TOR VERGATA
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Introduction to Distributed and Federated Machine Leaning

Corso di Sistemi e Architetture per Big Data

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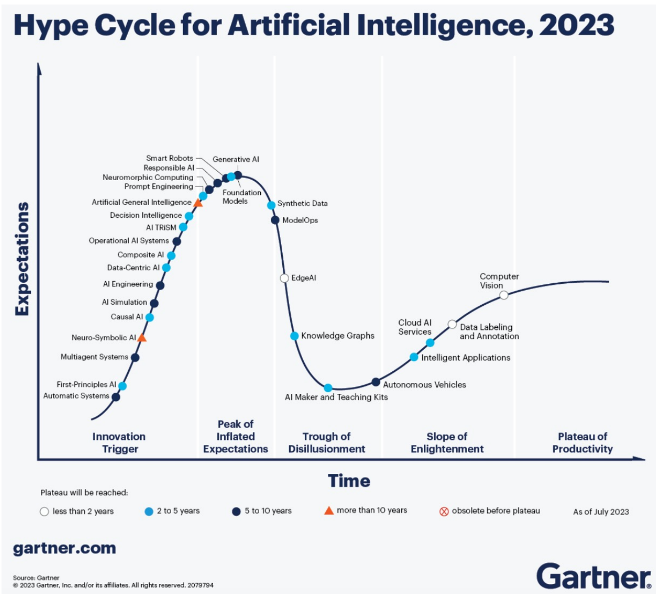
Laurea Magistrale in Ingegneria Informatica

Artificial Intelligence and Machine Learning

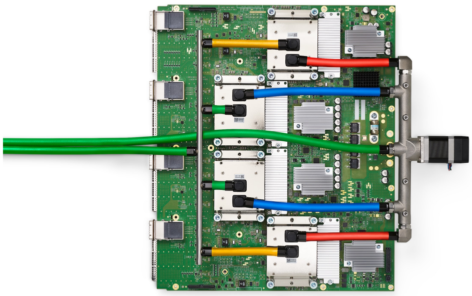
- AI and ML hype



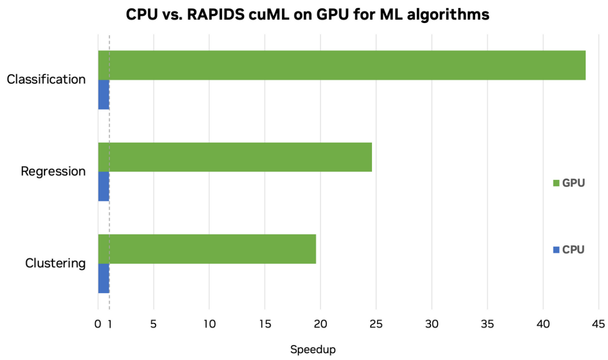
Machine Learning

- Enabled by huge leap in parallelization and innovation in ML infrastructure and tools

- **Tensor Processing Unit (TPU)**: AI accelerator application-specific integrated circuit (ASIC) specialized in calculations with *tensors* (multi-dimensional matrices)
- Also available as Cloud service: [Google Cloud TPU]

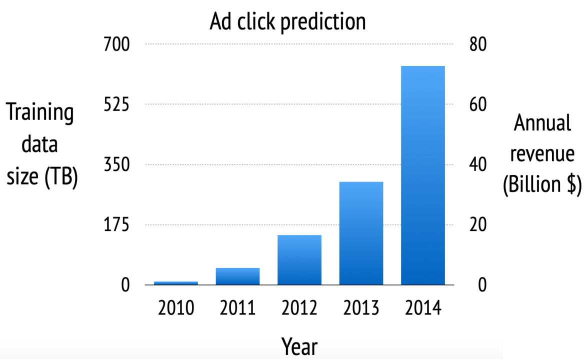


- Widely-used deep learning frameworks (e.g., TensorFlow, PyTorch, Scikit-learn) are GPU-accelerated
- Not only training, but also inference



Is there a case for distributed ML?

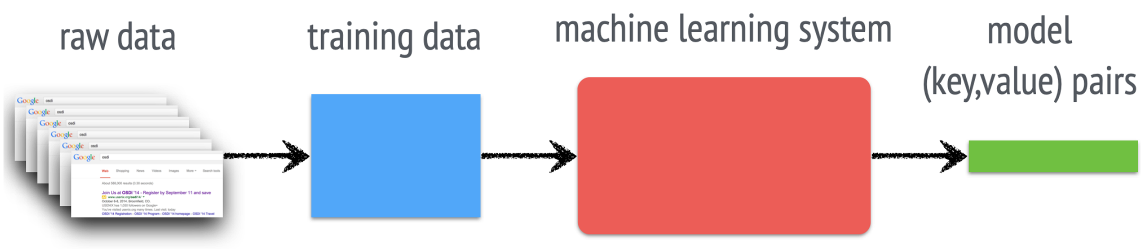
- ML systems:
  - Drive significant revenue
  - Benefit from humongous amount of data
  - Outscale even powerful machines (GPUs, TPUs)
- Which systems? Example: ad click prediction



- How to face scalability needs? Let's **distribute ML**

Li et al, [Scaling Distributed Machine Learning with the Parameter Server], OSDI'14

What do ML algorithms look like?



