CS6216 Advanced Topics in Machine Learning (Systems)

MLsys Foundations

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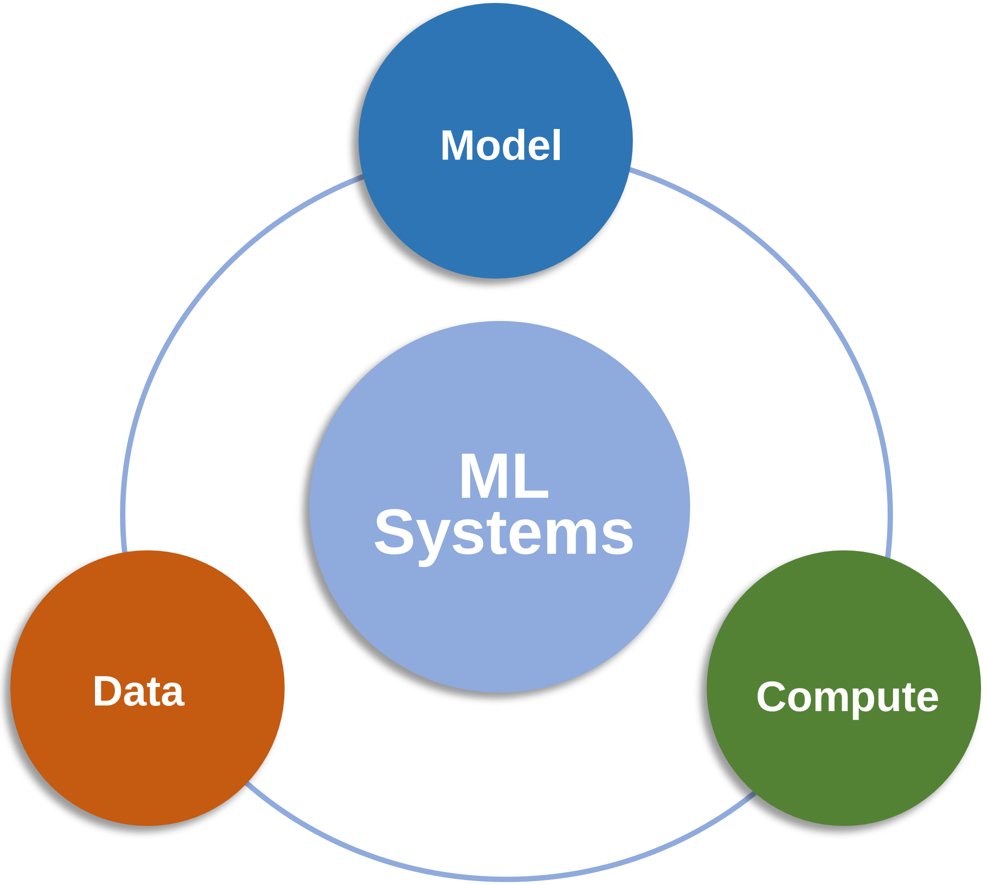
School of Computing

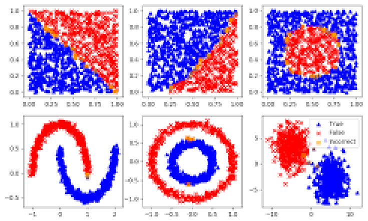
ML Systems Overview



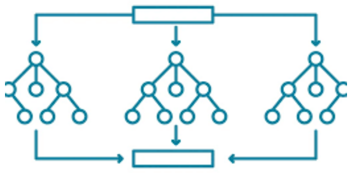
- Three components
- ML tasks
  - Training / tuning
  - Inference

Models

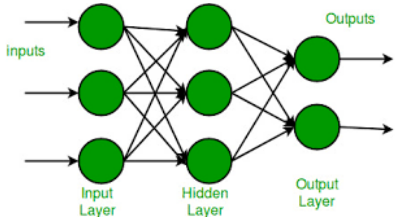
- What are models?



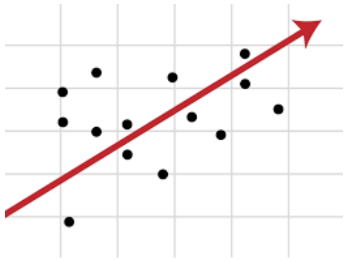
Clustering



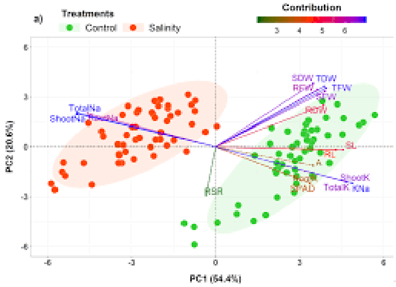
Random Forest



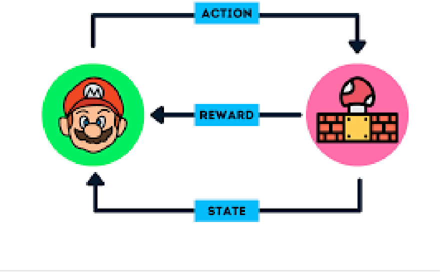
Perceptron



Linear regression



PCA

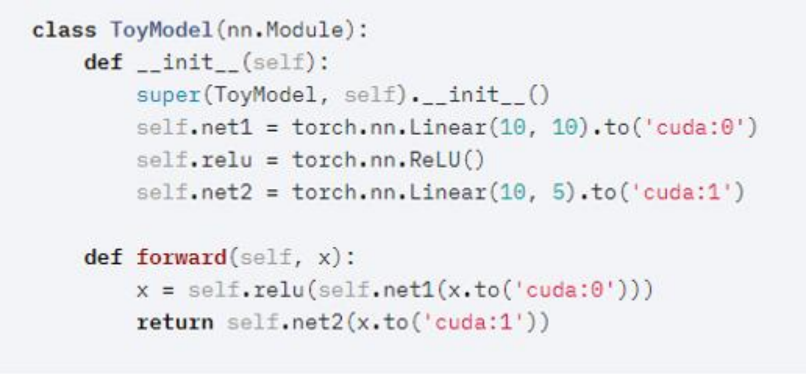


Reinforcement learning

- Models = algorithms?
- How to define, store & use models?

