

Production: Infrastructure and Organization

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$ echo "Data Sciences Institute"
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Agenda

8.1. Infrastructure for ML

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

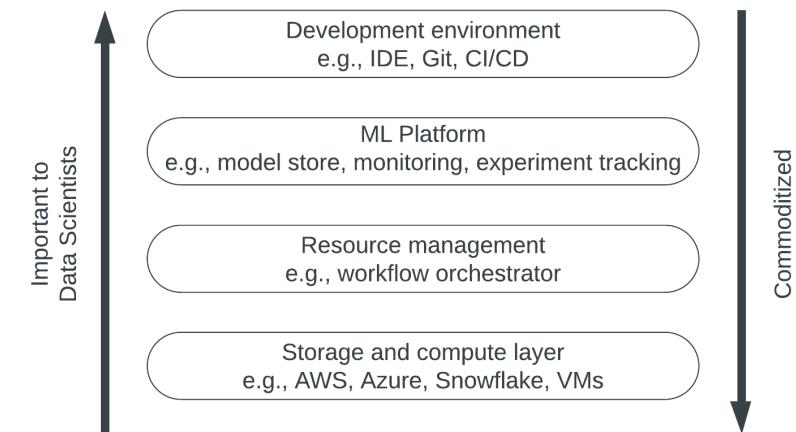
Topic 8.2. The Human Side of ML

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

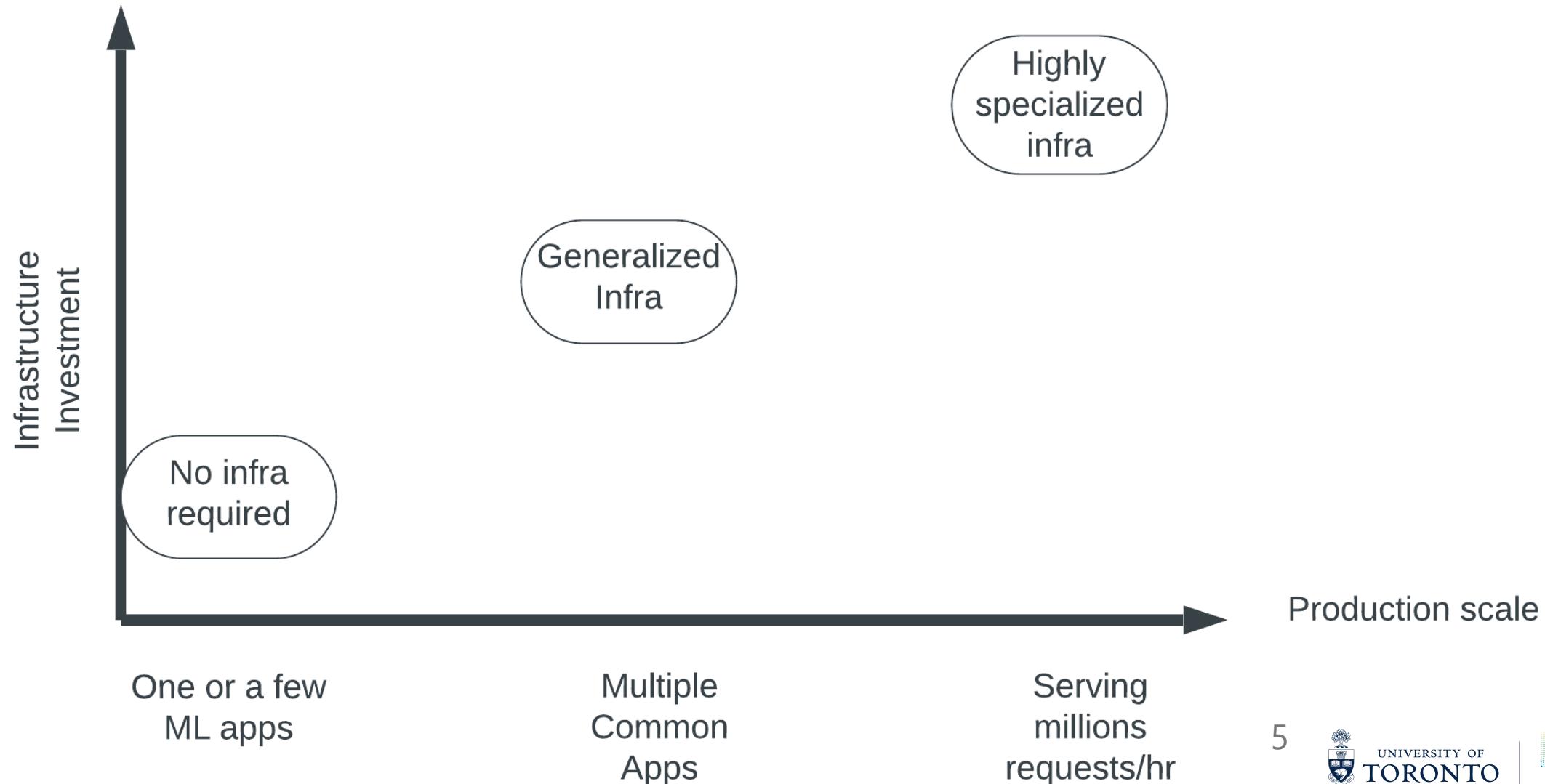
Infrastructure

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 SDD, but can also be blob (binary large object) storage.
