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BITS Pilani

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AMLCCZG516
ML System Optimization

Murali Parameswaran

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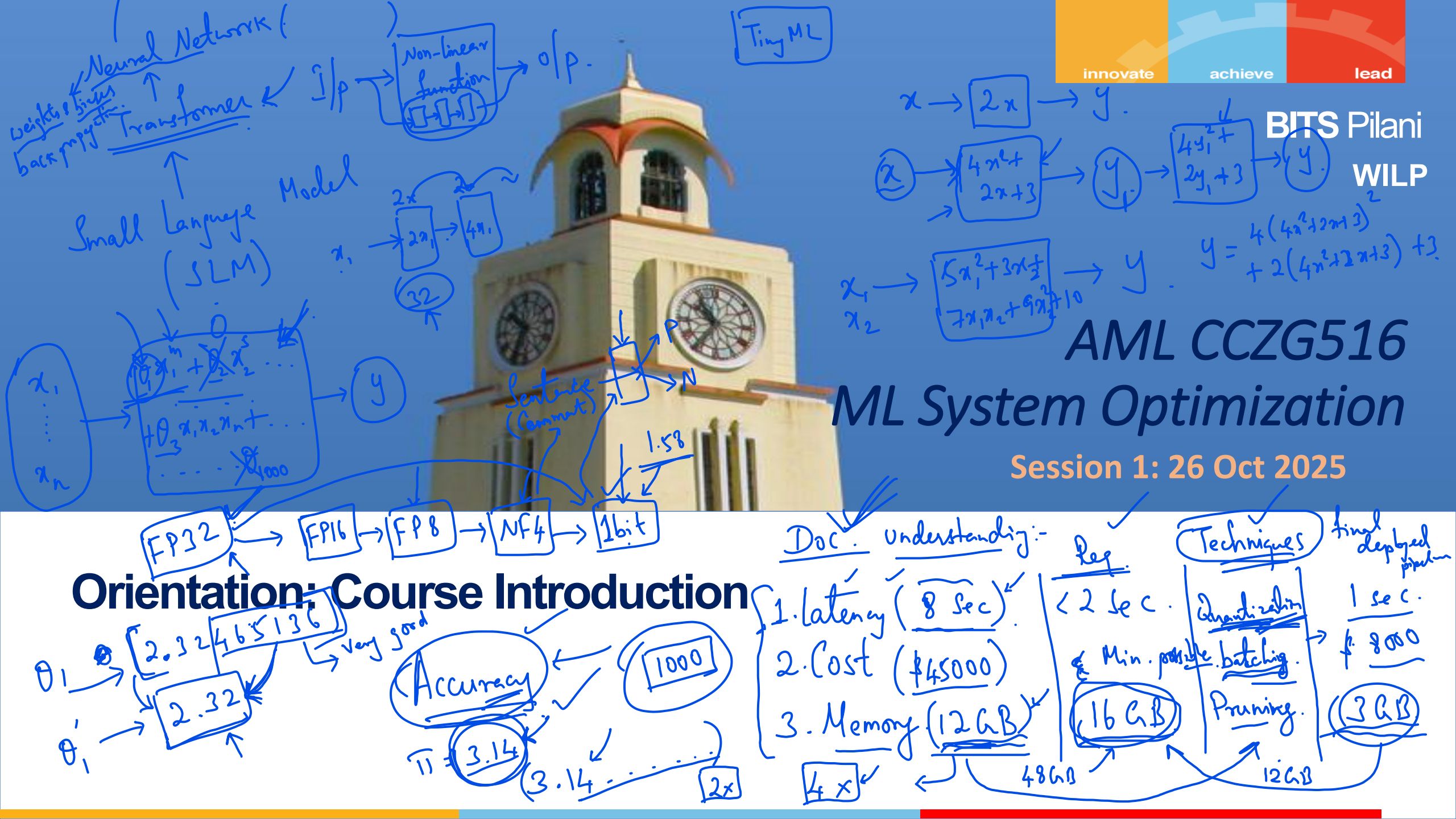
Session 1: 26 Oct 2025

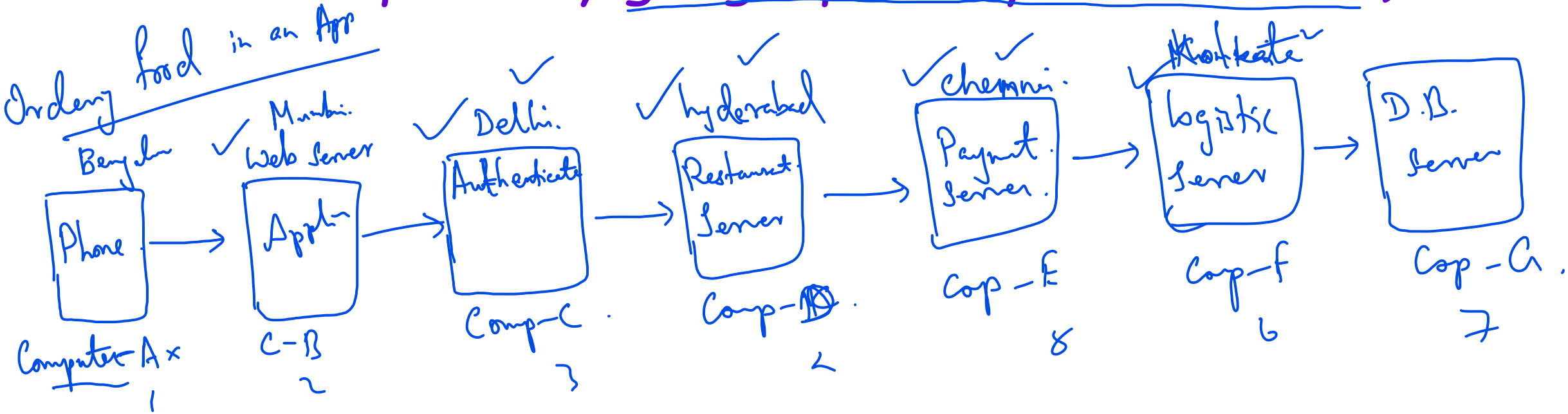
Orientation: Course Introduction



AI Engineering : Chip Huyen
chap-9, v.10

Distributed Computing

Running programs on multiple computers (in a network - possibly geographically distributed)



Distributed Computing

- Infrastructure (Hardware & Systems Software)
  for
  Applications (Algorithms, Software Solutions)

Content & Pedagogy

- Focus on principles, concepts, and design
  - Pragmatics and Implementation to be learnt by doing – enabled by Assignments and Project.

- Lecture Sessions are expected to be interactive:
  - students are expected to raise questions and
  - the instructor will ask questions (which the students are expected to answer)

Evaluation

- Mid-term test and final exam – centrally scheduled by BITS
  - A Total of 50% weight
- Assignment(s) and a Project
  - (10+10+30 =) 50%
- Recommended Programming Environment:
  - Java (preferably) or Python
  - C/C++/Rust

- Note: No prescribed textbooks for this course.

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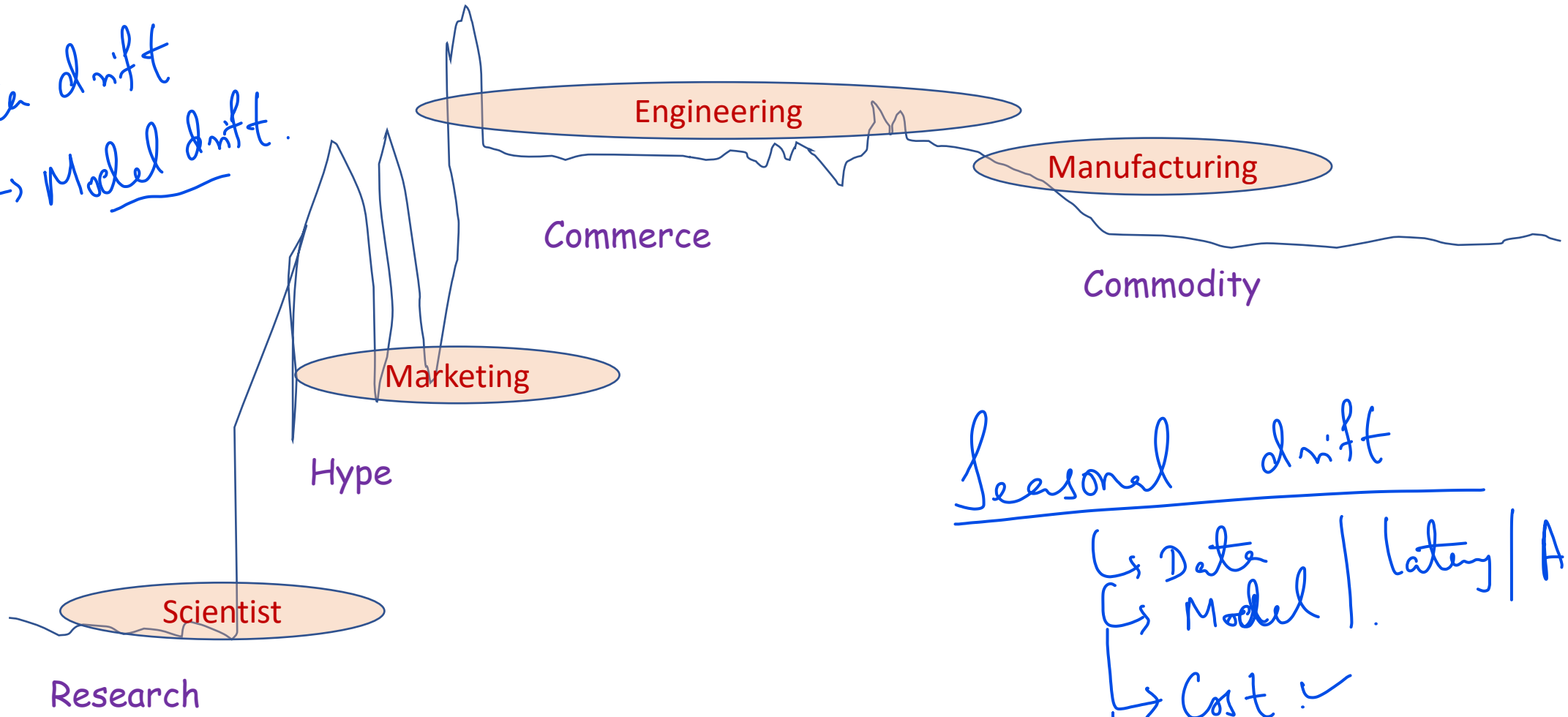
Session 1

