchestrating" systems

Data pipeline components

- **Storage and Ingestion Layers**, e.g., HDFS
  - Storage layers nowadays typically support [[polyglot persistence]].
  - Message Buses that help move chunks of data (sometimes at blazing speeds) from one system to another, e.g., Kafka, RabbitMQ, Kinesis
  - Serialization Frameworks, e.g., Protocol Buffers, Avro,
- **(Event Stream) Processing frameworks**, e.g., Kafka Streams, Flink
  - JVM Based
  - SQL Based
- **Workflow Management Tools** that supervise the processes which run inside your data pipelines, e.g., Airflow, Luigi, Dagster
  - "orchestrating" systems
  - "choreographing" systems

Data pipeline components

- **Storage and Ingestion Layers**, e.g., HDFS
  - Storage layers nowadays typically support [[polyglot persistence]].
  - Message Buses that help move chunks of data (sometimes at blazing speeds) from one system to another, e.g., Kafka, RabbitMQ, Kinesis
  - Serialization Frameworks, e.g., Protocol Buffers, Avro,
- **(Event Stream) Processing frameworks**, e.g., Kafka Streams, Flink
  - JVM Based
  - SQL Based
- **Workflow Management Tools** that supervise the processes which run inside your data pipelines, e.g., Airflow, Luigi, Dagster
  - "orchestrating" systems
  - "choreographing" systems
- **Query layer**, e.g., NoSQL Datamarts

Data pipeline components

- **Storage and Ingestion Layers**, e.g., HDFS
  - Storage layers nowadays typically support [[polyglot persistence]].
  - Message Buses that help move chunks of data (sometimes at blazing speeds) from one system to another, e.g., Kafka, RabbitMQ, Kinesis
  - Serialization Frameworks, e.g., Protocol Buffers, Avro,
- **(Event Stream) Processing frameworks**, e.g., Kafka Streams, Flink
  - JVM Based
  - SQL Based
- **Workflow Management Tools** that supervise the processes which run inside your data pipelines, e.g., Airflow, Luigi, Dagster
  - "orchestrating" systems
  - "choreographing" systems
- **Query layer**, e.g., NoSQL Datamarts
- **Analytics layer** (out of scope)

Project

The 2021 Data Engineering course features a project.

Goal of the Project: Design and implement a data pipeline using Apache Airflow

2021 Project Theme: **Internet Memes**

Project Structure and Assignments

Project will focus on the Processing Phase, i.e., ingestion, cleansing, and then query-based analyses

During the course, you'll be assigned simple tasks in Airflow, which will be the base for your project!

You can complete the project points step by step and ASK FOR FEEDBACKS early!

Project Structure Details

Every project must feature:

Natural language analyses will be provided to be implemented at point 3 and 5, a base example using the images (which are not stored) will be included in 4.

Project Structure Details

Every project must feature:

1. An initial pipeline where data are loaded from file (provided) and cleaned

Natural language analyses will be provided to be implemented at point 3 and 5, a base example using the images (which are not stored) will be included in 4.

Project Structure Details

Every project must feature:

1. An initial pipeline where data are loaded from file (provided) and cleaned
2. A second pipeline where data are loaded into an ingestion system and then cleaned and processed

Natural language analyses will be provided to be implemented at point 3 and 5, a base example using the images (which are not stored) will be included in 4.

Project Structure Details

Every project must feature:

1. An initial pipeline where data are loaded from file (provided) and cleaned
2. A second pipeline where data are loaded into an ingestion system and then cleaned and processed
3. A third pipeline where a relational view is built on the data to perform some analysis

Natural language analyses will be provided to be implemented at point 3 and 5, a base example using the images (which are not stored) will be included in 4.

Project Structure Details

Every project must feature:

1. An initial pipeline where data are loaded from file (provided) and cleaned
2. A second pipeline where data are loaded into an ingestion system and then cleaned and processed
3. A third pipeline where a relational view is built on the data to perform some analysis
4. A fourth pipeline where data are enriched (use your creativity)

Natural language analyses will be provided to be implemented at point 3 and 5, a base example using the images (which are not stored) will be included in 4.

Project Structure Details

Every project must feature:

1. An initial pipeline where data are loaded from file (provided) and cleaned
2. A second pipeline where data are loaded into an ingestion system and then cleaned and processed
3. A third pipeline where a relational view is built on the data to perform some analysis
4. A fourth pipeline where data are enriched (use your creativity)
5. A fifth pipeline where a graph view is built on the data to facilitate some analysis

Natural language analyses will be provided to be implemented at point 3 and 5, a base example using the images (which are not stored) will be included in 4.

Project Requirements and Grades

Project Requirements and Grades

- 1-3: Up to 71 Points

Project Requirements and Grades

- 1-3: Up to 71 Points
- 4: Up to 61 Points

Project Requirements and Grades

- 1-3: Up to 71 Points
- 4: Up to 61 Points
- Completing the base examples at 3,4,5 up to 91

Project Requirements and Grades

- 1-3: Up to 71 Points
- 4: Up to 61 Points
- Completing the base examples at 3,4,5 up to 91
- Re-implementing the pipeline as a streaming pipeline: up to 100

Project Requirements and Grades

- 1-3: Up to 71 Points
- 4: Up to 61 Points
- Completing the base examples at 3,4,5 up to 91
- Re-implementing the pipeline as a streaming pipeline: up to 100
- Presenting original work: new analysis, innovative solution up to 100