Production: Infrastructure and Organisation

```
$ echo "Data Sciences Institute"
```

Agenda

8.1. Infrastructure for ML

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

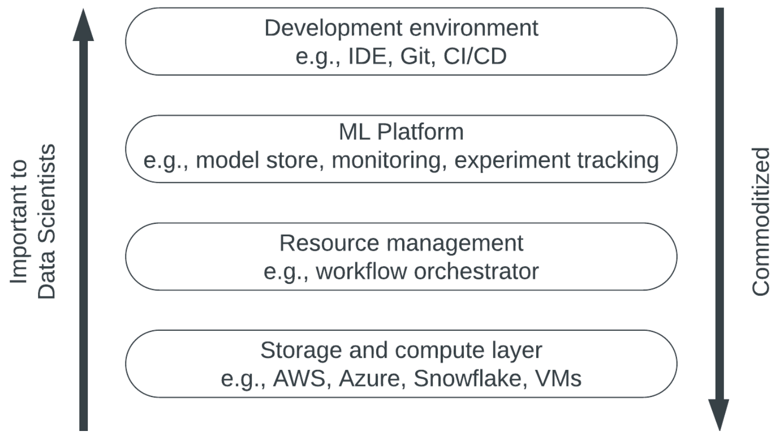
Topic 8.2. The Human Side of ML

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

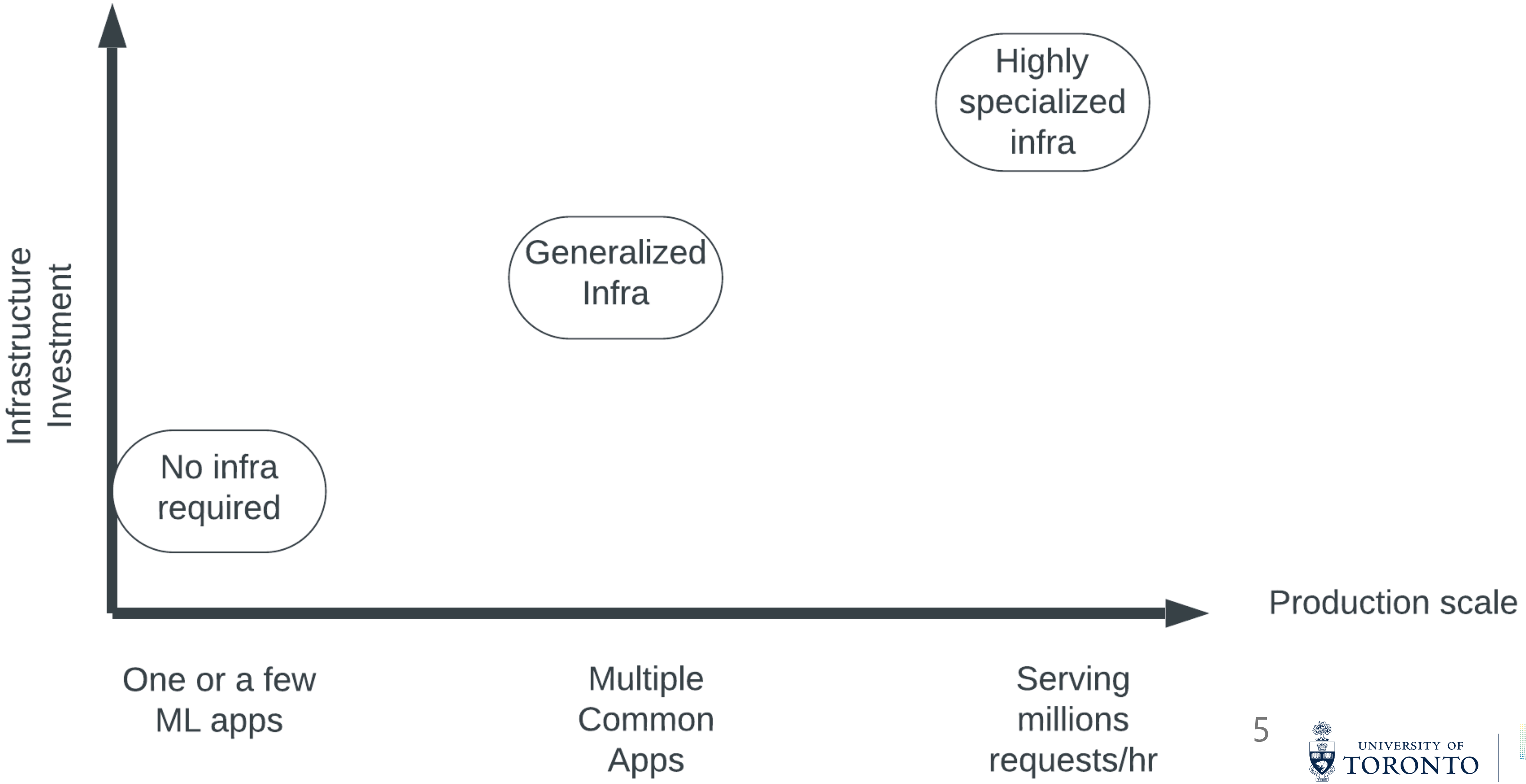
Infrastructure

What is Infrastructure?

- Infrastructure supports the development and maintenance of ML systems through four key layers:
    i. Storage and compute for data collection and ML workloads
    ii. Resource management for workload scheduling and orchestration
    iii. ML Platform with tools for ML application development
    iv. Development environment for coding and running experiments.



Infrastructure Investment Grows with Scale



Storage and Compute

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

Storage and Compute

