UNIVERSITY OF MARYLAND

UMD DATA605 - Big Data Systems

Lesson 2.2: Data Pipelines

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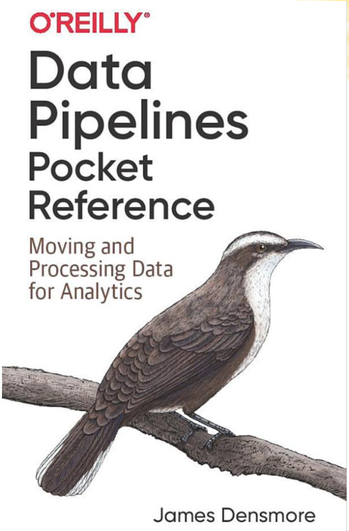
Data Pipelines: Resources

- Concepts in the slides
- Class project
- Mastery
  - Data Pipelines Pocket Reference

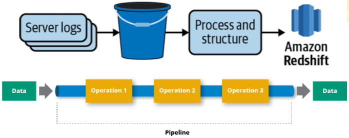


Data as a Product

- **Many services today "sell" data**
  - Services are typically powered by data and machine learning, e.g.,
    - Personalized search engine (Google)
    - Sentiment analysis on user-generated data (Facebook)
    - E-commerce + recommendation engine (Amazon)
    - Streaming data (Netflix, Spotify)
- **Several steps are required to generate data products**
  - Data ingestion
  - Data pre-processing
    - Cleaning, tokenization, feature computation
  - Model training
  - Model deployment
    - MLOps
  - Model monitoring
    - Is model working?
    - Is model getting slower?
    - Are model performance getting worse?
  - Collect feedback from deployment
    - E.g., recommendations vs what users bought
    - Ingest data from production for future versions of the model

Data Pipelines

- *"Data is the new oil"* . . . but oil needs to be refined
- **Data pipelines**
  - Processes that move and transform data
  - **Goal**: derive new value from data through analytics, reporting, machine learning



- **Data needs to be**:
  - Collected
  - Pre-processed / cleaned
  - Validated
  - Processed
  - Combined
- **Data ingestion**
  - Simplest data pipeline
  - Extract data (e.g., from REST API)
  - Load data into DB (e.g., SQL table)

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Roles in Building Data Pipelines

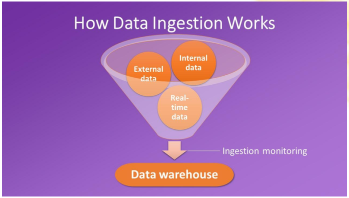
- **Data engineers**
  - Build and maintain data pipelines
  - Tools:
    - Python / Java / Go / No-code
    - SQL / NoSQL stores
    - Hadoop / MapReduce / Spark
    - Cloud computing
- **Data scientists**
  - Build predictive models
  - Tools:
    - Python / R / Julia
    - Hadoop / MapReduce / Spark
    - Cloud computing
- **Data analysts**
  - E.g., marketing, MBAs, sales, ...
  - Build metrics and dashboards
  - Tools:
    - Excel spreadsheets
    - GUI tools (e.g., Tableaux)
    - Desktop

Practical problems in Data Pipeline Organization

- **Who is responsible for the data?**
- **Issues with scaling**
  - Performance
  - Memory
  - Disk
- **Build-vs-buy**
  - Which tools?
  - Open-source vs proprietary?
- **Architecture**
  - Who is in charge of it?
  - Conventions
  - Documentation
- **Service level agreement (SLA)**
- **Talk to stakeholders on a regular basis**

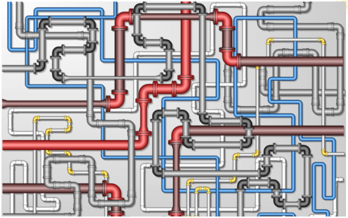
Data Ingestion

- **Data ingestion**
  - = extract data from one source and load it into another store
- **Data sources / sinks**
  - DBs
    - E.g., Postgres, MongoDB
  - REST API
    - Abstraction layer on top of DBs
  - Network file system / cloud
    - E.g., CSV files, Parquet files
  - Data warehouses
  - Data lakes
- **Source ownership**
  - An organization can use 10-1000s of data sources
  - Internal
    - E.g., DB storing shopping carts for a e-commerce site
  - 3rd-parties
    - E.g., Google analytics tracking website usage