- Over the last decade, storage has been commoditized 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

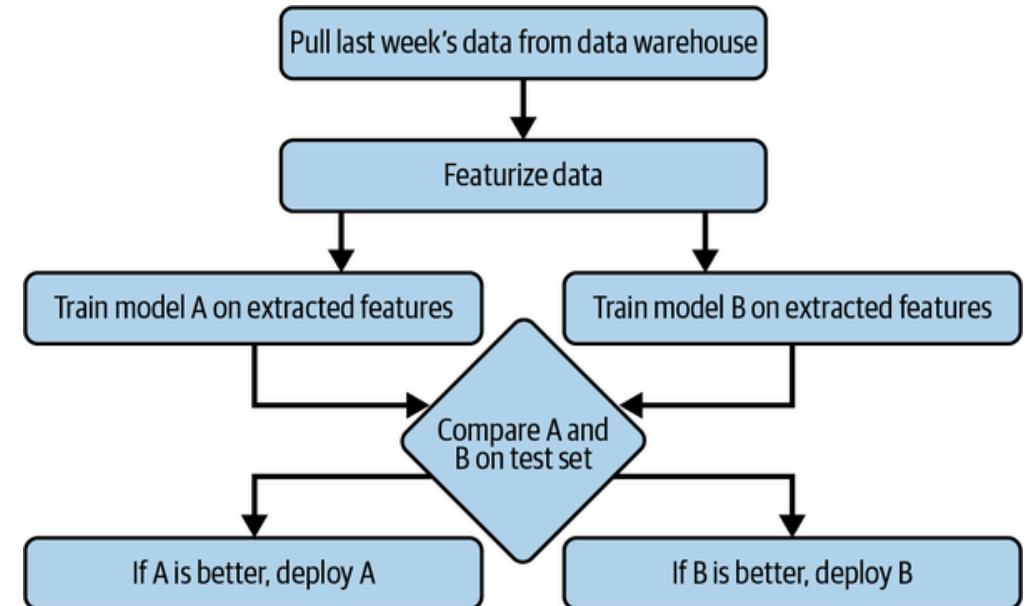
- Where ML engineers write code, run experiments, and interact with the production environment.
- Consists of IDE, versioning, and CI/CD.
- Dev environment setup should contain all the tools that can make it easier for engineers to do their job.

Development Environment

- 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.



The Human Side of ML

Roles, Tasks, and Skills

- 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

- 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.