- Common feature of ML algorithms?
  - Iterative in nature
- Key challenges:
  - Lots of data
  - Lots of parameters
  - Lots of iterations

Scale of industry ML problems

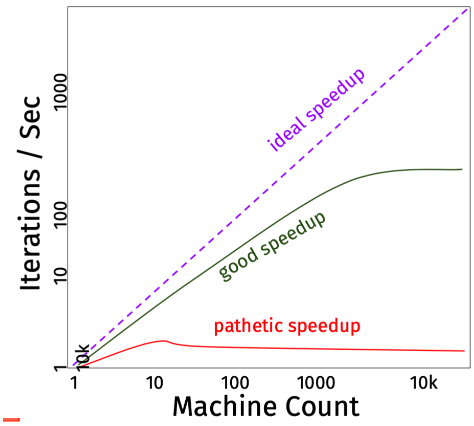
- A taste of scale of ML industry problems
  - 100 billion examples
  - 10 billion features
  - 10TB - 10P training data
  - 100 - 1000 machines
- It's a problem of scale and scale changes everything!

Scale has been the single most important force driving changes in system software over the last decade

– Technical perspective: Is scale your enemy, or is scale your friend?
John Ousterhout, CACM 54(7):110, July 2011.

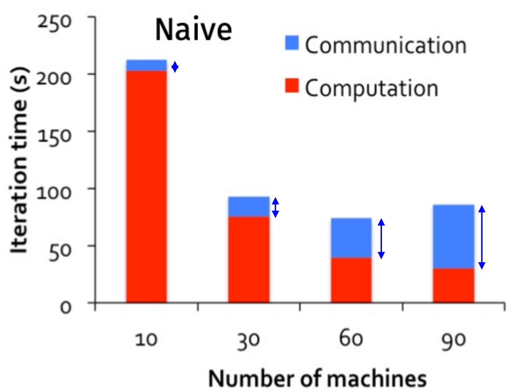
Scaling out distributed ML

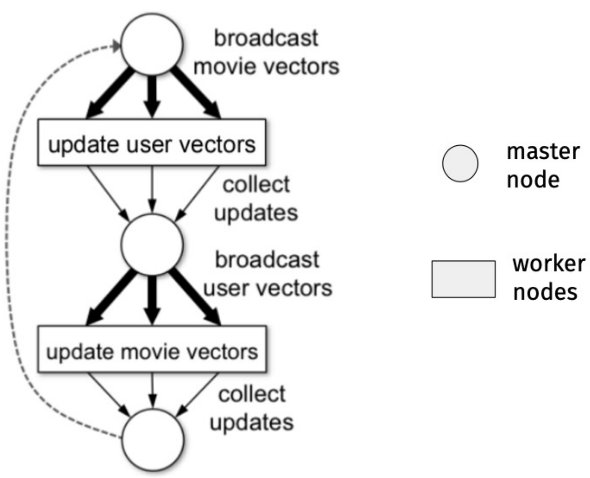
- 10-100s nodes enough for data/model
- Scale out for throughput
- Goal: more iterations/sec
  - Best case: 100x speedup from 1000 machines
  - Worst case: 50% slowdown from 1000 machines
- Can you think of reasons for performance degradation?



Challenge of communication overhead

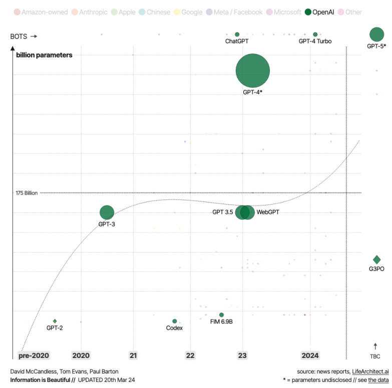
- Communication overhead scales badly with number of machines
  - E.g., Netflix-like recommender system based on matrix factorization