Model definitions

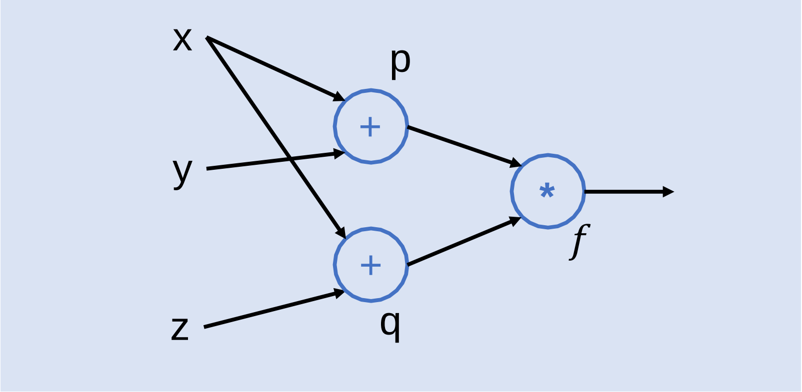
- PyTorch, Tensorflow, JAX etc. use functional declarations
  - Direct mapping to a compute graph, no ambiguity



```
class ToyModel(nn.Module):
    def __init__(self):
        super(ToyModel, self).__init__()
        self.net1 = torch.nn.Linear(10, 10).to('cuda:0')
        self.relu = torch.nn.ReLU()
        self.net2 = torch.nn.Linear(10, 5).to('cuda:1')

    def forward(self, x):
        x = self.relu(self.net1(x.to('cuda:0')))
        return self.net2(x.to('cuda:1'))
```

Model definition



(not matching code)

Algorithmic workflows

- Various ML systems exist for Boosting trees, Graph neural networks etc.

- This lecture focuses on Large Generative Models (LGMs)
  - Deep neural networks trained w/ Stochastic Gradient Descent (SGD)

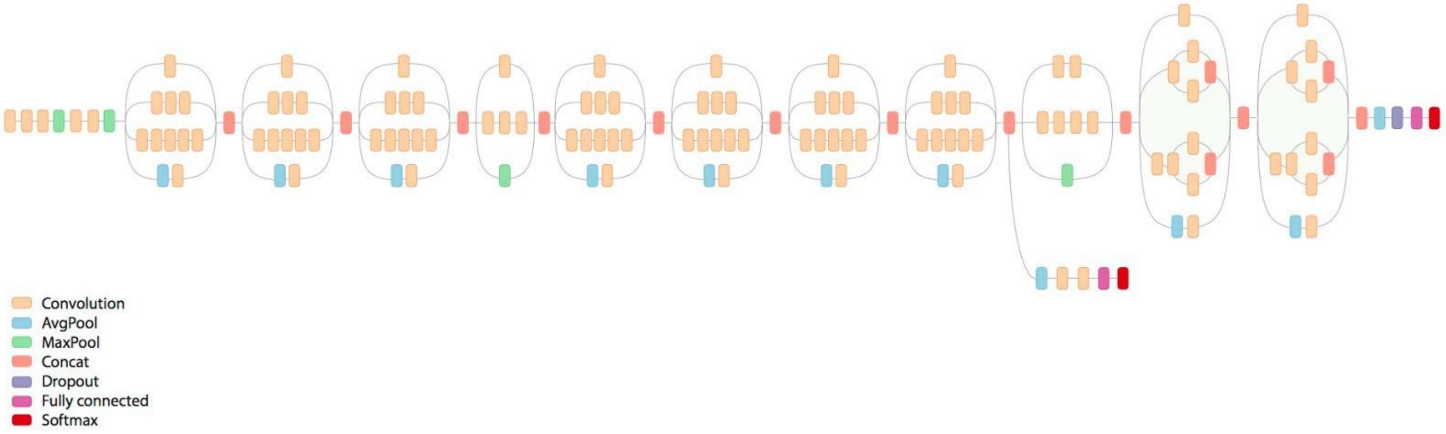
Algorithmic workflows: recap

Stochastic Gradient Descent (SGD)

Train ML models through many iterations of 3 stages

1. **Forward propagation**: apply model to a batch of input samples and run calculation through operators to produce a prediction
2. **Backward propagation**: run the model in reverse to produce error for each trainable weight
3. **Weight update**: use the loss value to update model weights

Model inputs



Model prediction

Algorithmic workflows: recap

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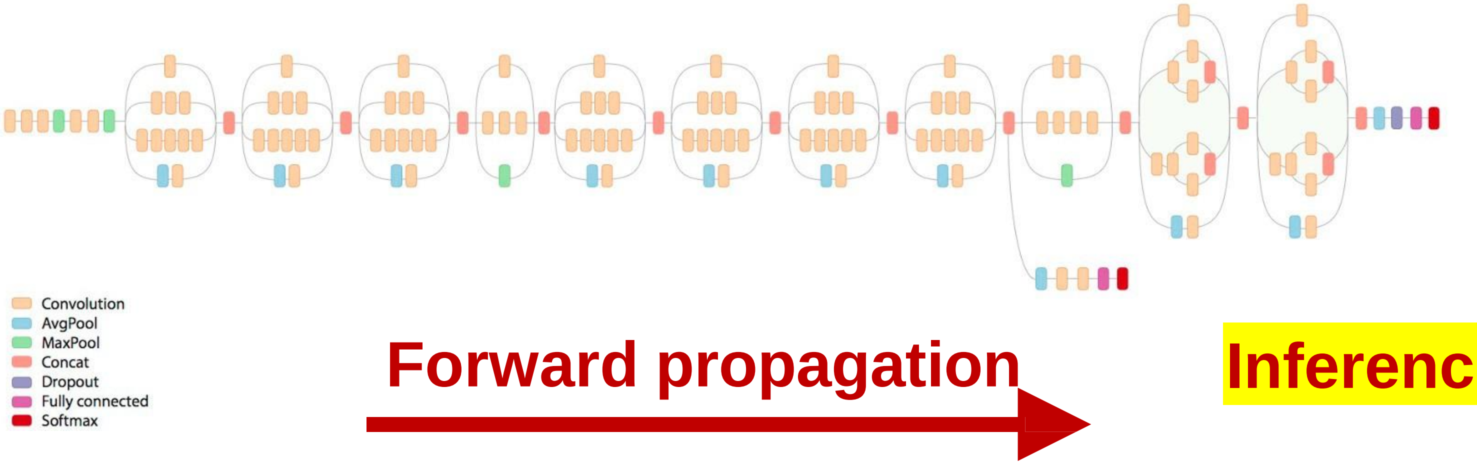