- 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 (1/2)

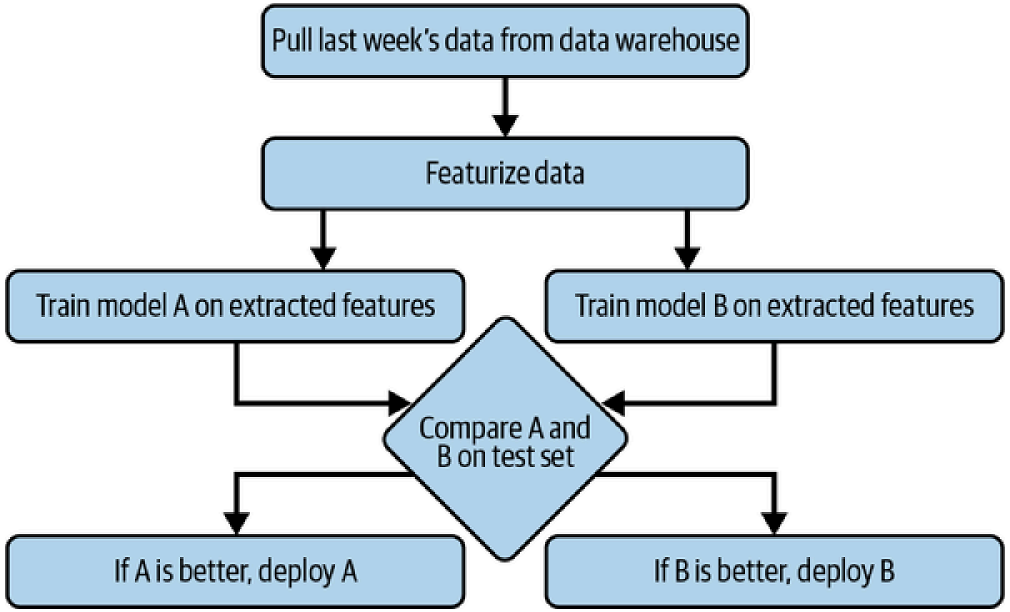
- Where ML engineers write code, run experiments, and interact with the production environment.
- Consists of IDE, versioning, and CI/CD.
- Dev environment setup should contain all the tools that can make it easier for engineers to do their job.

Development Environment (2/2)

- 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 the latest working version of the system.
- Dev Environment should resemble 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 utilisation.
- Two key characteristics to consider:
  - Repetitiveness.
  - Dependencies.



University of Toronto
Data Sciences Institute

The Human Side of ML

Roles, Tasks, and Skills (1/4)

- CDO/DS Leader:
  - Bridges the gap between business and data 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.