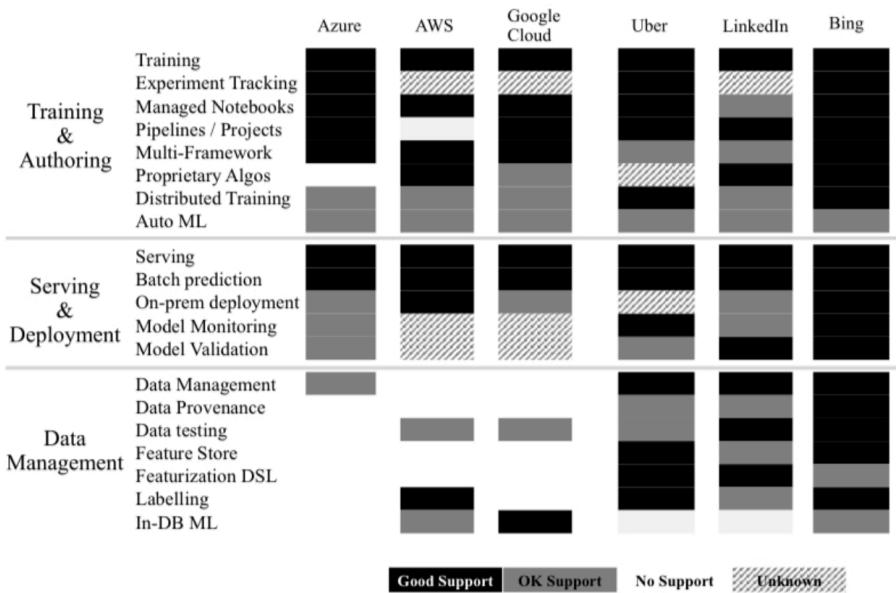
Roles, Tasks, and Skills (cont.)

- 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.

Roles, Tasks, and Skills

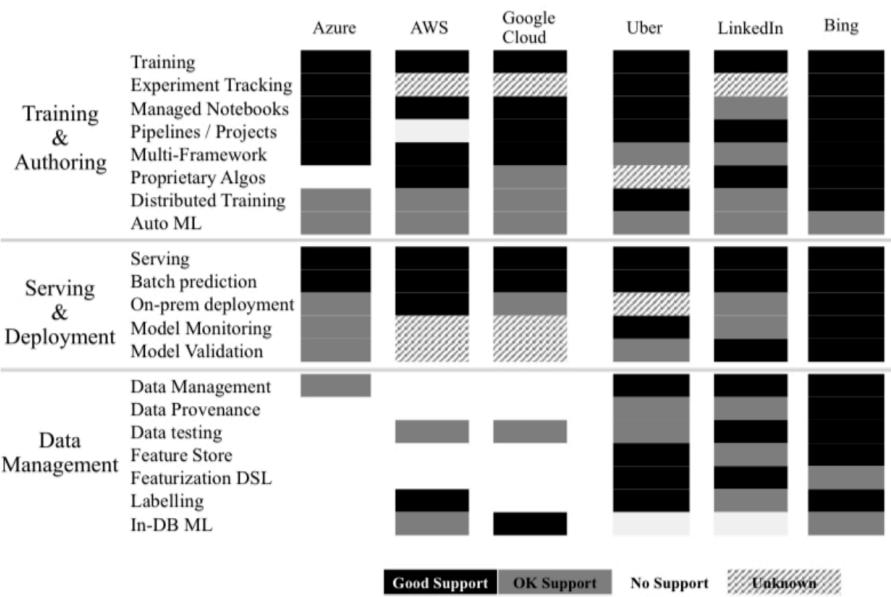
- Subject Matter Expert
 - Applies rigorous methods developed in area of expertise.
 - Help decision-makers come to conclusions safely beyond ML models.
 - Ex: Statistician, Actuary, Econometrician, Physicist, Epidemiologist
- Model validation
 - Independently validate models, including their interpretation.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

Where to Focus Our Efforts?



Start with the data:

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



Where to Focus Our Efforts?

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).