Course Introduction

Lifecycle of New Technologies



Data drift

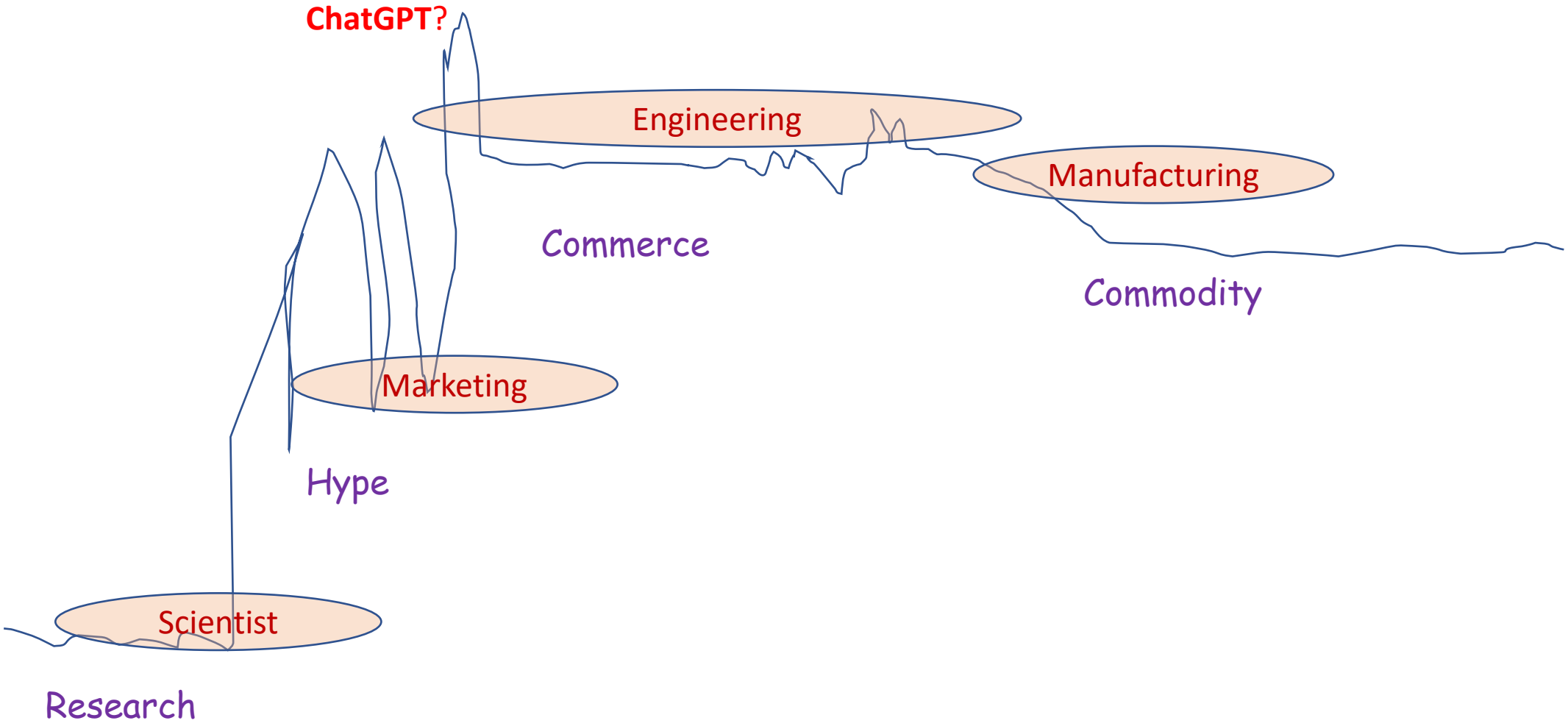
LLM → Model drift.
ML

Seasonal drift

↳ Data
↳ Model | latency | Acc.

→ ↳ Cost
↳ Storage

Lifecycle of AI/ML - Where are we ?



Machine Learning – Enterprise Practice

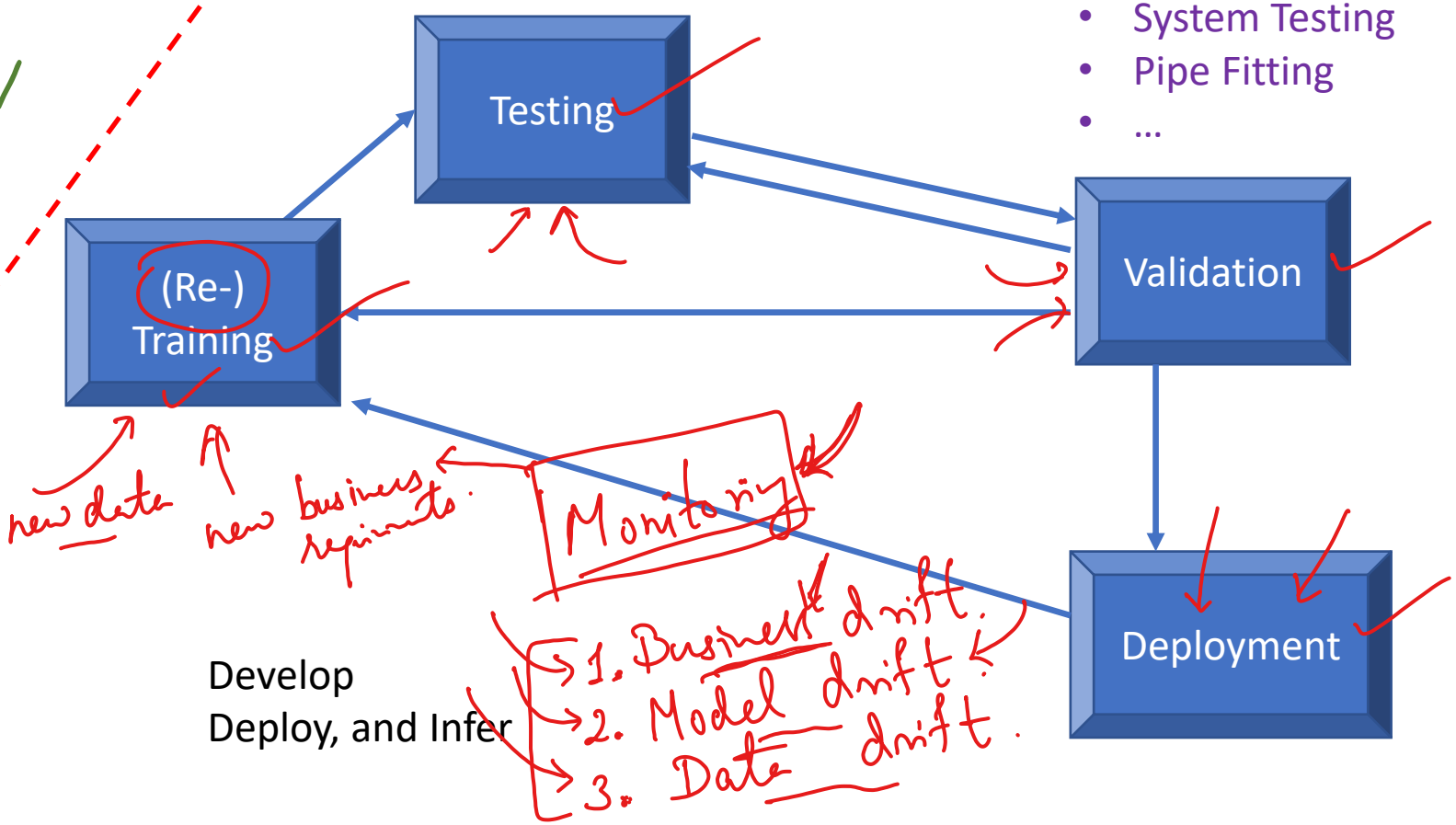
- AI and Machine Learning is becoming central to organizations:
  - No longer a one-off activity
  - Multiple problems / perspectives addressed through ML
  - Multiple ML solutions deployed
- ML is becoming a continual activity:
  - Data change; Context changes
    - Drift in the solution
  - Problems change; Requirements change;
    - New model(s) required
  - World changes; Expectations change
    - Performance and Standardization critical ==>
      - Packaging vs. Pricing