Model inputs

Model prediction

Forward propagation

Inference stops here

Algorithmic workflows: recap

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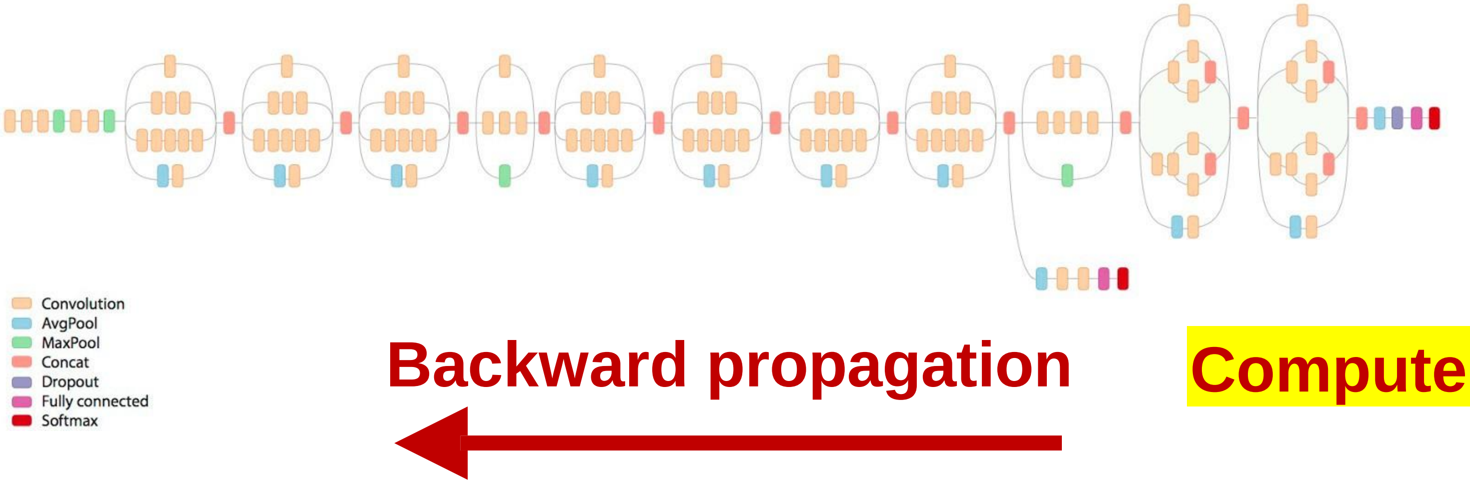
Model inputs



Model prediction

Backward propagation

Compute loss/gradients

Algorithmic workflows: recap

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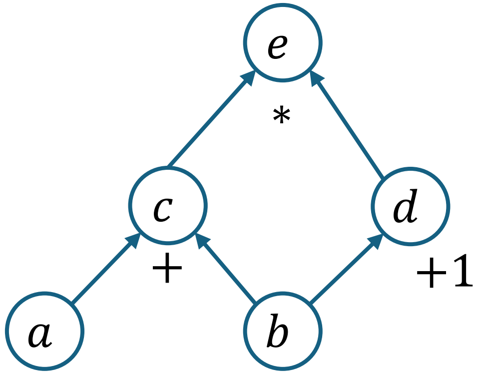
$$w_i := w_i - \gamma \nabla L(w_i) = w_i - \frac{\gamma}{n} \sum_{j=1}^{n} \nabla L_j(w_i)$$

Back propagation by example

- $e = (a + b) \cdot (b + 1)$, compute the following:



$$\frac{\partial e}{\partial c} =$$

$$\frac{\partial e}{\partial d} =$$

$$\frac{\partial e}{\partial a} =$$

$$\frac{\partial e}{\partial b} =$$

Applying chain rule to compute gradient

- Back-tracking from the root to write down partial derivatives. + for branches, * for adjacent nodes

Back propagation by example

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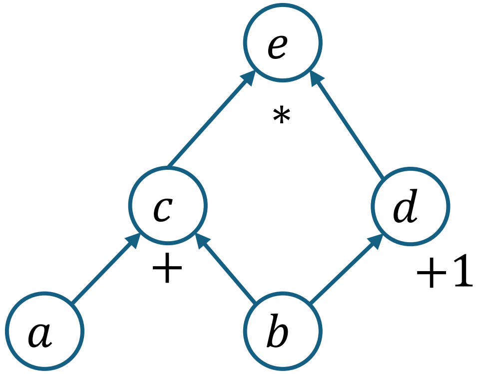

$$\frac{\partial e}{\partial c} = \frac{\partial (c \cdot d)}{\partial c} = d$$

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Applying chain rule to compute gradient

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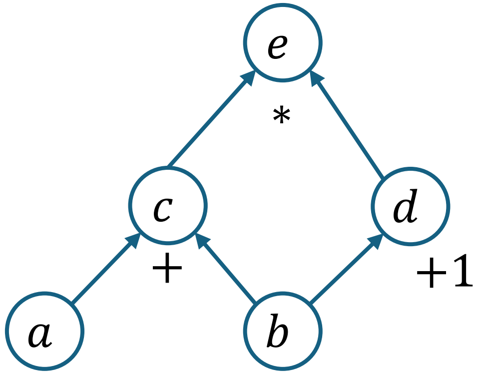