Roles, Tasks, and Skills (2/4)

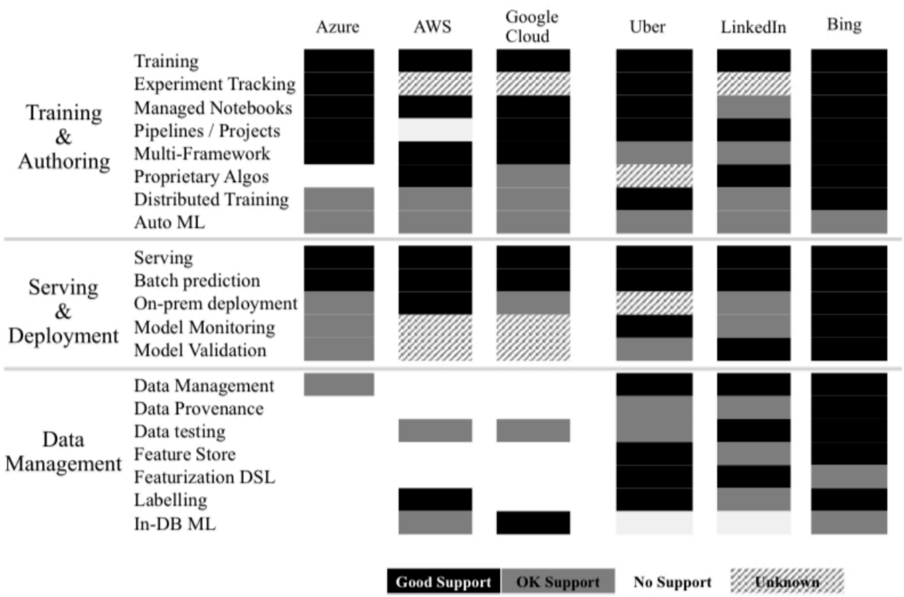
- Analyst:
  - Collects, cleans, and transforms data.
  - Interprets analytical results, reports and communicates.
  - Skills: R, Python, SQL, BI Tools.
- Visualisation Engineer
  - Makes sense of data and analysis output by showing it in the right context.
  - Articulate business problems and display solutions with data.
  - Skills: design thinking, BI Tools, presentation and writing.

Roles, Tasks, and Skills (3/4)

- 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 modelling to implement data-intensive products.
  - Deploys models into production and at scale.
  - Python, Spark, Julia, MLOps, DevOps, CI/CD.

Roles, Tasks, and Skills (4/4)

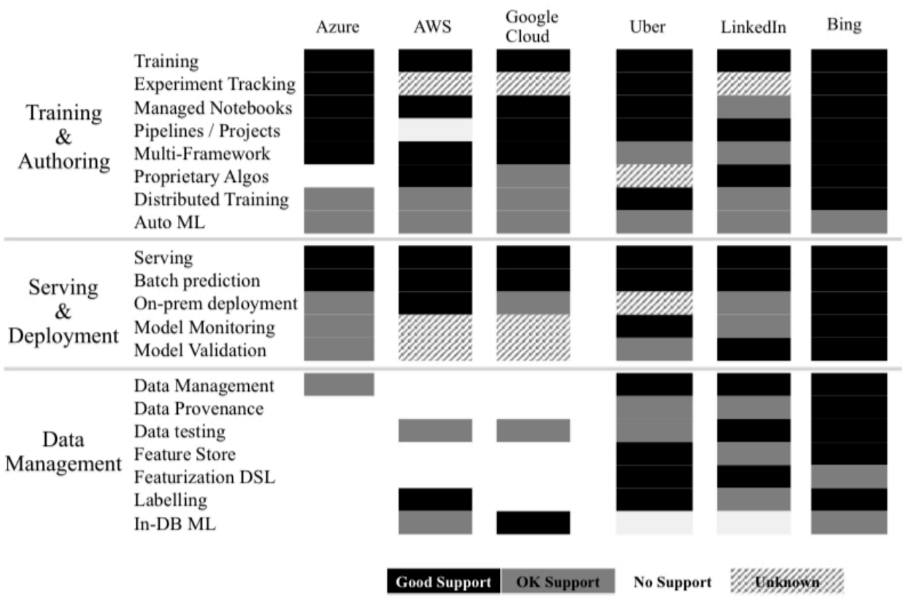
- Subject Matter Expert
  - Applies rigorous methods developed in the area of expertise.
  - Help decision-makers come to conclusions safely beyond ML models.
  - Ex: Statistician, Actuary, Econometrician, Physicist, Epidemiologist
- Model validation
  - Independently validate models, including their interpretation.
  - Perform technical testing.
  - Skills: similar to a data scientist/SME.



Where to Focus Our Efforts? (1/2)

Start with the data:

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



Where to Focus Our Efforts? (2/2)

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).