Operationalizing AI/ML

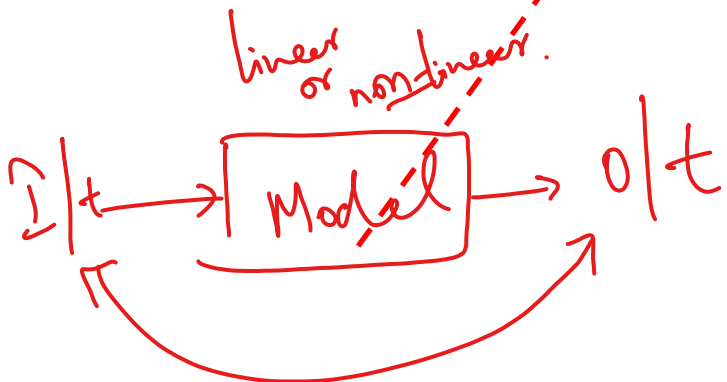
~2 Months. MLops V2 → Automatic.

- Class-room View :
  - Development
    - Model Building / Training
  - Deployment
    - Inference

- Enterprise View:



- Compliance
- System Testing
- Pipe Fitting
- ...



Operationalizing AI/ML

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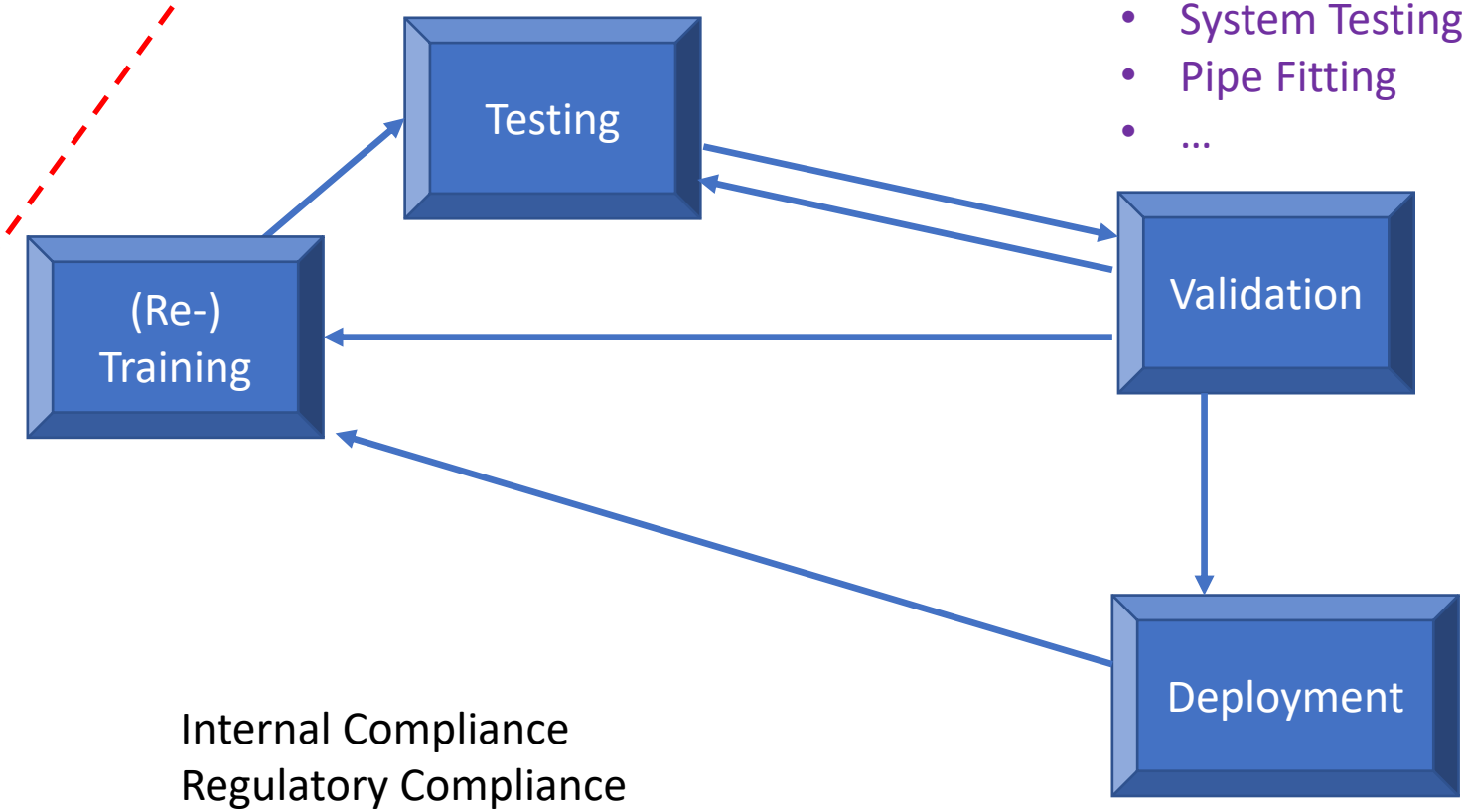

- Compliance
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- …

Internal Compliance
Regulatory Compliance

Operationalizing AI/ML

- Class-room View :
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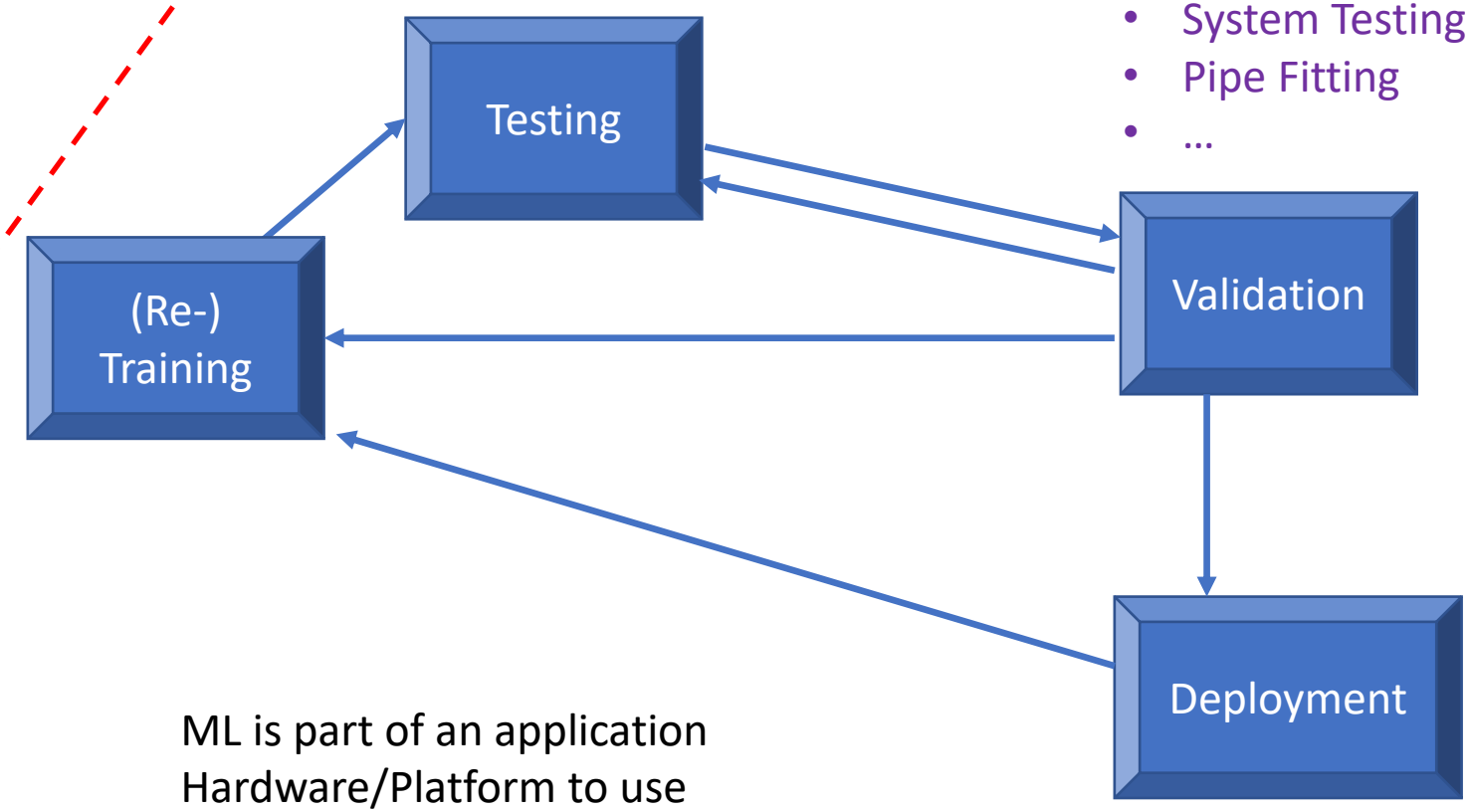
- Enterprise View:



- Compliance
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ML is part of an application
Hardware/Platform to use

Operationalizing AI/ML

- Class-room View :
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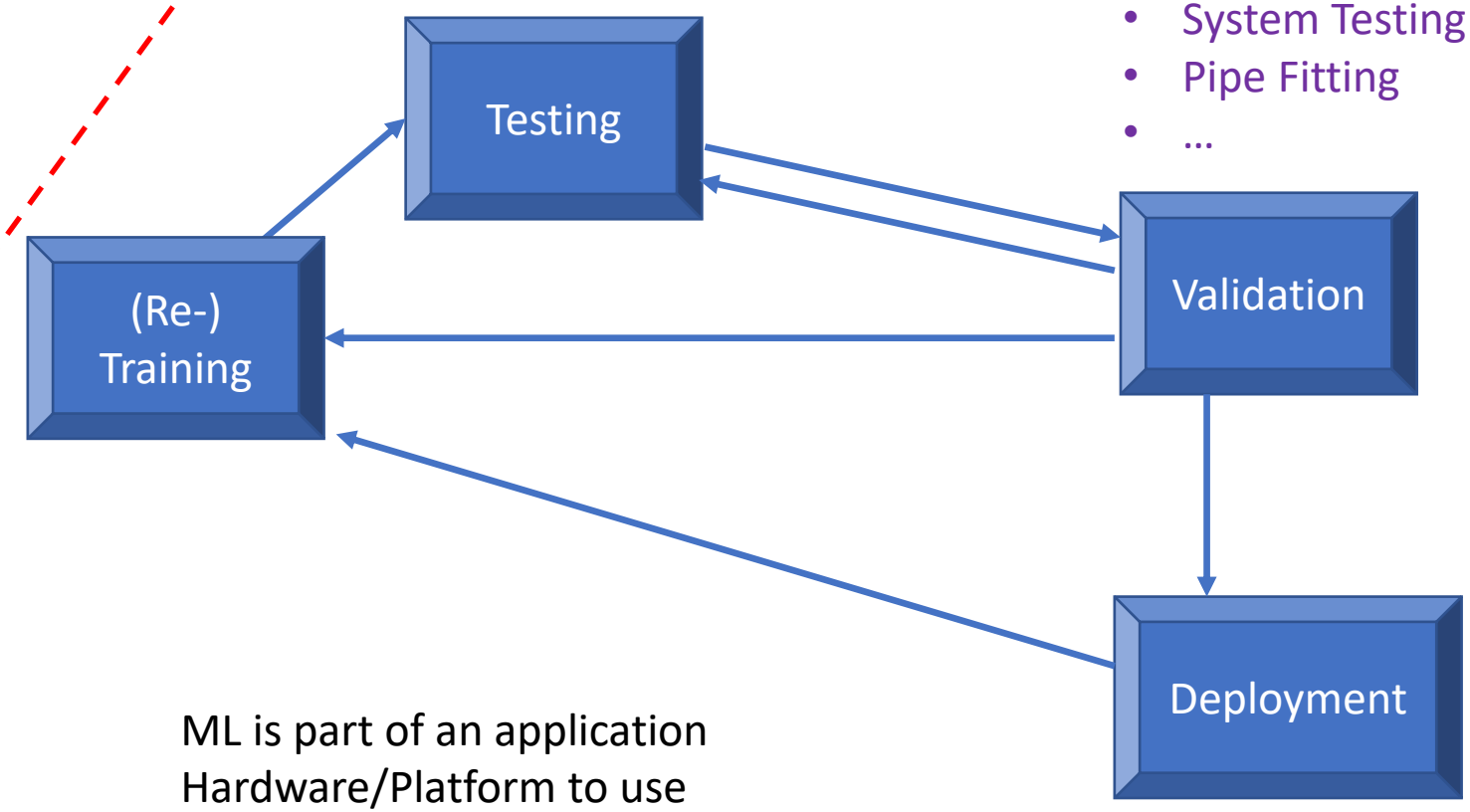
- Enterprise View:



- Compliance
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ML is part of an application
Hardware/Platform to use

Will our model fit in the pipeline?

Operationalizing AI/ML

- Class-room View :
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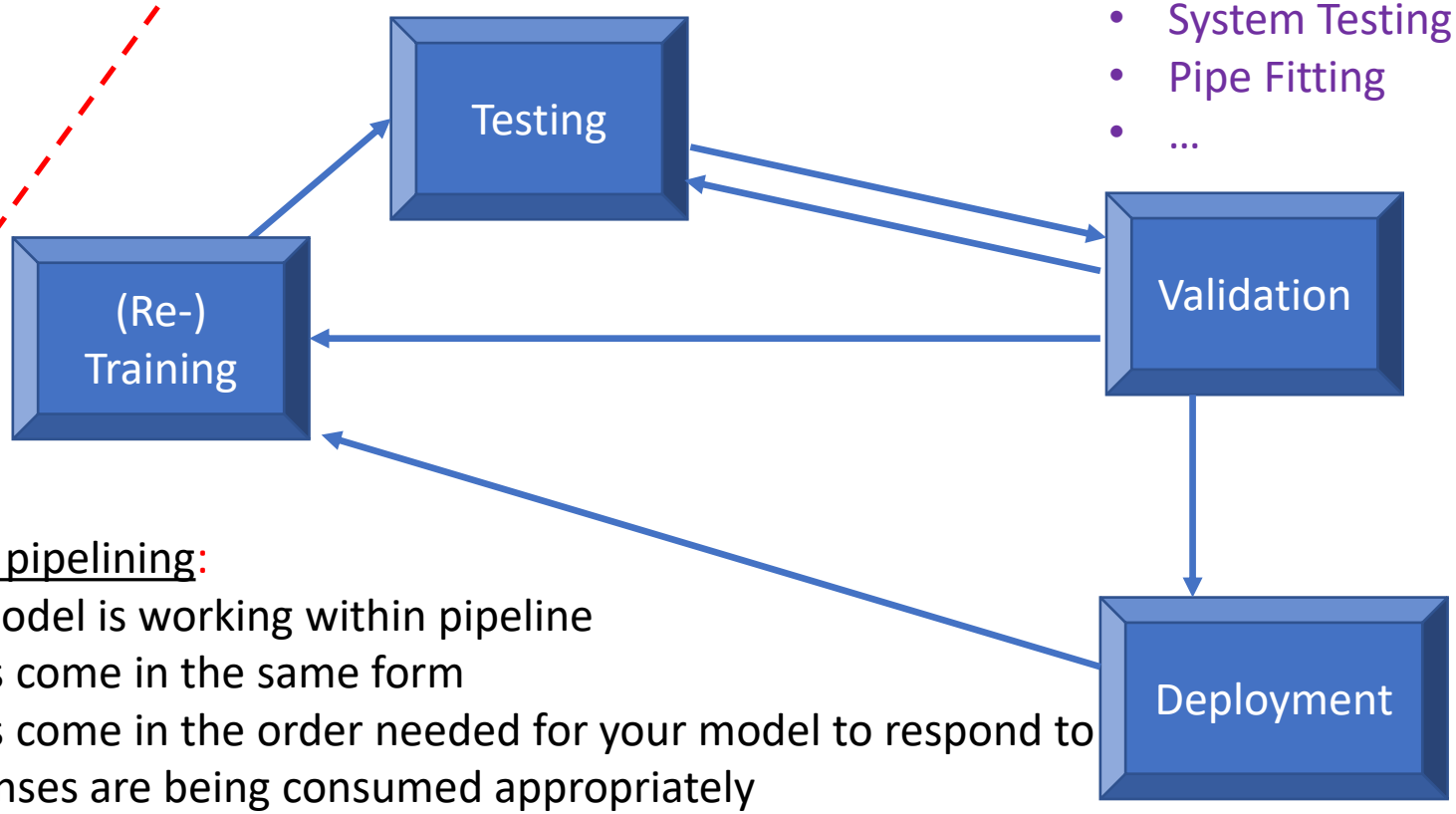
- Enterprise View:



- Compliance
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- Pipe Fitting
- …

Software pipelining:

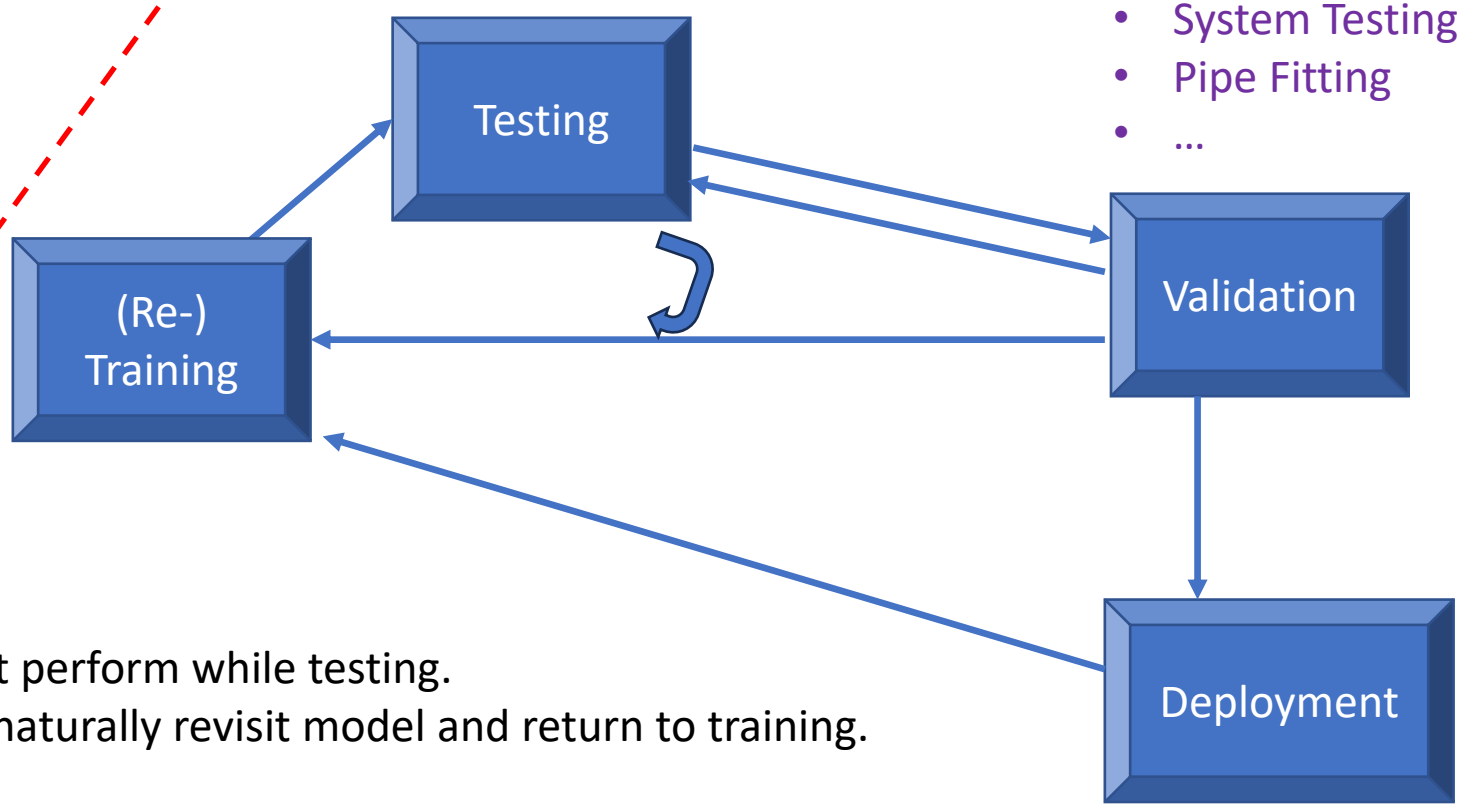
Test whether model is working within pipeline
Whether inputs come in the same form
Whether inputs come in the order needed for your model to respond to
Whether responses are being consumed appropriately
Whether responses are to consumed one at a time, or a sequence of responses have to be consumed

Operationalizing AI/ML

May need to return to training after validation/testing.

- Class-room View :
  - Development
    - Model Building / Training
  - Deployment
    - Inference

- Enterprise View:



- Compliance
- System Testing
- Pipe Fitting
- …

If model doesn't perform while testing.
AI scientist will naturally revisit model and return to training.

Operationalizing AI/ML

Can we stop after deployment?

- Class-room View :
  - Development
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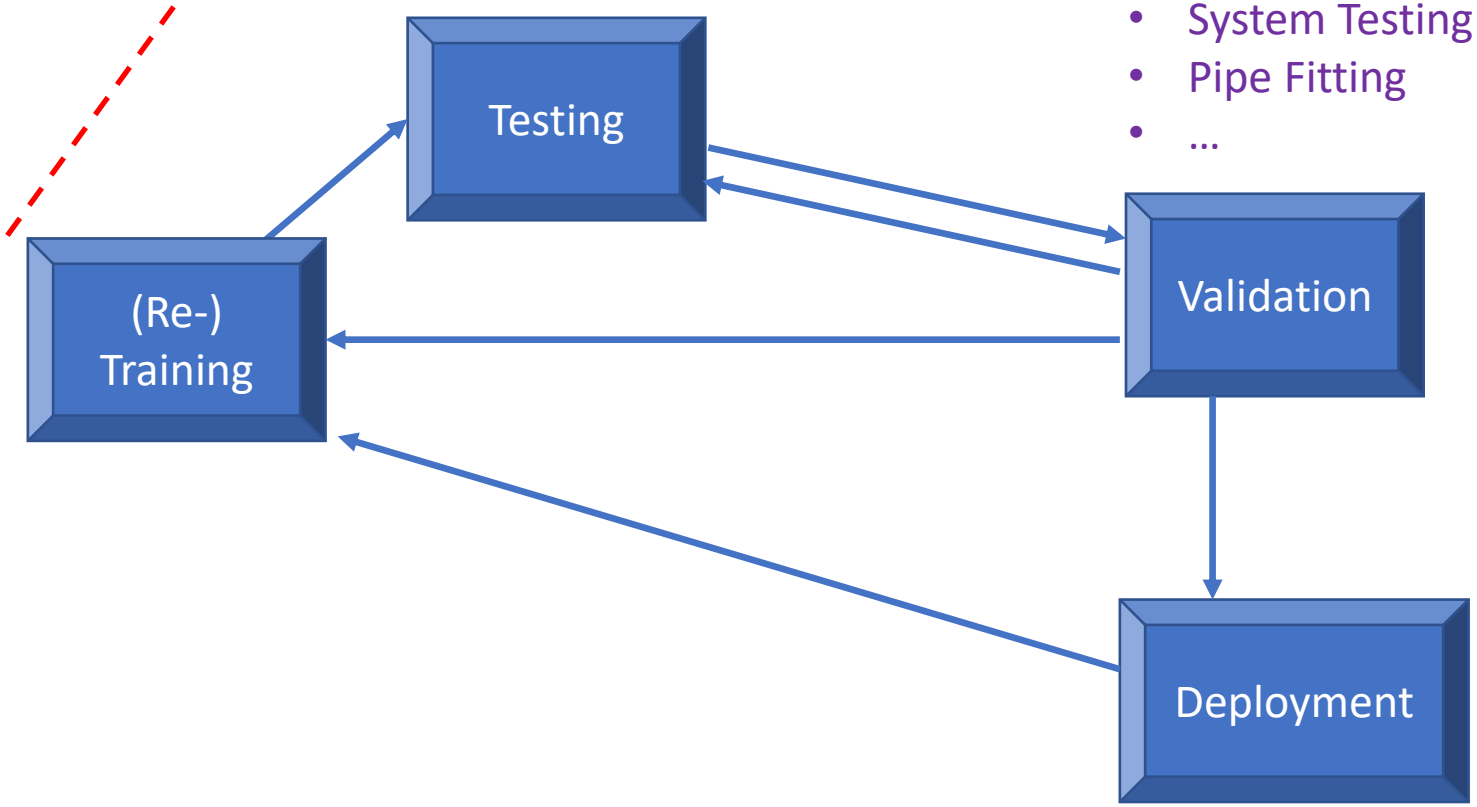
  - Deployment
    - Inference

- Enterprise View:



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Machine Learning – Enterprise Practice-Recap