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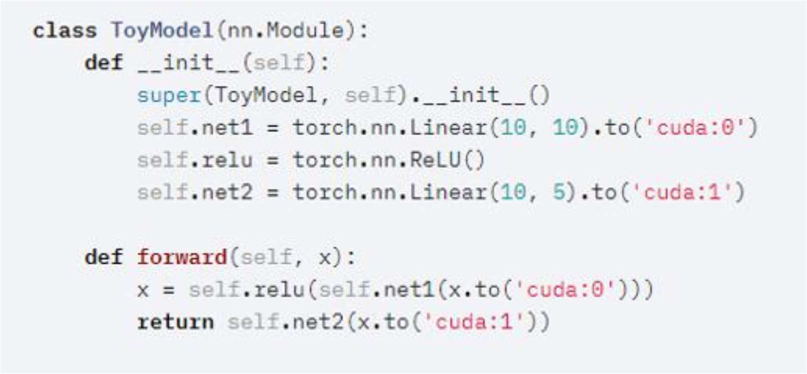
Applying chain rule to compute gradient

- Back-tracking from the root to write down partial derivatives. + for branches, * for adjacent nodes
- Given the actual Loss, compute gradient digits

A lot of repetitive compute

- Proper caching & reusing in the graph nodes

Building forward & backward compute graph



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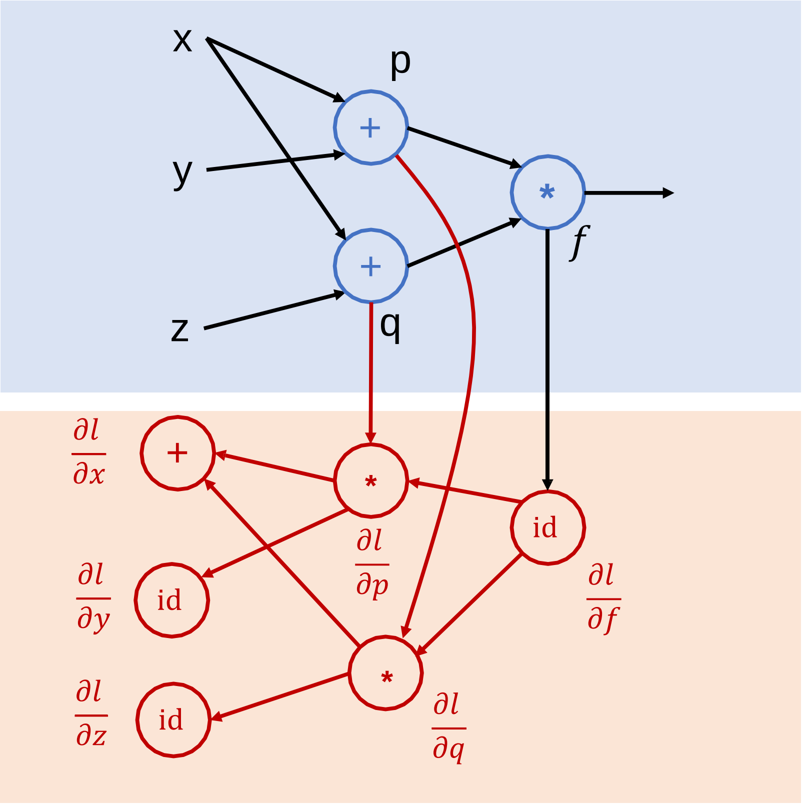
Model definition

Compute graph builder



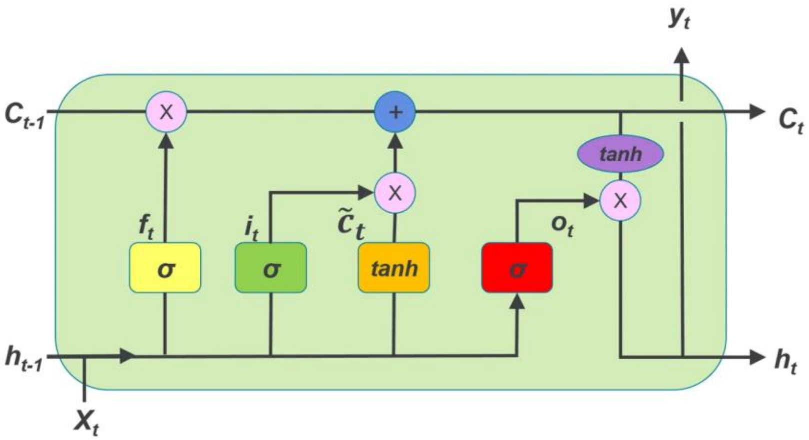
Forward computation graph

Backward computation graph

(not matching code)

Back propagation for LSTM

- Long-short term memory (LSTM)



$$f_t = \sigma_g\left(W_f \times x_t + U_f \times h_{t-1} + b_f\right)$$

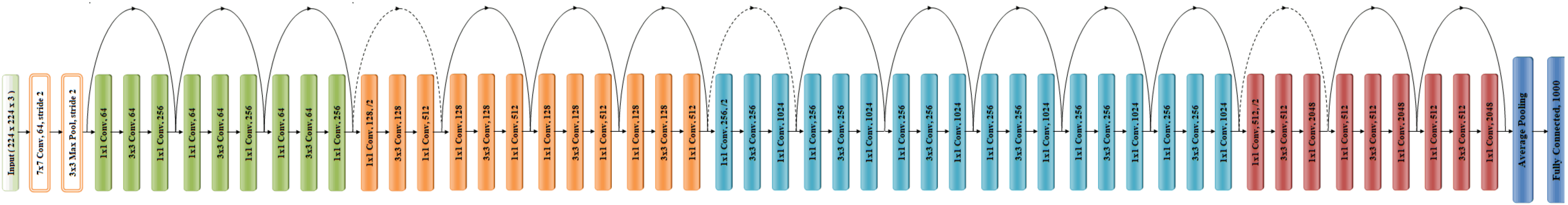
$$i_t = \sigma_g\left(W_i \times x_t + U_i \times h_{t-1} + b_i\right)$$
$$o_t = \sigma_g\left(W_o \times x_t + U_o \times h_{t-1} + b_o\right)$$
$$c'_t = \sigma_c\left(W_c \times x_t + U_c \times h_{t-1} + b_c\right)$$
$$c_t = f_t \cdot c_{t-1} + i_t \cdot c'_t$$
$$h_t = o_t \cdot \sigma_c(c_t)$$