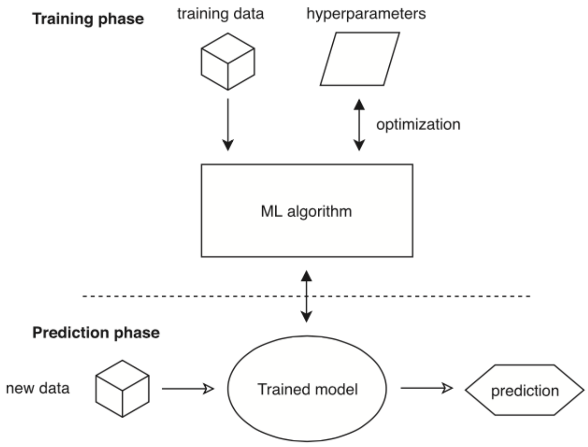
Requirements for distributed ML

- Scale to industry-size problems
  - Immense model size of large foundation models (e.g., LLMs), whose performance improve with model size and data volume
    - GPT-3 had 175 billion parameters (variables and inputs within model), GPT-4 is 10x larger
- Efficient communication
- Fault tolerance
- Easy to use



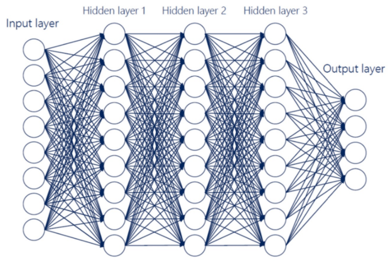
Distributed training and inference

- What can we perform in a distributed manner?
  - Training: process of using a ML algorithm to build a model
  - Inference: process of using a trained ML algorithm to make a prediction



Parallelization methods for distributed training

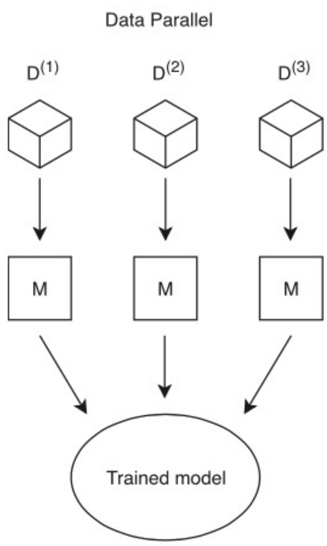
- Focus on distributed training
  - In particular, let's consider deep neural networks (DNNs), that is artificial neural networks that have an input layer, many hidden layers, an output layer

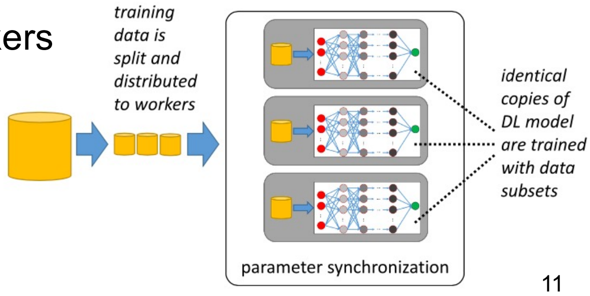


- Methods for distributed training
  1. Data parallelism: the usual SPMD approach
  2. Model parallelism
  3. Pipeline parallelism
  - Plus hybrid forms of parallelism that we do not explore

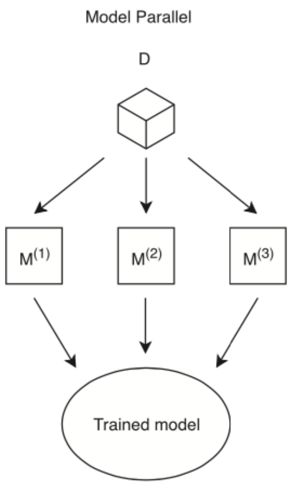
Method 1: Data parallelism

- Workers (machines or devices, e.g., GPUs) load an identical copy of model (M)
- Training data is split ($D^{(1)}$, $D^{(2)}$, …) into non-overlapping chunks or (slices) and fed into model replicas of workers for training
- Each worker performs training on its chunks of training data, which leads to updates of model parameters
  - Model parameters between workers need to be synchronized: how?