- AI and Machine Learning is becoming central to organizations:
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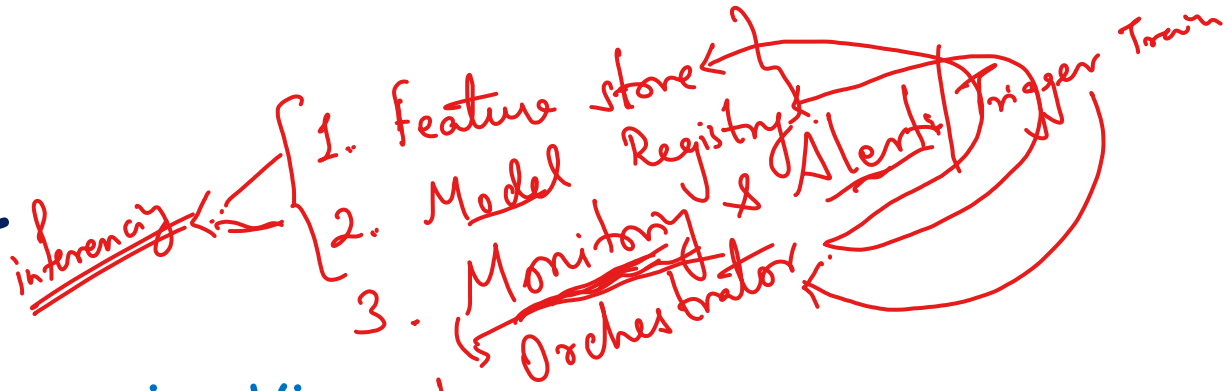
    - Drift in the solution
  - Problems change; Requirements change;
    - New model(s) required
  - World changes; Expectations change
    - Performance and Standardization critical ==>
      - Packaging vs. Pricing
        - Depends on competition
        - Cost for model inference

Operationalizing AI/ML



- Class-room View :
  - Development
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- Enterprise View:
  - Compliance
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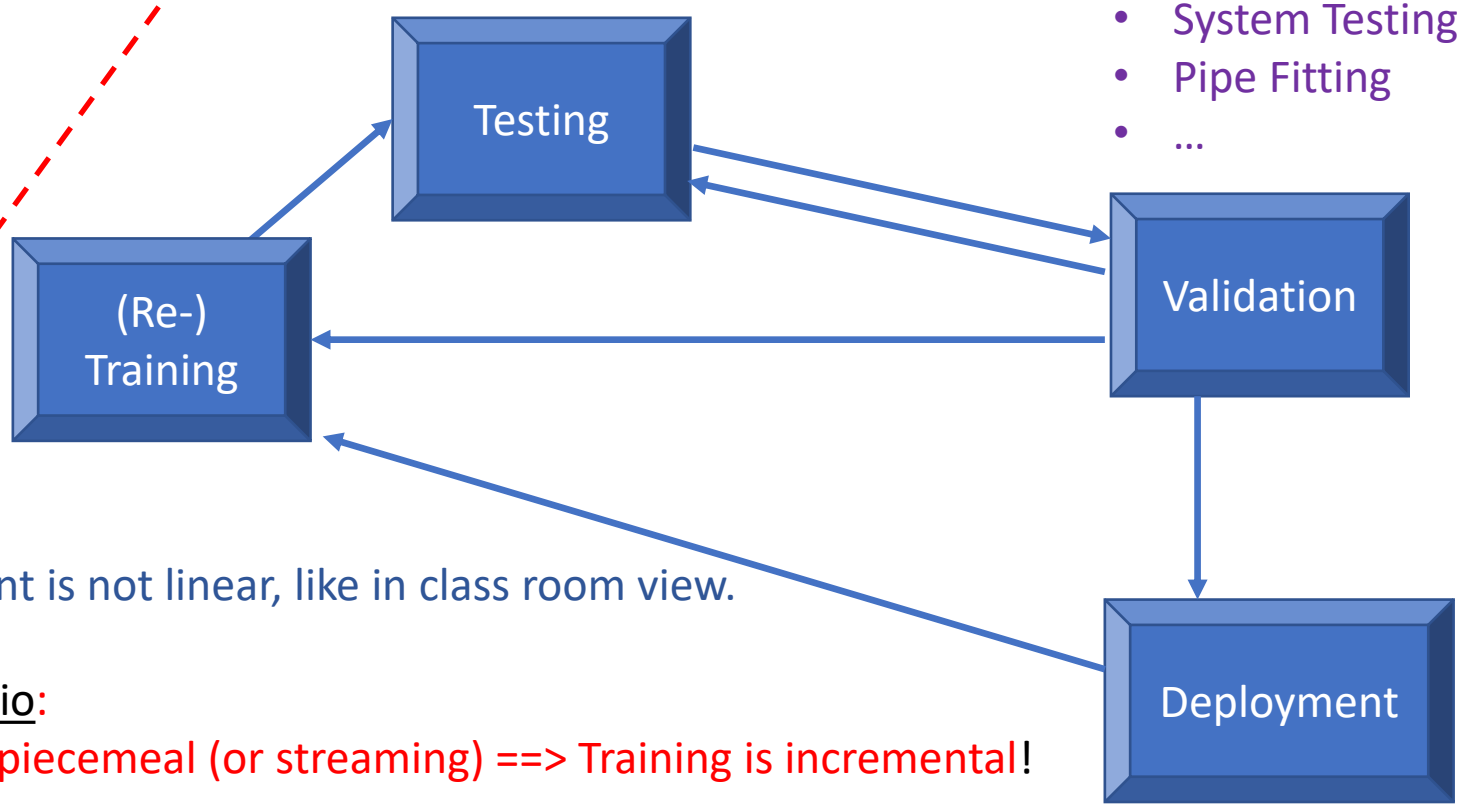


Development is not linear, like in class room view.

Extreme Scenario:

Data is arriving piecemeal (or streaming) ==> Training is incremental!

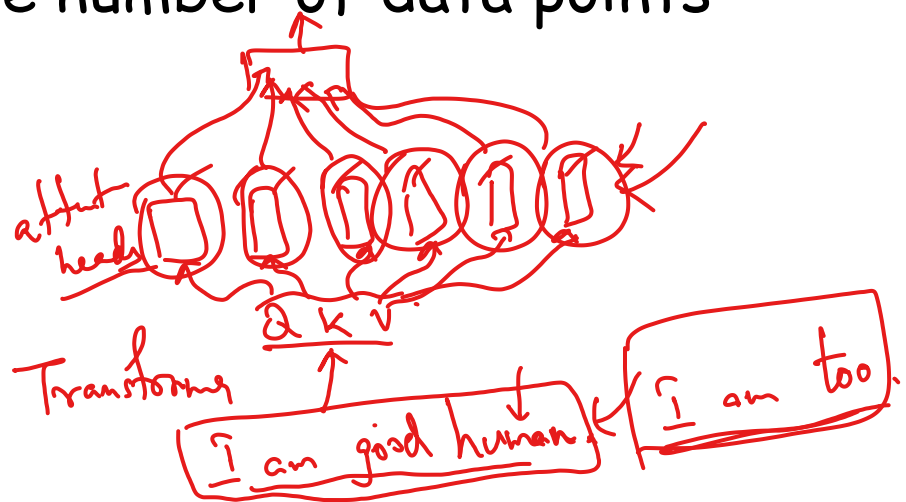
How is performance delivered?

Performance metrics?

Operationalizing AI / ML: Cost

Focus of this course

- Cost:
  - Time and Resources during Training vs Inference
- During Training:
  - Running Time of an algorithm:
    - E.g. k-means is an O(N*N) algorithm given N data points
    - E.g. SVM has a time complexity between $O(d*N^2)$ and $(d*N^3)$ where
      - d is the number of dimensions (of the data points) and
      - N is the number of data points



Cost during Training

Nvidia H100 → 80GB GPU:

LLM training → 5 years → Distributed? ✓ / Parallelization ✓

- Example
  - E.g. SVM has a time complexity between $O(d*N^2)$ and $(d*N^3)$ where
    - d is the number of dimensions (of the data points) and
    - N is the number of data points
  - For a large dataset N, say, $N = 10^9$ and $d=5$ this could be costly:
    - Assuming 2 simple arithmetic operations per data point:
    - this amounts to at least 10^{19} ($=5*2*10^9*10^9$) operations
  - Given a 2.5 GHz processor, i.e. 0.4ns clock cycle
  - and 1 CPI (i.e. cycles per instruction), a measure of processor throughput
    - [simplistic but close to reality!]
  - 10^{19} operations will take close to 5.3 years
- Reducing running time during training is a big focus in this course!