- Derive the back-prop formulations for all parameters

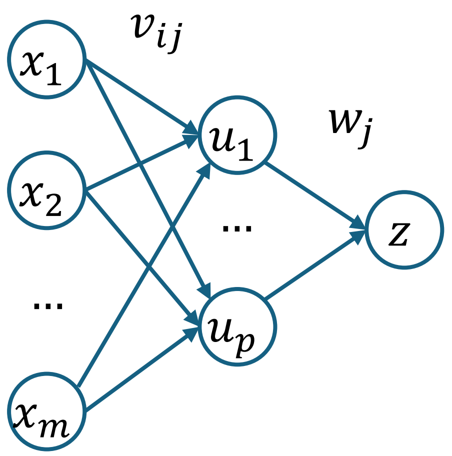
- Instructor’s experience 10 years back:
  - 1 full page of equations, 30~40 steps
  - Implementing on GPU, extremely hard to debug

How about very large neural networks?

- We need
  - Automatic computation of gradients
  - Optimization with proper caching and compute node reuse



Quiz : back propagation for MLP



- MLP is a simple DNN, where a single perceptron is defined as:

$$y = \sigma(W \cdot x + b)$$

- A 2-layer perceptron for univariate regression with l_2 loss:

$$z = \sigma(W \cdot u + b)$$
$$u = \sigma(V \cdot x + b)$$
$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

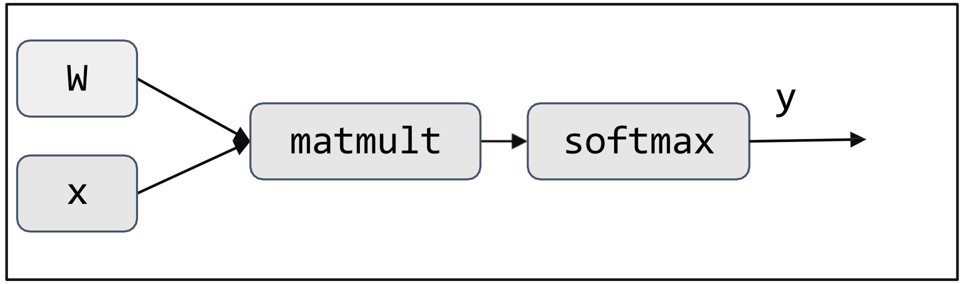
hint: $\sigma'(x) = \sigma(x)(1 - \sigma(x))$

derive gradients for W and V.

Computational graph construction by step

Construct the compute graph for $y = \text{softmax}(W \cdot x)$ with cross entropy loss

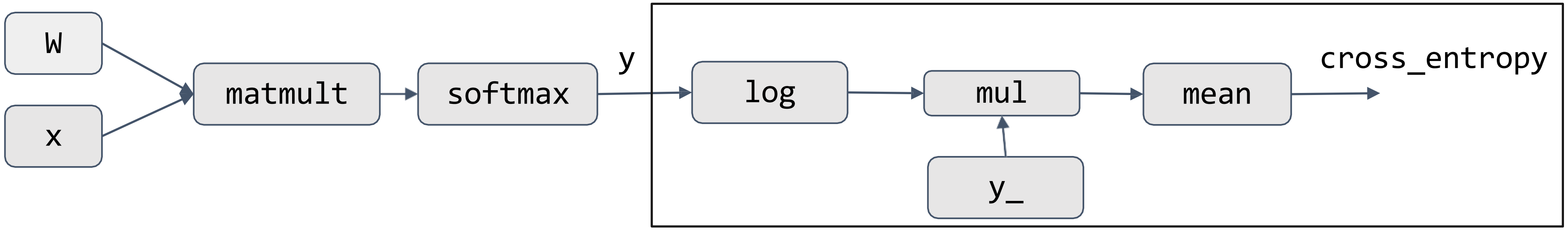
1. Construct forward graph



Computational graph construction by step

Construct the compute graph for $y = \text{softmax}(W \cdot x)$ with cross entropy loss

1. Construct forward graph
2. Add loss compute nodes



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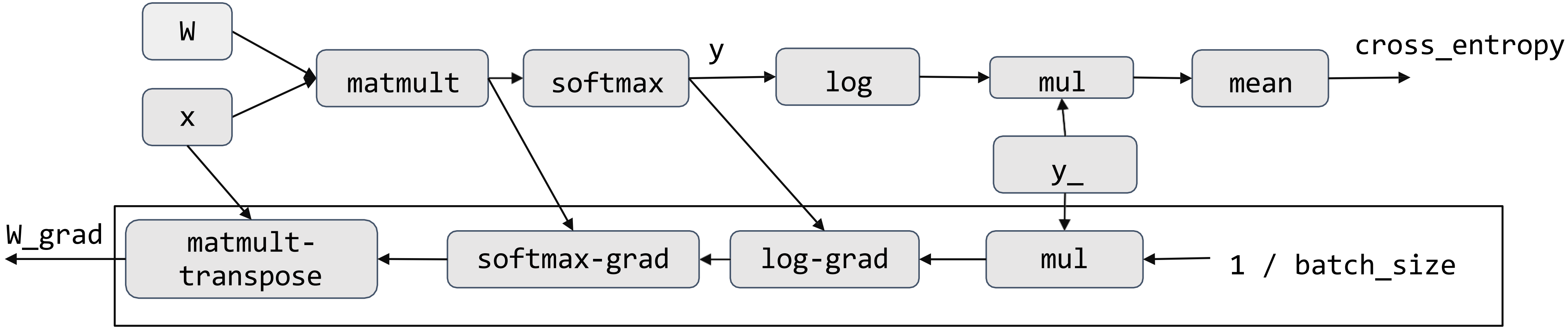

