Infrastructure and Organization

Production

Jesús Calderón

Agenda

8.1. Infrastructure for ML

- Infrastructure
- Storage and Compute
- Development Environments
- Resource Management

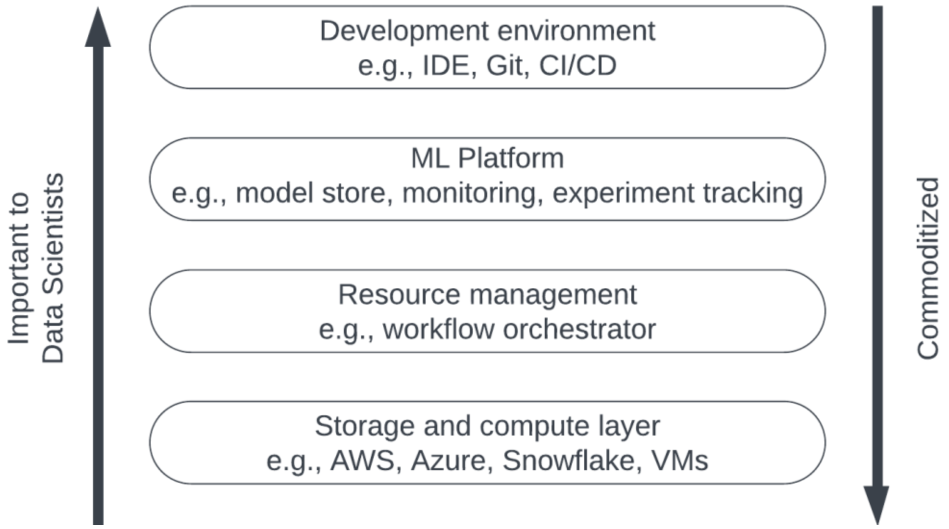
Topic 8.2. The Human Side of ML

- Roles, Tasks, and Skills
- Where to Focus our Efforts?

Infrastructure

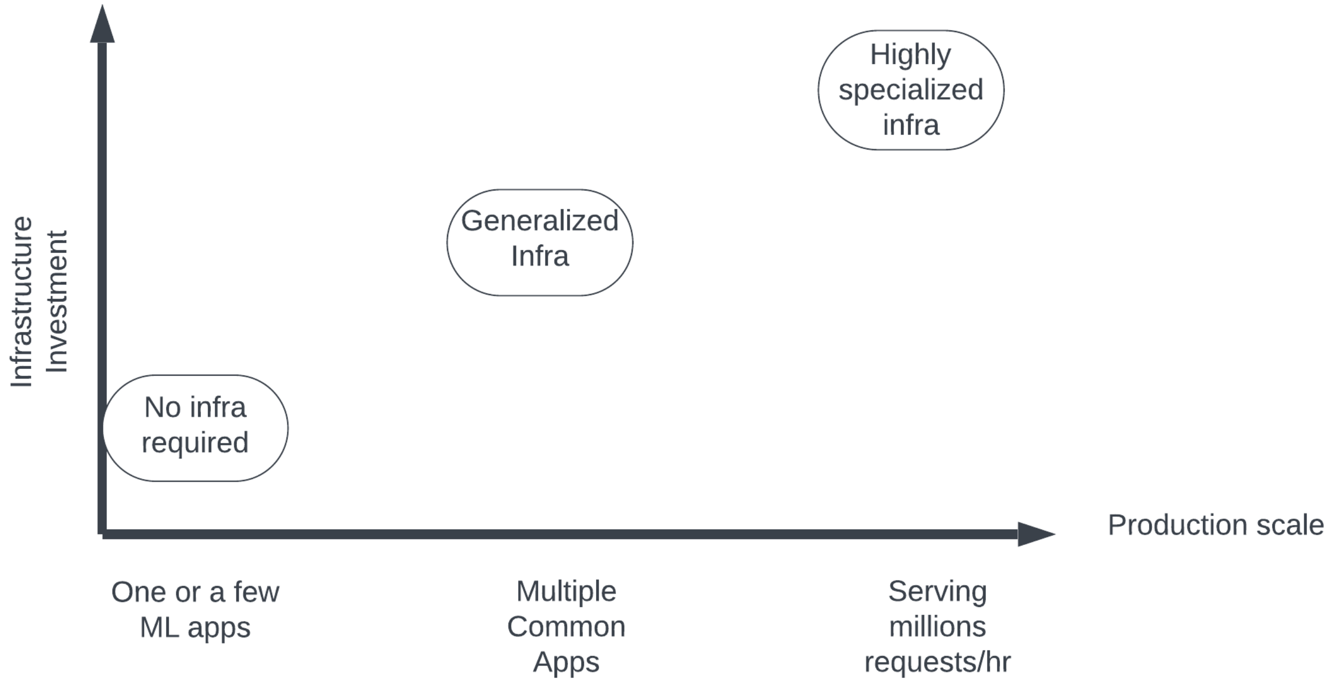
What is Infrastructure?