Reducing running time

- Typical methods:
  - Parallelize or distribute computation:
    - Multi-threaded programming on multi-core processors
    - Massively multi-threaded programming on many-core GPGPUs
    - Distributed Programming on Scale-out Clusters of CPUs or GPUs
  - Hand-tuning or compiler-performed code optimization
    - Rewritten for parallelism or generated by compilers
  - Process = Program + Address Space (at run time)
    - Threads share address space:
      - Each thread gets its own call stack
      - Heap and global area are shared by all threads
      - Threads run on a shared memory model (e.g., multi-core, many-core processors)
    - Distributed programming is on Distributed memory ie. Memory of multiple computers (Processor+memory+disk+OS)

Cost during training

- Megatron-Turing NLG:
  - 530 billion parameters
- Microsoft and Nvidia claim to have used hundreds of DGX A100 servers
  - Each server costs ~200,000 $
    - Add the networking cost, the infrastructure cost is ~100M$
  - Each server consumes 6.5kW of power
    - Add a comparable cooling cost!
- We will NOT do much about power consumption in this course!
  - But we will look at reducing model size as an important aspect!

Sizes of NLP models over the years

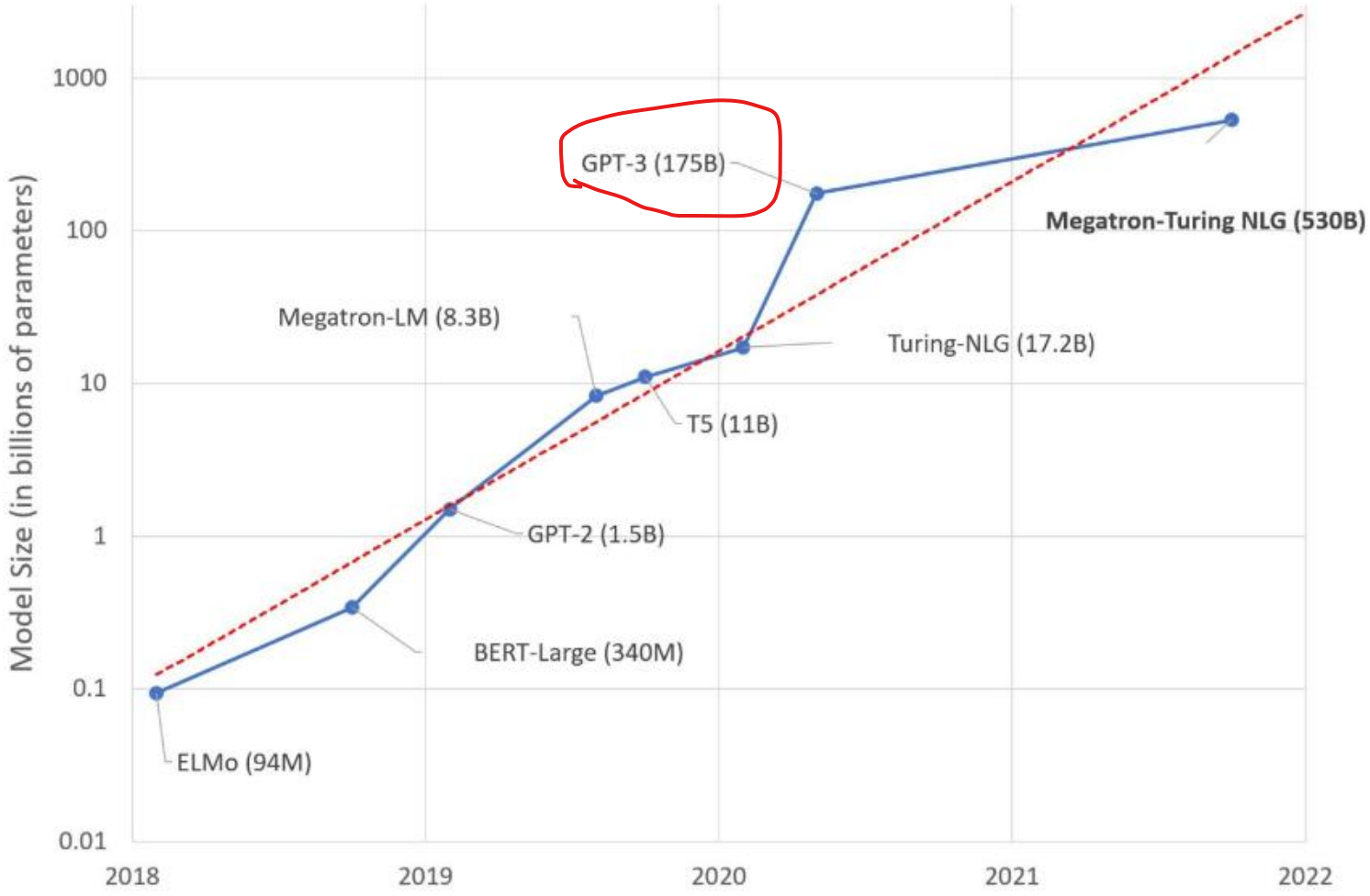
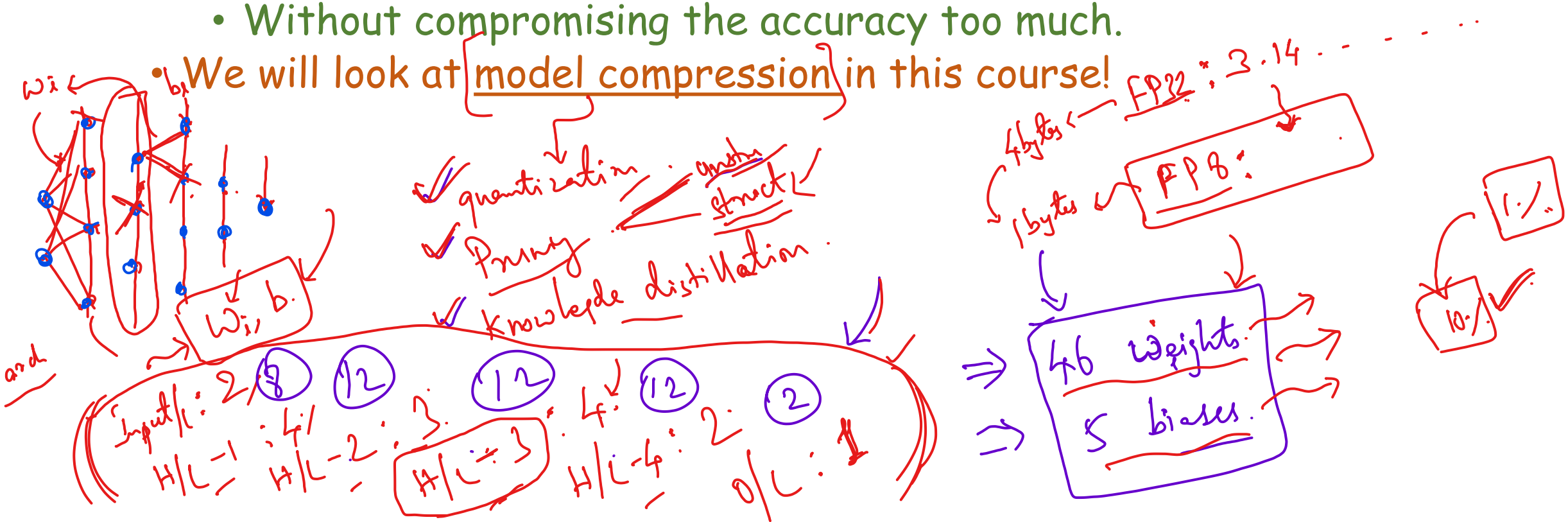