3. Construct backward graph by automatic differentiation More details in the next lecture

Computational graph construction by step

Construct the compute graph for $y = \mathrm{softmax}(W \cdot x)$ with cross entropy loss

1. Construct forward graph
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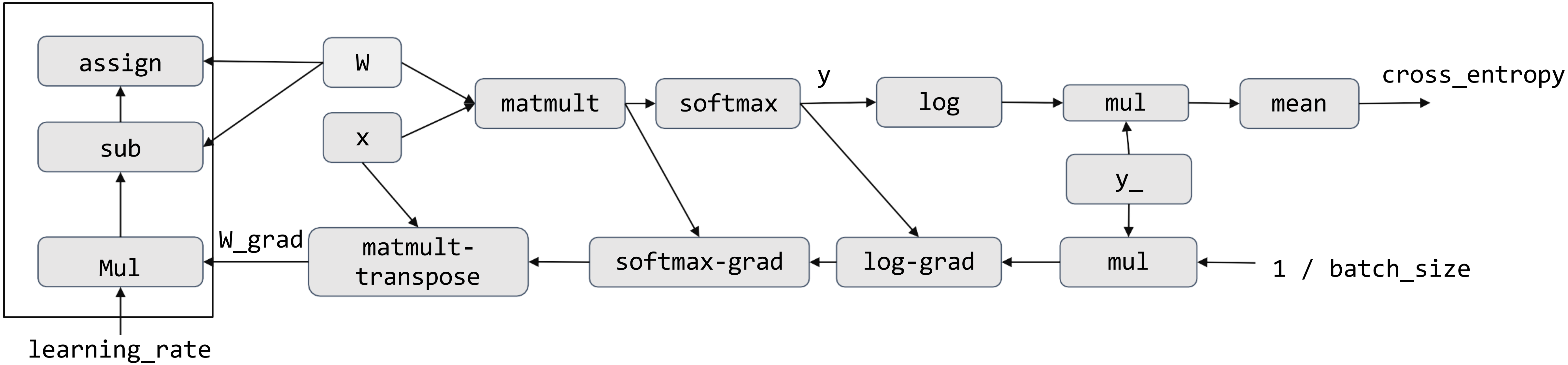
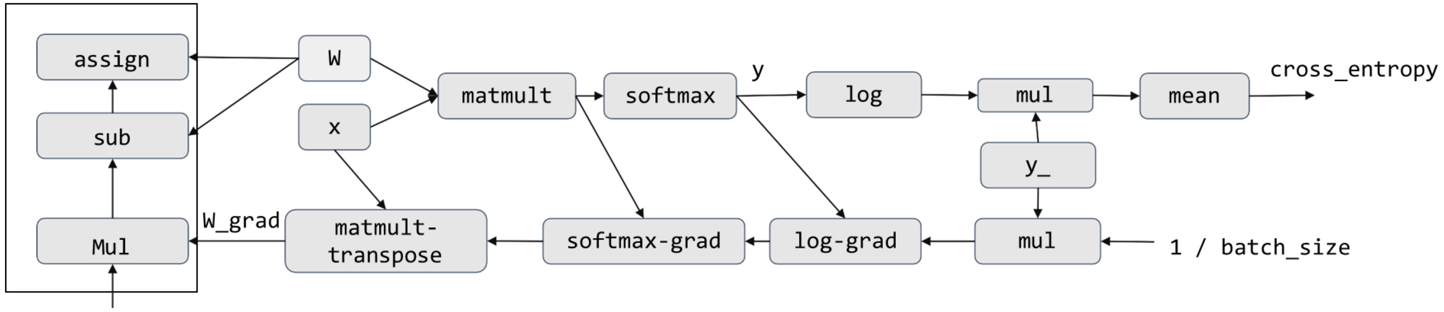


3. Construct backward graph by automatic differentiation
4. Update model weights

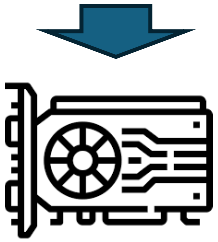
Mapping compute graph to actual runtime

- Key factors to consider:
  - Graph dependency
  - Parallelism & batching
  - Driver & API