Data Pipeline Paradigms

- There are **several styles of building data pipelines**
- **Multiple phases**
  - Extract
  - Load
  - Transform
- **Phases arranged in different ways** depending on philosophy about data / roles
  - ETL
  - ELT
  - EtLT



ETL Paradigm: Phases

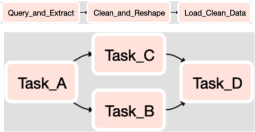
- **Extract**
  - Gather data from various data sources, e.g.,
    - Internal / external data warehouse
    - REST API
    - Data downloading from API
    - Web scraping
- **Transform**
  - Raw data is combined and formatted to become useful for analysis step
- **Load**
  - Move data into the final destination, e.g.,
    - Data warehouse
    - Data lake
- **Data ingestion pipeline = E + L**
  - Move data from one point to another
  - Format the data
  - Make a copy
  - Have different tools to operate on the data

ETL Paradigm: Example

- **Extract**
  - Buy-vs-build data ingestion tools
    - Vendor lock-in
- **Transform**
  - Data conversion (e.g., parsing timestamp)
  - Create new columns from multiple source columns
    - E.g., year, month, day $\rightarrow$ `yyyy/mm/dd`
  - Aggregate / filter through business logic
    - Try not to filter, better to add tags / mark data
  - Anonymize data
- **Load**
  - Organize data in a format optimized for data analysis
    - E.g., load data in relational DB
  - Finally data modeling

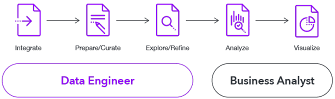
Workflow Orchestration

- Companies have **many data pipelines** (10-1000s)
- **Orchestration tools**, e.g.,
  - Apache Airflow (from AirBnB)
  - Luigi (from Spotify)
  - AWS Glue
  - Kubeflow
- **Schedule and manage** flow of tasks according to their dependencies
  - Pipeline and jobs are represented through DAGs
- Monitor, retry, and send alarms



ELT Paradigm

- **ETL** has been the standard approach for long time
  - Extract → Transform → Load
  - **Cons**
    - Need to understand the data at ingestion time
    - Need to know how the data will be used
- Today **ELT** is becoming the pattern of choice
  - Extract → Load → Transform
  - **Pro**:
    - No need to know how the data will be used
    - Separate data engineers and data scientists / analysts
    - Data engineers focus on data ingestion (E + L)
    - Data scientists focus on transform (T)



- ETL → ELT **enabled by new technologies**
  - Large storage to save all the raw data (cloud computing)
  - Distributed data storage and querying (e.g., HDFS)
  - Columnar DBs
  - Data compression

Row-based vs Columnar DBs

- **Row-based DBs**
  - E.g., MySQL, Postgres
  - Optimized for reading / writing rows
  - Read / write small amounts of data frequently

OrderId	CustomerId	ShippingCountry	OrderTotal
1	1258	US	55.25
2	5698	AUS	125.36
3	2265	US	776.95
4	8954	CA	32.16

- **Columnar DBs**
  - E.g., Amazon Redshift, Snowflake
  - Read / write large amounts of data infrequently
  - Analytics requires a few columns
  - Better data compression

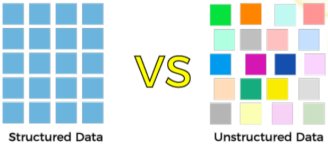
Block 1	1, 1258, US, 55.25
Block 2	2, 5698, AUS, 125.36
Block 3	3, 2265, US, 776.95
Block 4	4, 8954, CA, 32.16