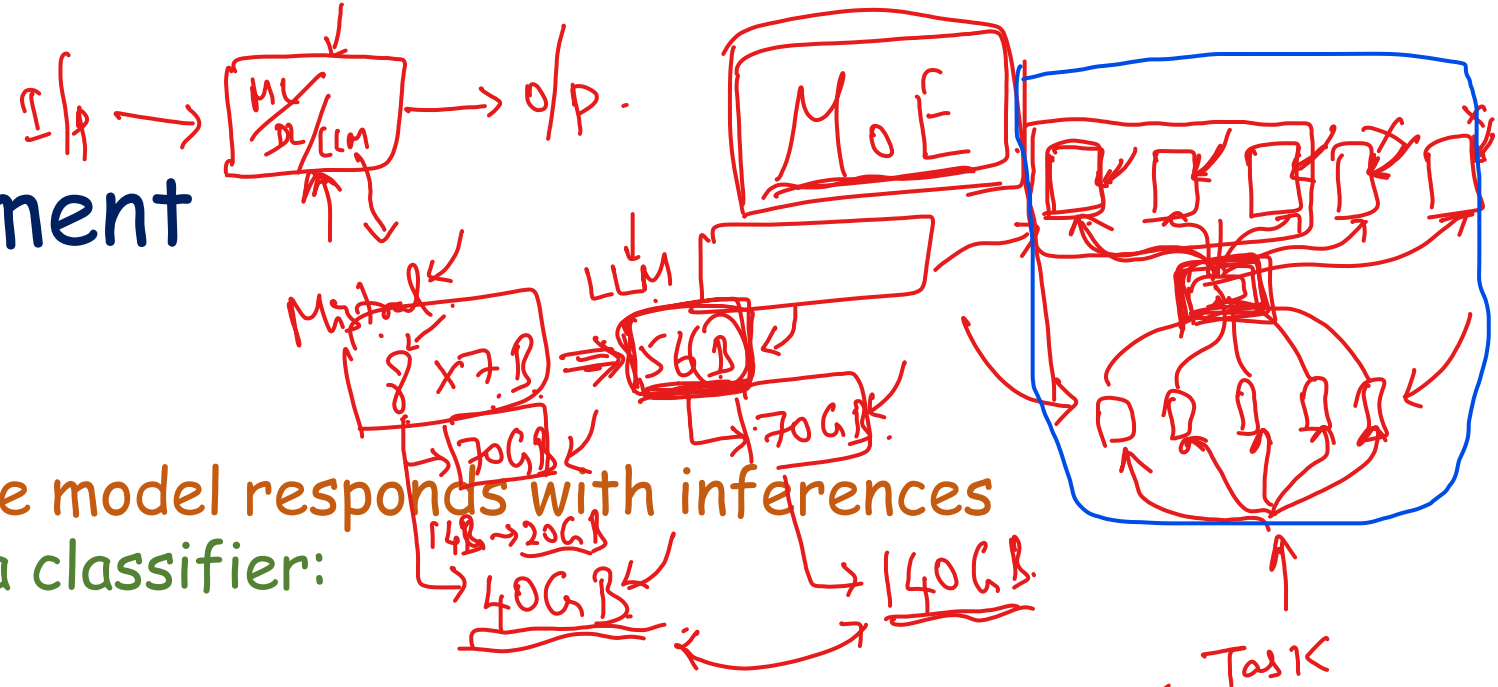
Figure 1. Trend of sizes of state-of-the-art NLP models over time

Model Size

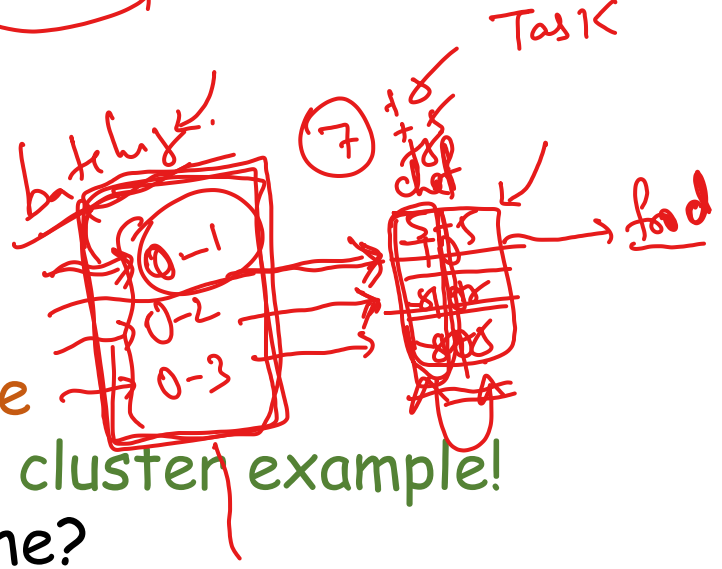
- LLMs (Large Language Models) like GPT-4 and Bard are notoriously large.
  - But there are systematic approaches to reduce model size
    - Without compromising the accuracy too much.
  - We will look at model compression in this course!



Cost during Deployment



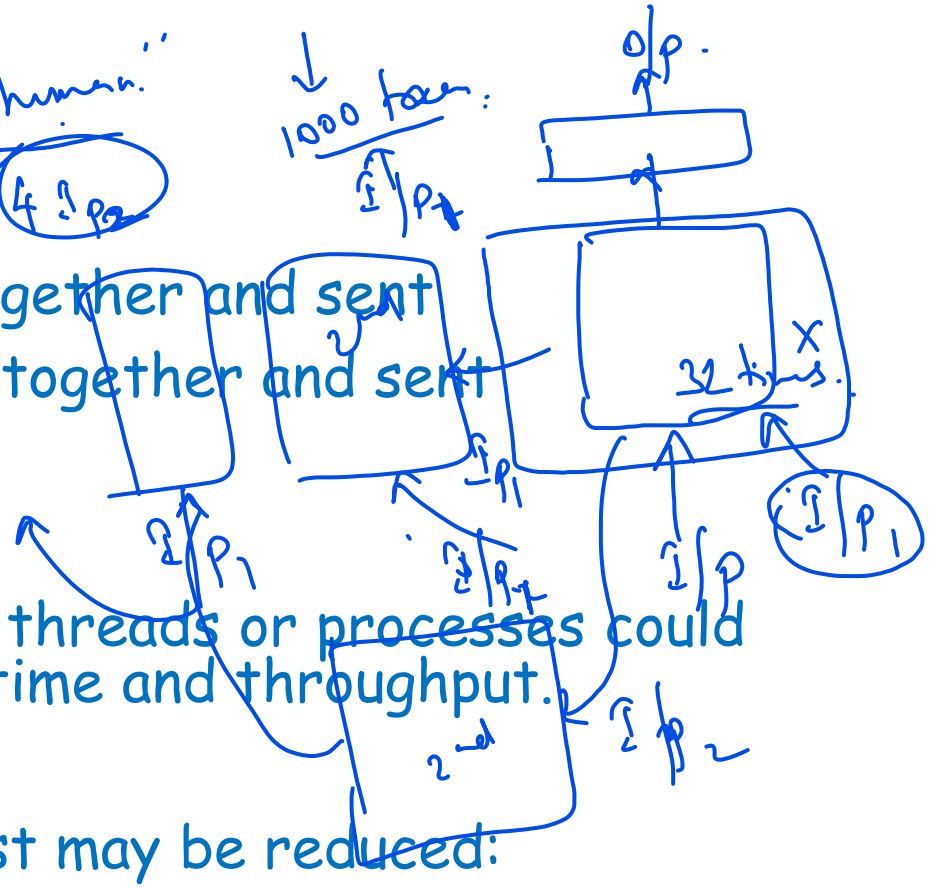
- When a model is deployed:
  - Requests come in and the model responds with inferences
    - E.g. if your model is a classifier:
      - For a new input x,
      - the response is C(x) such that $x \in C(x)$
- Performance Parameters for this phase:
  - Throughput: ↑
    - Number of inferences over a unit of time
  - Response Time: Time take to serve one inference
    - Consider the classifier example with a (data) cluster example!
      - Will there be a difference in response time?



Deployment Range

- The model (that has been trained) or an application using the model could be deployed on a variety of platforms:
  - A server (or a workstation)
    - What if the model is large?
  - The Cloud
    - The cloud can provision large infrastructure to host a large model:
      - Increase the number of servers hosting and accepting requests thereby improving throughput and response time!
        - But there is always delay
          - i.e., network latency in reaching a remote server or a server on the cloud (and getting the response back)
  - A mobile phone:
    - best end-user response time but cannot host large models.

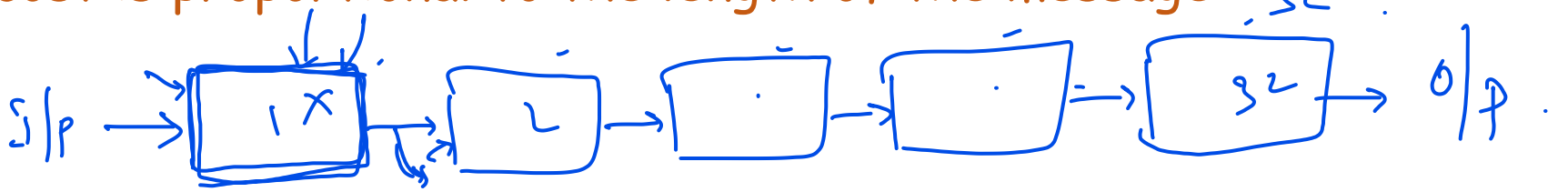
Sequential vs. Batch



- BATCH (Assumption): Requests are collected together and sent
- Responses are collected together and sent

- Ans.
- Part (A) If the model server is parallel multiple threads or processes could respond in parallel thereby improving response time and throughput.

- Part (B) [Always] Messaging/Communication cost may be reduced:
- Communication cost = setup-cost + transmission cost
  - set-up cost is fixed per message
  - Transmission cost is proportional to the length of the message



Content & Pedagogy

- Focus on systems, programming techniques, and analysis
  - Pragmatics and Implementation to be learnt by doing – enabled by Assignments and Project.

- Lecture Sessions are expected to be interactive:
  - students are expected to raise questions and
  - the instructor will ask questions (which the students are expected to answer)

Assignment and Project

- They are meant for learning
  - Expected:
    - One complex-end-to-end piece of optimization completed
    - One cutting-edge optimization technique learnt
  - Team-work with identifiable and quantifiable individual contributions
    - Evaluation both at team level and individual level