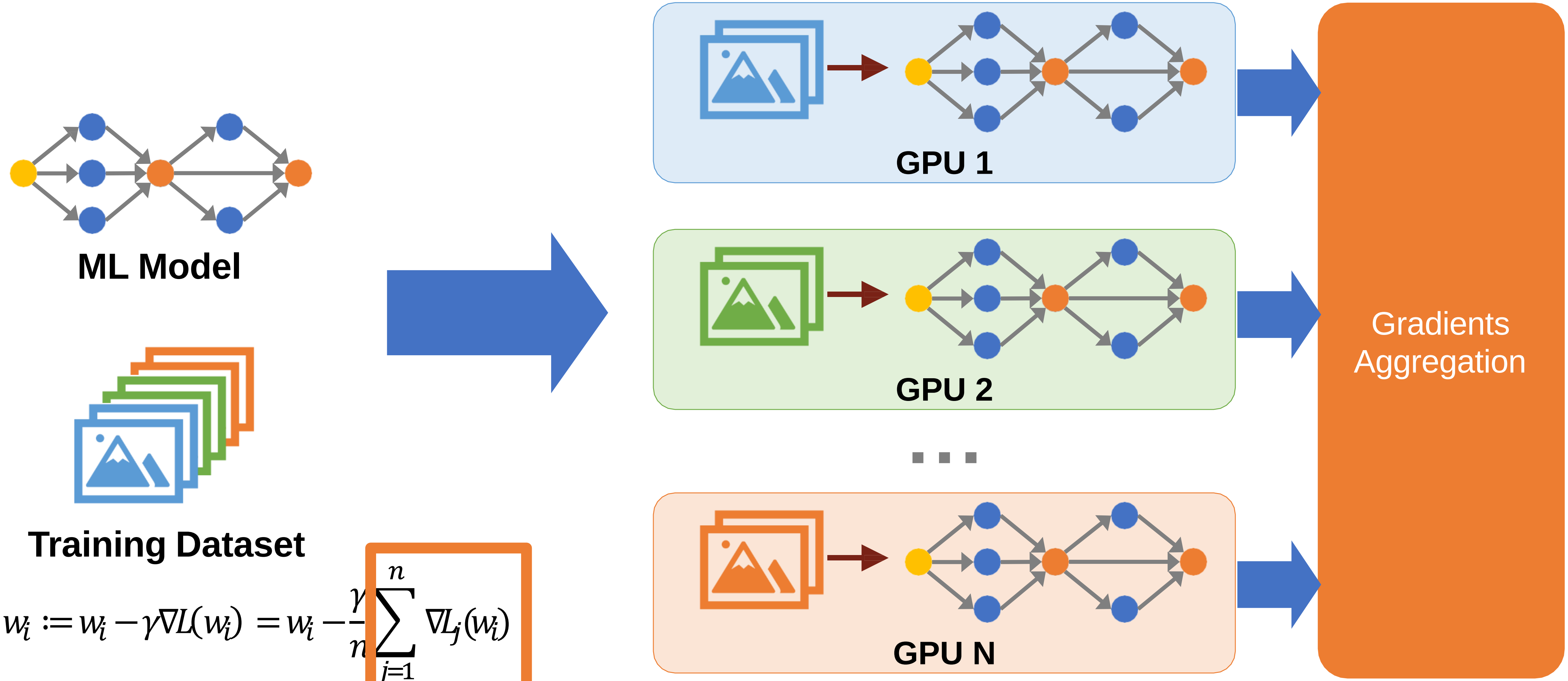
assign
sub
Mul
W
x
W_grad
matmult
softmax
y
log
mul
mean
cross_entropy
y_
mul
1 / batch_size
matmult-transpose
softmax-grad
log-grad

- CPU, GPU, TPU, FPGA, etc.
  - Each architecture has corresponding libraries and APIs



- Optimizations:
  - Operator code-gen and fusion
  - Graph-level optimizations

Execution of the compute graph: data parallelism



$$w_i := w_i - \gamma \nabla L(w_i) = w_i - \frac{\gamma}{n} \boxed{\sum_{j=1}^{n} \nabla L_j(w_i)}$$