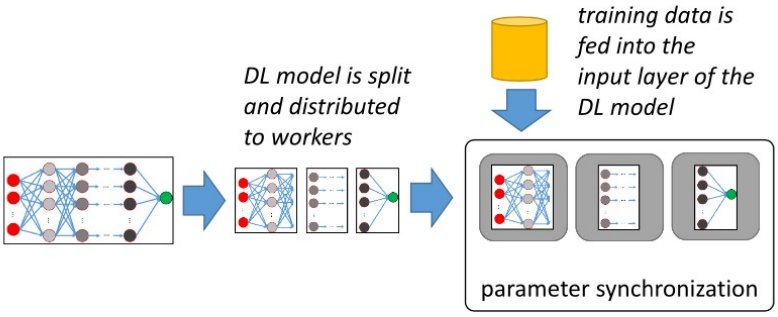


Method 2: Model parallelism



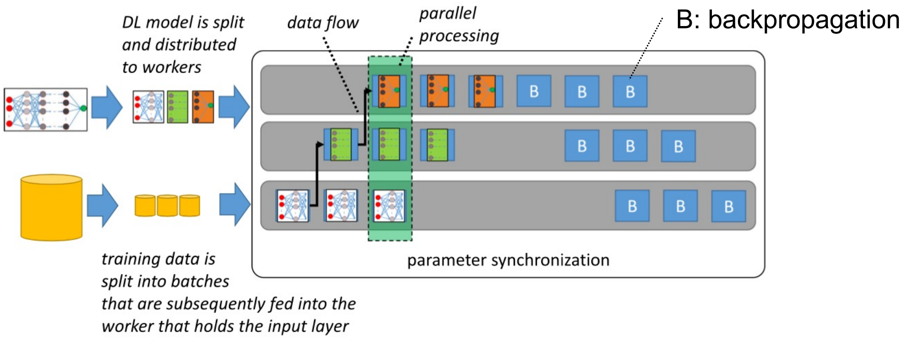
- Model is split ($M^{(1)}$, $M^{(2)}$, …) and each worker loads a different part of model for training
  – The model is the aggregate of all model parts
- Workers load an identical copy of data (D)

Method 2: Model parallelism



- Use case: Deep Learning (DL)
- Main idea: partition DNN layers among different workers
  – Worker(s) that hold input layer of DL model are fed with training data
  – In the forward pass, they compute their output signal which is propagated to workers that hold the next layer of DL model
  – In the backpropagation pass, gradients are computed starting at workers that hold the output layer of the DL model, propagating to workers that hold the input layers of the DL model

Method 3: Pipeline parallelism



- Combines model parallelism with data parallelism
- Use case: DL
  - Model is split and each worker loads a different part of model for training; training data is split into micro-batches
  - Every worker computes output signals for a set of micro-batches, propagating them to subsequent workers
  - In the backpropagation pass, workers compute gradients for their model partition for multiple micro-batches, immediately propagating them to preceding workers

Parallelization methods: Pros and cons

- Data parallelism
  - ✓ Can be used with every ML algorithm with an independent and identical distribution (i.i.d.) assumption over data samples (i.e., most ML algorithms)
  - ✓ Does not require domain knowledge of model
  - ✗ Parameter synchronization may become bottleneck
  - ✗ Does not help when model size is too large to fit on a single machine

Parallelization methods: Pros and cons

- Model parallelism
  - ✗ Challenge: how to split the model into partitions that are assigned to parallel workers
    - Cannot automatically be applied to every ML algorithm, because model parameters generally cannot be split up
  - ✓ Reduced model's memory footprint
    - As the model is split, less memory is needed for each worker
  - ✗ Heavy communication needed between workers

Optimizations for data parallelism

- Challenges of parameter synchronization in data parallelism

1. How to synchronize parameters
   – Centralized or decentralized manner?
2. When to synchronize parameters
   – Should workers be forced to synchronize after each batch, or do we allow them more freedom to work with potentially stale parameters?

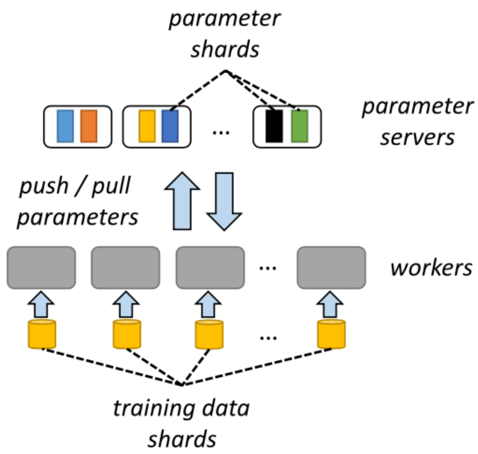
- How to minimize communication overhead for parameter synchronization

How to synchronize parameters: architecture

1. *How to synchronize parameters*
   – Centralized or decentralized manner?