- Infrastructure is the set of fundamental facilities that support the development and maintenance of ML systems.
- Four layers can, at least, be considered:
  - Storage and compute: data is collected and stored in the storage layer. Using the compute layer, we run the ML workloads (training, feature generation, etc.)
  - Resource management: schedule and orchestrate workloads.
  - ML Platform: tools to aid the development of ML applications like model stores, feature stores, and monitoring tools.
  - Development environment: where code is written and experiments are run.



(Adapted from Huyen, 2021)

Infrastructure Investment Grows with Scale



(Adapted from Huyen, 2021)

Storage and Compute

- ML systems require and produce a lot of data.
- Storage layer can be HDD or SDD, but can also be blob (binary large object) storage.
- Over the last decade, storage has been commoditized in the cloud.

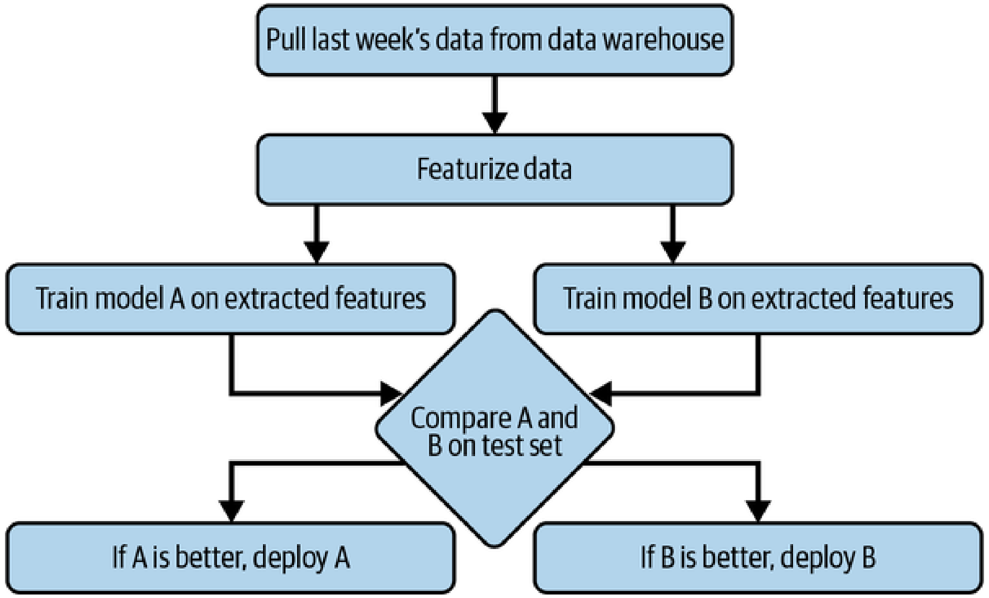
- Compute layer can be sliced into smaller compute units: instead of a large job, some jobs can be partitioned and computed with a distributed cluster of processors.
- Compute can be permanent or ephemeral:
  - Training has spiky compute requirements that tend to be ephemeral.
  - DB will require some compute to operate and, generally, this compute is permanent.
- Compute and storage can scale: cloud infrastructure is attractive for its elasticity (it grows with needs.)
- Compute must have access to storage, therefore, it is important to consider the cost of data transmission.

Development Environment

- Where ML engineers write code, run experiments, and interact with the production environment.
- Consists of IDE, versioning, and CI/CD.
- Dev environment setup should contain all the tools that can make it easier for engineers to do their job.
- Versioning is fundamental for ML System implementation.
- Dev environment should be built for CI/CD:
    - Automated testing.
    - Continuous integration.
    - Andon Cord: capability to revert to latest working verison of system.
- Dev Environment should ressemble the production environment as closely as possible.

Resource Management

- In terrestrial data centres, storage and compute are finite.
- With cloud infrastructure, storage and compute are elastic, but they are charged by utilization.
- Two key characteristics to consider:
  - Repetitiveness.
  - Dependencies.