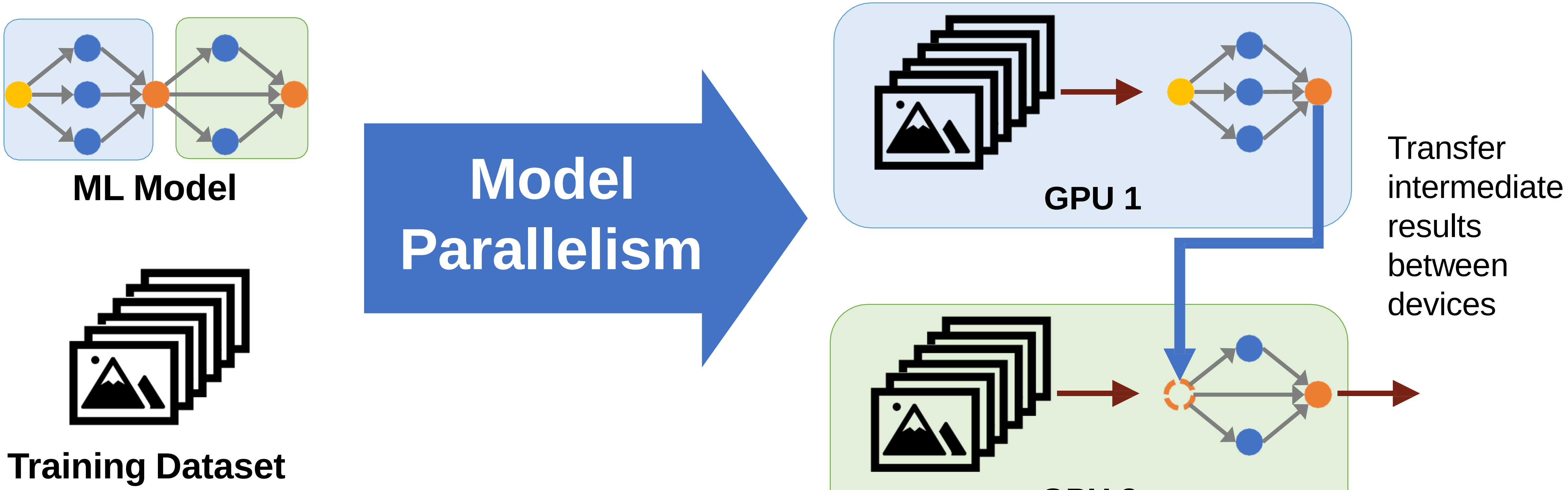
1. Partition training data into batches

2. Compute the gradients of each batch on a GPU

3. Aggregate gradients across GPUs

Execution of the compute graph: model parallelism

- Split a model into multiple subgraphs and assign them to different devices



ML Model

Model Parallelism

GPU 1

Transfer intermediate results between devices

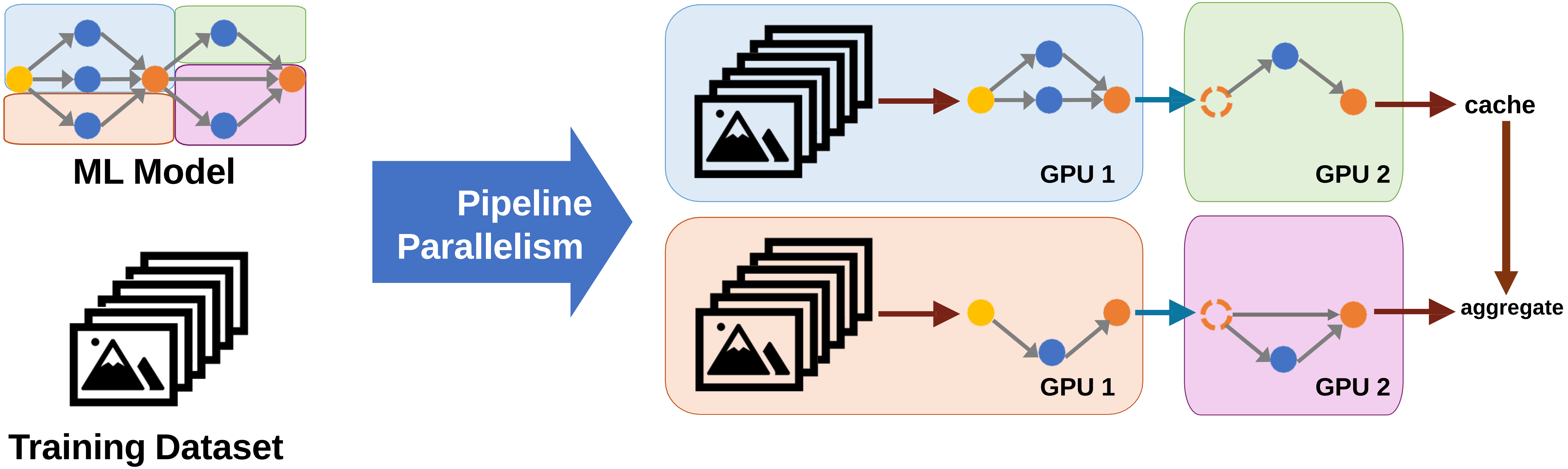
GPU 2

Training Dataset

$$w_i := w_i - \gamma \nabla L(w_i) = w_i - \frac{\gamma}{n}\sum_{j=1}^{n} \nabla L_j(w_i)$$

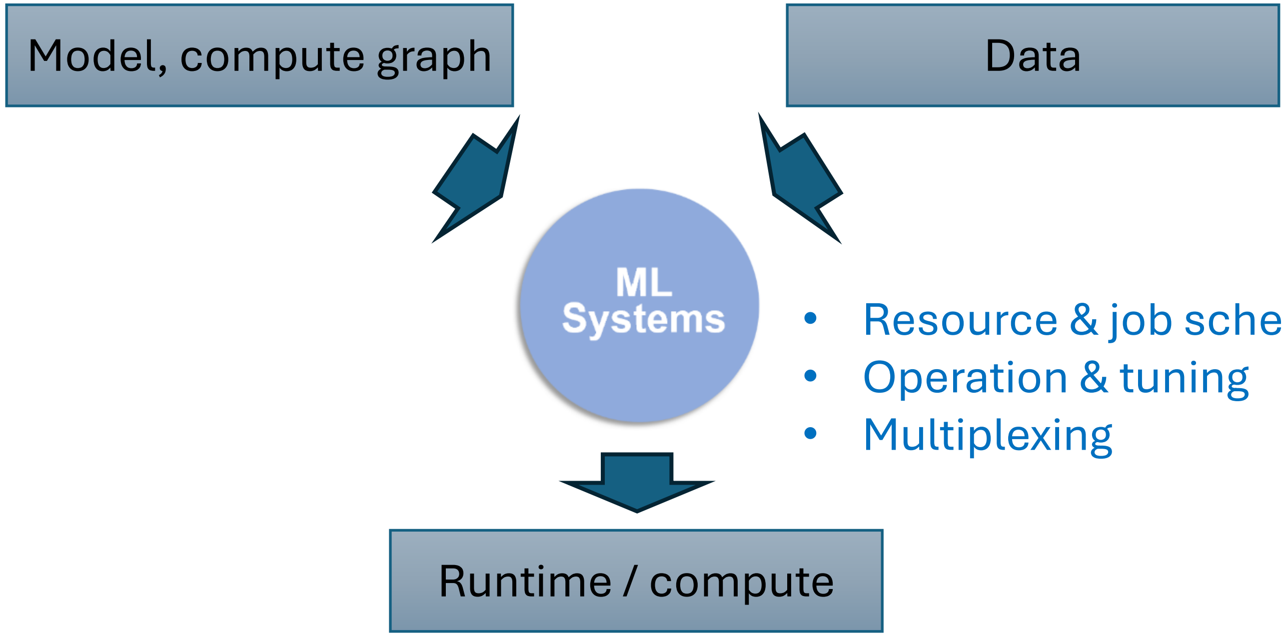
Execution of the compute graph: pipeline parallelism

- Split a model into multiple subgraphs and assign them to different devices. Run them by proper scheduling.



$$w_i := w_i - \gamma \nabla L(w_i) = w_i - \frac{\gamma}{n}\sum_{j=1}^{n} \nabla L_j(w_i)$$

Summary: core modules in MLsys



- Graph optimization
- Model specific technologies

Model, compute graph

- Storage & caching
- Data preparation & quality

Data

ML Systems

- Resource & job scheduling
- Operation & tuning
- Multiplexing

Runtime / compute

- Kernel optimization
- Code generation
- New hardware

- R&D optimizes for
  - Training / Tuning:

    efficiency & scalability

  - Inference / Serving:

    latency & throughput

  - Cloud efficiency

Outlook of the course content

- Upcoming lectures
  - Task/Model specific technologies
  - LLM serving
  - Scale up and out
  - AI for systems

- Overview of Homework 2-4
  - HW2: back propagation and autograd
  - HW3: framework & LLM inference
  - HW4: LLM serving

Reading list for the next lecture

- How to read a paper

- TensorFlow: A System for Large-Scale Machine Learning
  OSDI 2016

- Questions will be posted on Canvas

No in-person lecture next week

- Lecture recordings will be provided.