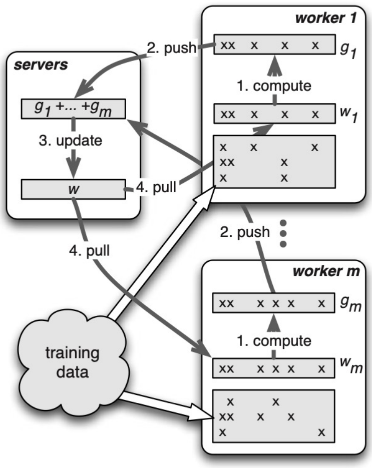
- Centralized: parameter server
- Decentralized: all-reduce

Centralized: Parameter server



- The most prominent architecture of data parallel ML systems
- Workers periodically push their computed parameters (or parameter updates) to a parameter server (PS), which keeps the shared model, and pull the updated model parameters from PS

Parameter server: distributed gradient descent



Algorithm 1 Distributed Subgradient Descent

Task Scheduler:

issue LoadData() to all workers
for iteration $t = 0, \ldots, T$ **do**
  issue WORKERITERATE(t) to all workers.
end for

Worker $r = 1, \ldots, m$:

function LOADDATA()
  load a part of training data $\{y_{i_k}, x_{i_k}\}_{k=1}^{n_r}$
  pull the working set $w_r^{(0)}$ from servers
end function
function WORKERITERATE(t)
  gradient $g_r^{(t)} \leftarrow \sum_{k=1}^{n_r} \partial\ell(x_{i_k}, y_{i_k}, w_r^{(t)})$
  push $g_r^{(t)}$ to servers
  pull $w_r^{(t+1)}$ from servers
end function

Servers:

function SERVERITERATE(t)
  aggregate $g^{(t)} \leftarrow \sum_{r=1}^{m} g_r^{(t)}$
  $w^{(t+1)} \leftarrow w^{(t)} - \eta \left(g^{(t)} + \partial\Omega(w^{(t)})\right)$
end function

$l(x_i, y_i, w)$ is a loss function (e.g., regression or classification error) that depends on data x_i, labels y_i and parameters w

Workers send gradients to PS

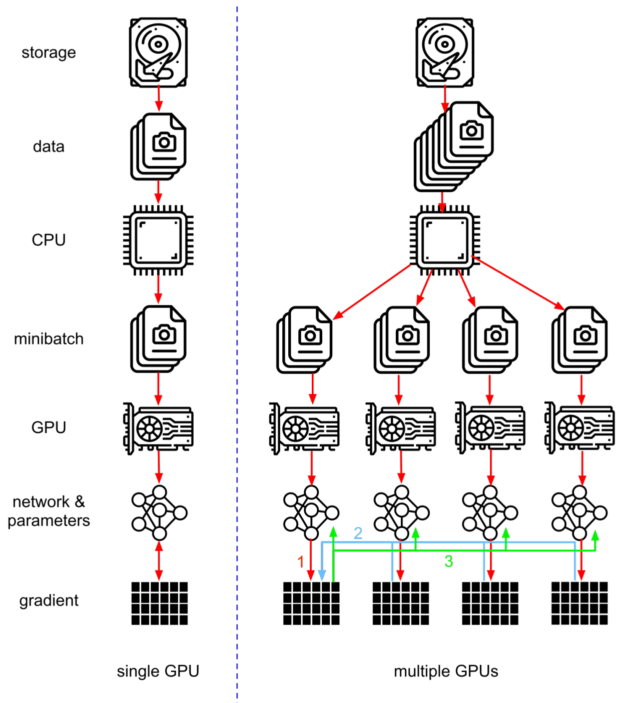
Workers pull weights from PS

PS updates the model weights

Li et al., [Scaling distributed machine learning with the parameter server](), OSDI 2014

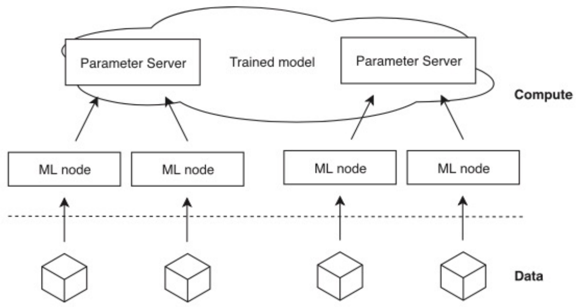
Parameter server: on multiple GPUs

1. Compute loss and gradient on each GPU
2. All gradients are aggregated on one GPU acting as parameter server
3. Parameter update happens and parameters are re-distributed to all GPUs



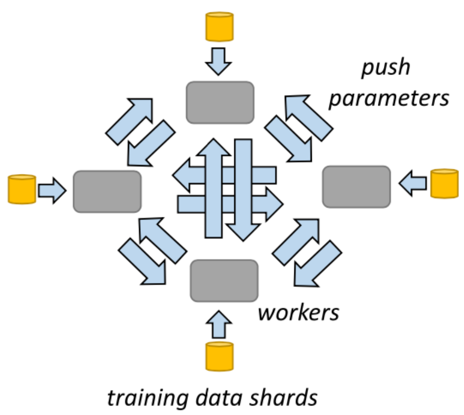
Centralized: Multiple parameter servers

- To mitigate performance bottleneck and SPoF, there can be multiple parameter servers which manage the model's parameters