EtLT

- **ETL**
  - Extract → Transform → Load
- **ELT**
  - Extract → Load → Transform
  - Transformation / data modeling ("T") according to business logic
- **EtLT**
  - Sometimes transformations with limited scope ("t") are needed
    - De-duplicate records
    - Parse URLs into individual components
    - Obfuscate sensitive data (for legal or security reasons)
  - Then implement rest of "LT" pipeline

Structure in Data (or Lack Thereof)

- **Structured data**: there is a schema
  - Relational DB
  - CSV
  - DataFrame
  - Parquet
- **Semi-structured**: subsets of data have different schema
  - Logs
  - HTML pages
  - XML
  - Nested JSON
  - NoSQL data
- **Unstructured**: no schema
  - Text
  - Pictures
  - Movies
  - Blobs of data



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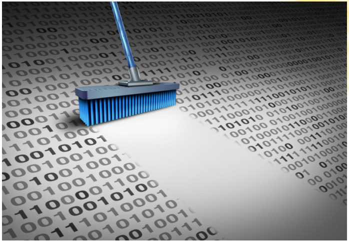
Data Cleaning

- **Data cleanliness**
  - Quality of source data varies greatly
  - Data is typically messy
    - Duplicated records
    - Incomplete or missing records (nans)
    - Inconsistent formats (e.g., phone with / without dashes)
    - Mislabeled or unlabeled data
- **When to clean it?**
  - As soon as possible!
  - As late as possible!
  - In different stages
  - $\rightarrow$ Pipeline style: ETL vs ELT vs EtLT
- **Heuristics when dealing with data**
  - Hope for the best, assume the worst
  - Validate data early and often
  - Don't trust anything
  - Be defensive



OLAP vs OLTP Workloads

- There are two classes of data workloads
- OLTP
  - On-Line Transactional Processing
  - Execute large numbers of transactions by a large number of processes in real-time
  - **Lots of concurrent small read / write transactions**
  - E.g., online banking, e-commerce, travel reservations
- OLAP
  - On-Line Analytical Processing
  - Perform multi-dimensional analysis on large volumes of data
  - **Few large read or write transactions**
  - E.g., data mining, business intelligence

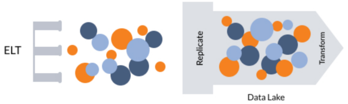
Challenges with Data Pipelines

- High-volume vs low-volume
  - Lots of small reads / writes
  - A few large reads / writes
- Batch vs streaming
  - Real-time constraints
- API rate limits / throttling
- Connection time-outs
- Slow downloads
- Incremental mode vs catch-up

Data Warehouse vs Data Lake

- **Data warehouse**
  - = DB storing data from different systems in a structured way
  - Corresponds to ETL data pipeline style
  - E.g., a large Postgres instance with many DBs and tables
  - E.g.,
    - AWS Athena, RDS
    - Google BigQuery

- **Data lake**
  - Data stored semi-structured or unstructured
  - Corresponds to ELT data pipeline style
  - E.g., aWS S3 bucket storing blog posts, flat files, JSON objects, images



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Data Lake: Pros and Cons

- **Data lake**
  - Stores semi-structured or unstructured data
- **Pros**
  - Cheaper cloud storage
  - Easier changes to types or properties
    - E.g., JSON documents
  - Data scientists
    - Initially unsure how to access and use data
    - Want to explore raw data
- **Cons**
  - Not optimized for querying like structured data warehouse
    - Tools query data lake similar to SQL
    - E.g., AWS Athena, Redshift Spectrum

Advantages of Cloud Computing

- **Ease of building and deploying:**
  - Data pipelines
  - Data warehouses
  - Data lakes
- **Managed services**
  - No need for admin and deploy
  - Highly scalable DBs
    - E.g., Amazon Redshift, Google BigQuery, Snowflake
- **Rent-vs-buy**
  - Easy to scale up and out
  - Easy to upgrade
  - Better cash-flow
- **Cost of storage and compute is continuously dropping**
  - Economies of scale
- **Cons**
  - The flexibility has a cost (2x-3x more expensive than owning)
  - Vendor lock-in