Tasks can be organized in Directed Acyclical Graphs (DAGs) using orchestrators (Huyen, 2021)

The Human Side of ML

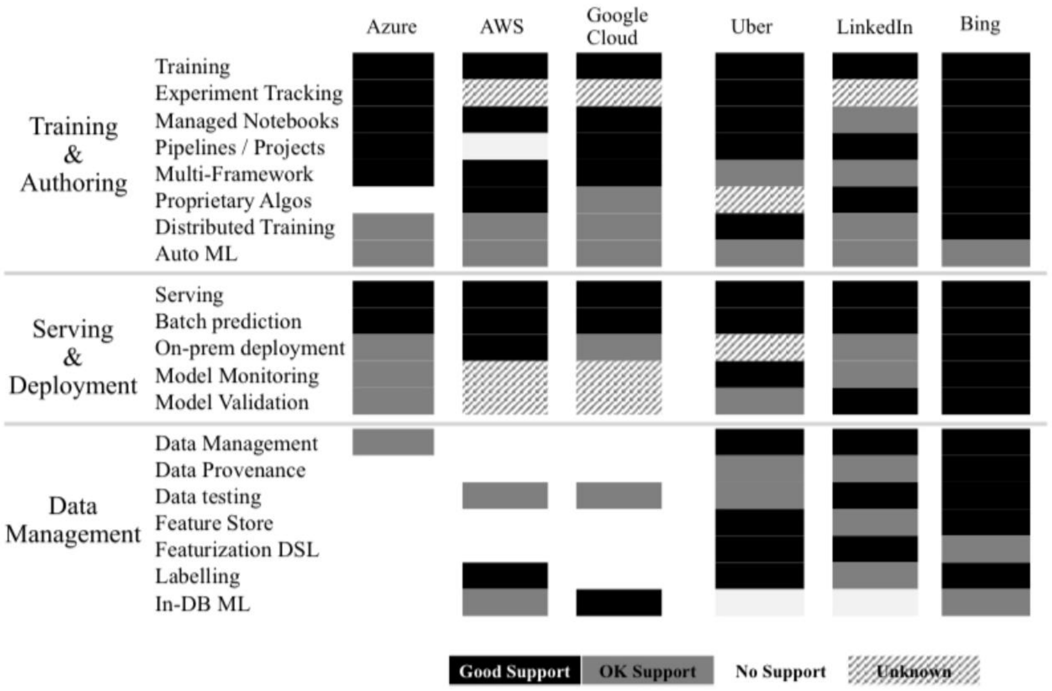
Roles, Tasks, and Skills

- CDO/DS Leader:
  - Bridges the gap between business and datas science.
  - Defines the vision and technical lead.
  - Skills: leadership, design thinking, data science/ML, domain experience.
- Data engineer:
  - Implement, test, and maintain infrastructural components for data management.
  - Define data models and systems architecture.
  - Skills: SQL/NoSQL, Hive/Pig/HDFS, Python, Scala/Spark.
- Analyst:
  - Collects, cleans, transforms data.
  - Interprets analytical results, reports and communicates.
  - Skills: R, Python, SQL, BI Tools.
- Visualization Engineer
  - Makes sense of data and analysis output by showing it in the right context.
  - Articulate business problems and display solutions with data.
  - Skills: design thinking, BI Tools, presentation and writing.

Roles, Tasks, and Skills (cont.)

- Data Scientist
  - Solves business tasks using ML and data.
  - Data preparation, training, and evaluating models.
  - Skills: R, Python, modelling, data manipulation.
- ML Engineer
  - Combines software engineering and modeling to implement data intensive products.
  - Deploys models into production and at scale.
  - Python, Spark, Julia, MLOps, DevOps, CI/CD.
- Subject Matter Expert
  - Applies rigorous methods developed in area of expertise.
  - Help decision-makers come to conclusions safely beyond ML models.
  - Ex: Statistician, Actuary, Econometrician, Physicist, Epidemiologist
- Model validation
  - Independently validate models, including their interpretation.
  - Perform technical testing.
  - Skills: similar to data scientis/SME.

Where to Focus Our Efforts?



(Aggrawal et al. 2020)

Start with the data:

- Mature proprietary solutions have stronger support for data management.
- Providing complete and useable thrid-party solutions is non-trivial.
- There is no data analysis without data.

Then, focus on serving and deployment:

- Consider self-service approaches.
- Automate, automate, and automate.

References

- Agrawal, A. et al. “Cloudy with a high chance of DBMS: A 10-year prediction for Enterprise-Grade ML.” arXiv preprint arXiv:1909.00084 (2019).
- Huyen, Chip. “Designing machine learning systems.” O’Reilly Media, Inc.(2022).