  – Parameters are partitioned among multiple PSs and each PS is only responsible for maintaining the parameters in its partition
  – When a worker wants to send a gradient, it partitions that gradient vector and send each chunk to the corresponding PS; later, it will receive the corresponding chunk of the updated model from that parameter server

Decentralized: All-reduce




```
grad = gradient(net, w)

for epoch, data in enumerate(dataset):
  g = net.run(grad, in=data)
  gsum = comm.allreduce(g, op=sum)

  w -= lr * gsum / num_workers
```

- All-reduce: collective communication which computes some reduction (e.g., sum) of data (e.g., gradients) on multiple workers and make the result (e.g., weights) available on all the workers
- All-reduce should be implemented efficiently because naïve solution (all-to-all) is too costly: communication cost of fully connected network is O(n^2) with n workers
- How? Use different topologies, such as ring or tree

Decentralized: Pros and cons

- Decentralized architecture pros
  - ✓ No need of implementing parameter server(s), which also eases deployment
  - ✓ Easier to achieve fault tolerance: no SPoF (if single PS)
    - When a node in the decentralized architecture fails, other nodes can easily take over its workload and training proceeds without interruptions
    - Heavy-weight checkpointing of parameter server state is not necessary
- Decentralized architecture cons
  - ✗ Communication cost increases (at most quadratically) with number of workers
  - ✗ Changing the communication topology or partitioning the gradients induces new complexities and trade-offs

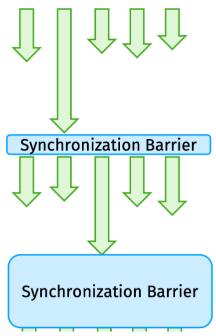
When to synchronize

2. *When to synchronize parameters*
   - Should workers be forced to synchronize after each batch, or do we allow them more freedom to work with potentially stale parameters?

- Synchronous
- Bounded asynchronous
- Asynchronous

When to synchronize: sync

- Synchronous (sync)
  - After each iteration (i.e., processing of a batch), workers synchronize their parameter updates, so that all workers use the same synchronized set of model parameters
  - Requires barriers between iterations
  - ✓ Reasoning about model convergence is easier
  - ✗ *Straggler* problem, where the slowest worker slows down all others

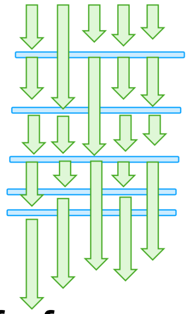


When to synchronize

- How to address straggler problem?
- Let's relax the synchronization requirement
- How?
  - Asynchronous manner: a worker who finishes processing a batch can pull the current parameters from PS and start the next batch, even if other workers haven't finished processing the earlier batch
  - Asynchronous manner is suitable to geo-distributed training servers
- But be careful: this is the usual trade-off between performance and model guarantees

When to synchronize

- Bounded asynchronous
  - Workers may train on stale parameters, but staleness is bounded
    - ML algorithms are robust, converge even with some stale state



  ✓ Allows for mathematical analysis and proof of model convergence properties

  ✓ Bound allows workers for more freedom in making training progress independently from each other, which mitigates the straggler problem and increases throughput

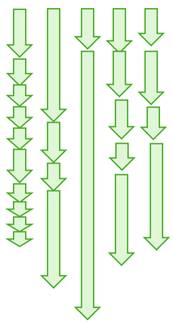
When to synchronize: async

- Asynchronous (async)
  - No barriers at all: workers update their model completely independently from each other

  ✓ Completely avoids straggler problem

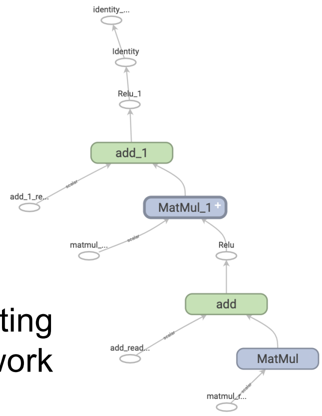
  ✗ No guarantees on a staleness bound, i.e., a worker may train on an arbitrarily stale model

  ✗ Hard to mathematically reason about model convergence



Example: TensorFlow

- TensorFlow: Python-friendly open-source software library for ML and AI
  - Can be used across a range of ML and AI tasks, but focus on training and inference of DNNs
  - Initially developed by Google Brain team for internal Google use in research and production, then released in 2015
  - A TensorFlow computation is described by a DAG with operations and units of data that flow between operations
  - Can run also on multiple devices
    - CPUs and accelerators (TPUs and GPUs)



TensorFlow graph representing a 2-layer neural network

Example: TensorFlow

- tf.distribute.Strategy: TensorFlow API to distribute training across multiple devices
- Uses data parallelism to scale out model training
  - Supports both centralized (based on parameter server) and decentralized (based on all-reduce)
  - Supports both synchronous and asynchronous parameter update

