

#### **11. Data Engineering**

DATA SCIENCE ESSENTIALS

## Background

One of the data science challenge: putting large troves of data into formats that can be **read** by algorithms.

Data engineering is related to processing an ever-increasing supply of data.

After processing, data scientists develop **proofs-of-concept**; AI/ML engineers translate these into **deployable models**.

Data/ML engineering have been around a while (software logs); with the rise of **cloud computing**, some argue that expertise in these fields is becoming more sought after than expertise in data analysis (at least, in some circles).

## Data Roles (Reprise)

#### **Data Engineers**

- receive data from a source
- structure, distribute, and store data into data lakes and warehouses
- create tools and data models which data scientists can use to query the data

#### **ML Engineers**

- apply and deploy data models
- bridge gaps between data engineers and data scientists
- take proof-of-concept ideas to large scale

#### **Data Scientists**

- receive data procured/provided by DE
- extract value from the data
- build proof-of-concept predictive models
- measure and improve results
- build analytical models

#### **Data Roles**

In smaller organizations, data engineering and data science are typically **blended** into the same role.

Larger companies have **dedicated** data engineers on staff, who build **data pipelines** and manage **data warehouses** (populating them with data and creating table schemas to keep track of the stored data).

In general,  $DE \neq DS$ .

#### **Data engineering**

- operations that create **interfaces** and **mechanisms** for the flow and access of information
- setting up **data infrastructure**, preparing it for further analysis by data scientists

Data can arise from many **sources** (and types of sources), and in a variety of formats and size.

Transforming this into a process that data scientists can use and from which they can derive meaning is known as **building a data pipeline**.



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Main data engineering challenge:

- building a pipeline that runs in (close to) real-time whenever it is requested
- so that users get **up-to-date information** from the source with **minimal delays**

Working pipeline proof-of-concept solutions are passed on to ML engineers for **deployment** and **production**. Some of the work surrounding this includes:

- data quality checks
- optimizing query performance
- creating a continuous integration/continuous delivery ecosystem around model changes
- ingesting data from various sources into the data model
- carrying machine learning and data science techniques to distributed systems.

Common themes (operations/framework/tasks/sources) for pipeline steps :

- data collection: applications, mobile apps, microservices, Internet of Things (IoT) devices, websites, instrumentation, logging, sensors, external data, user generated content, etc.
- data storage: Master Data Management (MDM), warehouse, data lake, etc.
- **data integration/preparation:** ETL, stream data integration, etc.
- data analysis: machine learning, predictive analytics, A/B testing, experiments, artificial intelligence (AI), deep learning, etc.
- delivery and presentations: dashboards, reports, microservices, push notifications, email, SMS, etc.

#### **Data Collection**



#### **ETL – Extract**



#### **ETL – Transform**





#### ETL – Load





## **Data Pipeline: Open Source**



# Data Pipeline: GoC (?)



### **Data Pipeline Tools**

Pipelines let users split large tasks **Data pipeline tools** select the best into a series of smaller sequential framework/language for each pipeline steps, which can help **optimize** each component/task: step.

If using TensorFlow for the analysis component of a DL pipeline which consists of a single large script, then everything from data collection to presentation has to be done with TensorFlow; may not be optimal.

- Luigi (Spotify)
- Airflow (AirBnB)
- scikit-learn
- pandas/tidyverse
- etc.

## **Data Engineering Tools**

It is unlikely that one data engineer could achieve mastery over all possible data engineering tools, but teams might get a lot of **coverage**:

- analytical databases (Big Query, Redshift, Synapse, etc.)
- **ETL** (Spark, Databricks, DataFlow, DataPrep, etc.)
- scalable compute engines (GKE, AKS, EC2, DataProc, etc.)
- process orchestration (AirFlow/Cloud Composer, Bat, Azure Data Factory, etc.)
- platform deployment and scaling (Terraform, custom tools, etc.)
- visualization tools (Power BI, Tableau, Google Data Studio, D3.js, ggplot2, etc.)
- programming (tidyverse, numpy, pandas, matplotlib, scikit-learn, scipy, Spark, Scala, Java, SQL, T-SQL, H-SQL, PL/SQL, etc.)



## What is Data Governance?

Data governance encompasses:

- people
- processes
- Information technology

It is required to create a **consistent** and **proper** handling of an organization's data across the enterprise.

It provides the foundation, strategy, and structure to ensure that data is managed as an **asset** and transformed into **meaningful** information.

#### **Data Governance**

#### **Goals:**

- create self-service data culture
- establish internal rules for data use
- implement compliance requirements
- improve internal and external comms
- increase value of data
- reduce costs
- continually manage risks
- ensure continued existence



#### Suggested Reading

Data Engineering

Data Understanding, Data Analysis, Data Science Data Engineering and Management

**Background and Context** 

#### **Data Engineering**

- Data Pipelines
- Automatic Deployment and Operations
- Scheduled Pipelines and Workflows
- Data Engineering Tools

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#### **Exercises**

Data Engineering

- What does your (or your organization's) data science pipeline look like? Could it be improved?
- 2. Identify instances where you have had issues due to data availability, usability, consistency, integrity, quality, security, or trustworthiness.
- 3. Complete any of the previous exercises you have not had the chance to finish.