Example: Apache MXNet

- MXNet: open-source DL framework
  - No longer developed from Sept. 2023
- Distributed training on multiple devices (CPUs, GPUs) by means of data parallelism and parameter servers
  mxnet.apache.org/versions/1.9.1/api/faq/distributed_training
  - Supports both sync. and async. parameter update
- MXNet's Parameter Server (KVStore) is implemented on top of a traditional key-value store
  - Goal: efficient parameter synchronization
  - Devices push KV pairs to KVStore and pull current value of a key from KVStore: each parameter array in DNN is assigned a key, and value refers to weights of that parameter array
  - KVStore can be distributed (i.e., multiple parameter servers)
- Apache Singa is an open-source alternative for distributed DL

Example: Pytorch

- Pytorch: open-source ML framework based on Torch library
- Scalable distributed training on multiple devices (CPUs, GPUs) by means of data parallelism and decentralized all-reduce
  pytorch.org/docs/stable/generated/torch.nn.parallel.DistributedDataParallel.html
  - All-reduce is built on top of efficient collective communication libraries: gloo, MPI, and NVIDIA Collective Communications Library (NCCL)
- Also supports RPC-based distributed training for general distributed training scenarios
  - Can be used to implement parameter servers

Issues to address in distributed ML

- Efficient communication among computing nodes
- Heterogeneity of computing nodes
- Resource and energy-hungry
  - E.g., pre-training of LLaMa-2-70B takes $1.7\text{x}10^6$ of GPU hours and consumes 2.5×10^{12} J of energy
- Fault tolerance
- Privacy protection
  - Let's consider federated learning

What is federated learning?

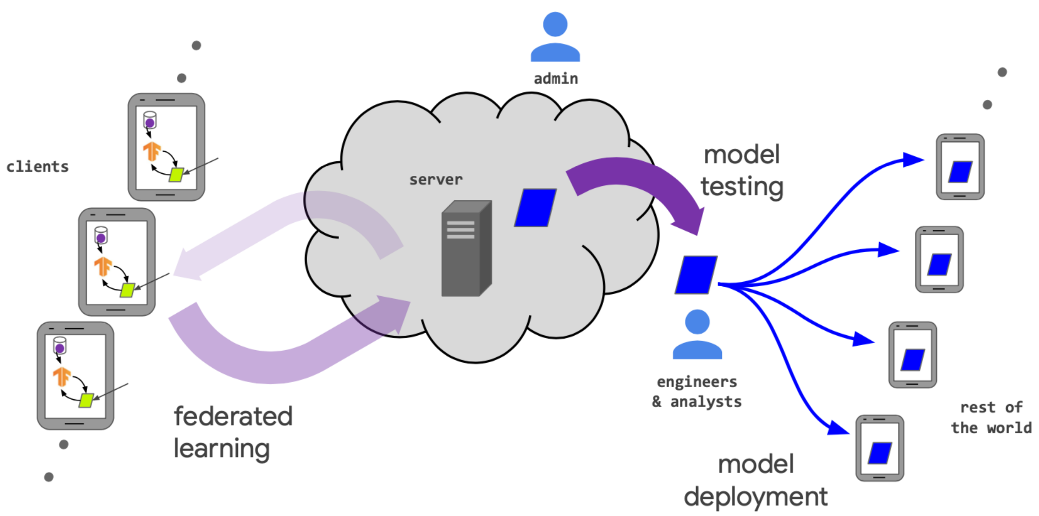
- Scenario: training setting is distributed, collaborative, with multiple devices/clients
- Goal: train collaboratively a ML model on multiple client devices located at the network edge, where data is generated locally and remains decentralized
  - No centralized training data: each client stores its own data and cannot read data of other clients
  - Data is not independently or identically distributed

What is federated learning?

- Federated leaning (FL): distributed ML setting where multiple clients collaborate in training a ML model, under the coordination of a central server (or service provider)
- Each client's raw data is stored locally and not exchanged or transferred; instead, focused updates intended for immediate aggregation are used to achieve the learning objective
- Constraint: given an evaluation metric (e.g, accuracy), performance of model learned by FL should be better than that of model learned by local training with the same model architecture

FL system

- Major components: parties (e.g., clients), manager (e.g., server), and communication-computation framework to train the machine learning model.
  - A central orchestration server organizes the training, but never sees raw data



FL training process

- A server orchestrates the training process, by repeating the following steps until training is stopped:

1. **Client selection**: server samples from a set of clients meeting eligibility requirements (e.g., in order to avoid impacting user device)
2. **Broadcast**: selected clients download the current model weights and a training program (e.g., a TensorFlow graph) from server
3. **Client computation**: each selected client locally computes a model update by executing the training (e.g., running stochastic gradient descent, SGD) on local data and sends the model weight updates to server

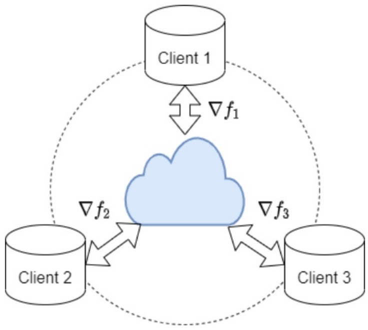
FL training process

4. **Aggregation**: server combines the model updates received by the selected clients
   - For efficiency, stragglers might be dropped
   - This stage is also the integration point for many other techniques, including: secure aggregation for added privacy, lossy compression of aggregates for communication efficiency, and noise addition and update clipping for differential privacy
5. **Model update**: server locally updates the shared model based on the aggregated update computed from clients that participated in the current round

- These steps are repeated until model converges or maximum number of iterations is reached

Approaches for FL training

- Federated averaging (*FedAvg*): the first and most widely used approach
  - It runs a number of steps of SGD in parallel on a small sampled subset of devices and then averages the resulting model updates via a central server once in a while

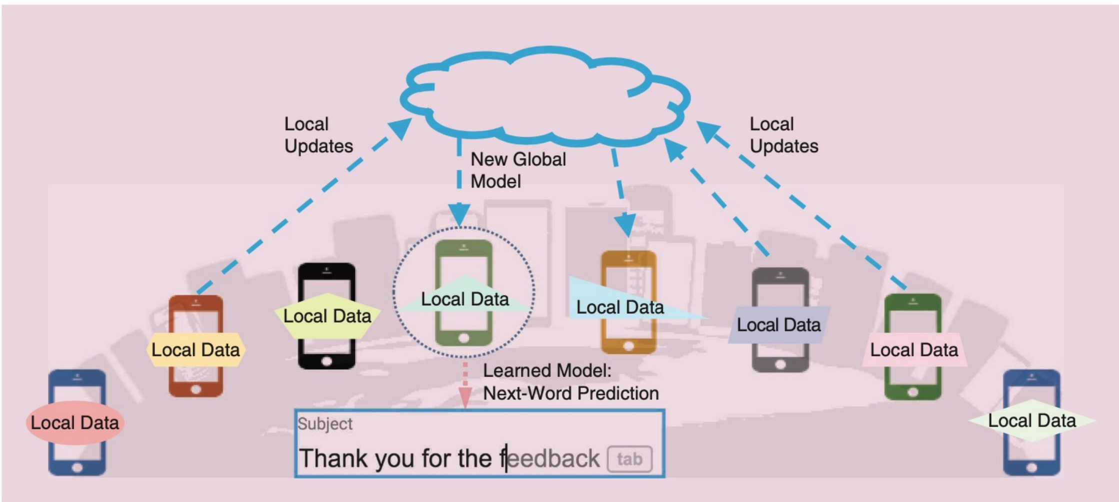


$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t - \eta \cdot \sum_{k=1}^{K} \frac{n_k}{n} \nabla f_k$$

- Decentralized FL approaches also exist

Example: FL application

- Next-word prediction on mobile phones, while preserving privacy of data and reducing strain on network



Example: FL application

- Goal: train a predictor in a distributed fashion, rather than sending raw data to a central server
- How it works
  - Remote mobile devices communicate with a central server periodically to learn a global model
  - At each communication round, a subset of selected devices performs local training on their non-identically distributed user data, and sends these local updates to the server
  - After aggregating updates using FedAvg, the server sends back the new global model to (possibly another) subset of devices
  - Iterative training process continues until convergence is reached or some stopping criterion is met

McMahan et al., Communication-Efficient Learning of Deep Networks from Decentralized Data, ArXiV, 2016.

FL main challenges

- Communication overhead
  - Can be addressed with decentralized architecture (P2P, graph, blockchain)
- System heterogeneity
  - Constrained resources on edge devices, including limited network bandwidth and latency
- Statistical heterogeneity
- Privacy concerns
  - Although local data are not exposed in FL, exchanged model parameters may still leak sensitive information about data (e.g., model inversion attack and membership inference attack)
  - How to address? Using cryptographic methods (e.g., homomorphic encryption), secure multi-party computation, differential privacy

FL frameworks

- Some open-source frameworks for federated learning
  - Flower flower.ai
  - PySyft github.com/OpenMined/PySyft
  - TensorFlow Federated www.tensorflow.org/federated
  - FedN github.com/scaleoutsystems/fedn
  - FedML fedml.ai

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