Distributed Systems for Machine Learning

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April 13, 2022

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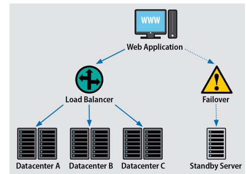
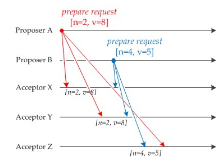
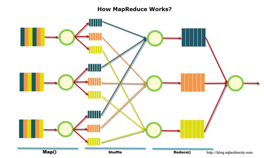
Fundamentals of Distributed Systems



Fault Tolerance



Synchronization/Consensus



Massive Parallelization

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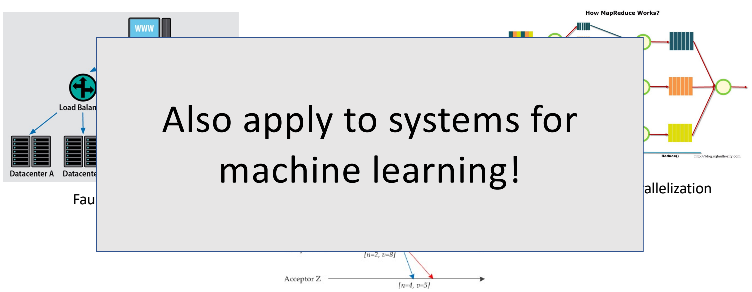
Fundamentals of Distributed Systems



Also apply to systems for machine learning!

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Lecture Goals

- Define systems for machine learning
- Understand challenges and considerations in designing such systems
- Explore a widely deployed system for ML (TensorFlow)

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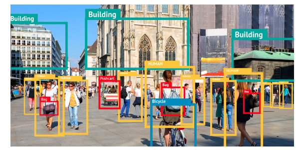
Agenda

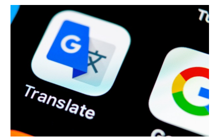
- What's led to the success of machine learning?
- What's a typical machine learning job?
- Systems for machine learning
  - Definition
  - Challenges:
    - How to handle distributed computation?
    - How to support execution in diverse environments/heterogeneous hardware?
    - Developer interface: Tradeoff between flexibility and efficiency
- Case Study: TensorFlow

The Success of Machine Learning Today

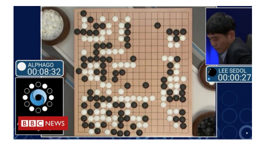


Object detection

Autonomous vehicles



Language Modeling

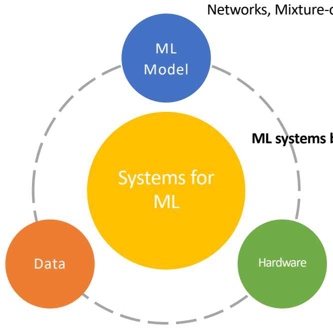


Game playing

Adapted from Zhihao Jia

The Ingredients in ML Success

ResNet, Transformers, Graph Neural Networks, Mixture-of-Experts, …



ML systems bridge model, data, and hardware

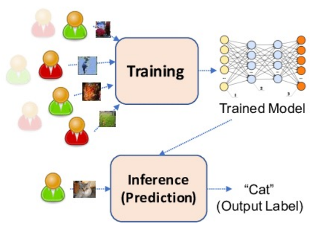
GPUs, TPUs, Supercomputers, FPGAS

ImageNet, Kaggle, Flickr, NetFlix, …

Slide credits: Zhihao Jia

What is a typical machine learning job?

Note on Training vs Inference

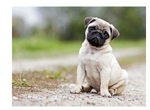


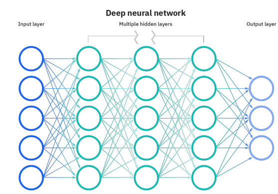
In today's discussion, will focus on training!

Will briefly discuss inference later!

Machine Learning Training Pipeline

1. **Users select a model architecture!**
   - Typically Deep Neural Networks (DNNs)
   - Others types/variants: Recurrent Neural Networks, Graph Neural Networks, etc.



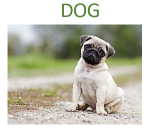


DOG

Machine Learning Training Pipeline

2. Users provide a large labeled dataset
- images + classification labels
- images + captions
- sentence + sentimental analysis

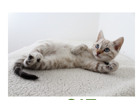
DOG



CAT

Images + labels

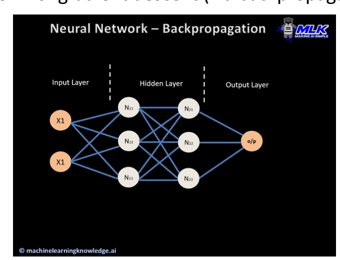
DOG



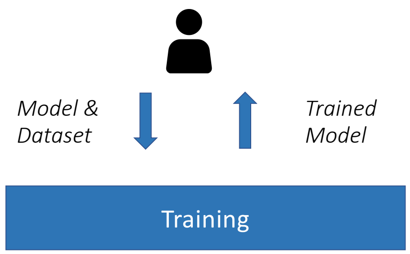
CAT

Machine Learning Training Pipeline

3. Train the model!
- sequentially process the dataset
- learn using a form of gradient descent (via backpropagation)



Machine Learning Training Pipeline



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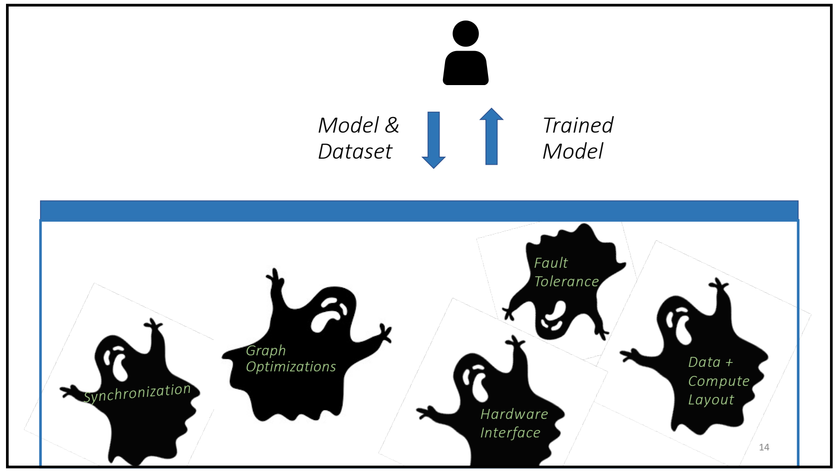

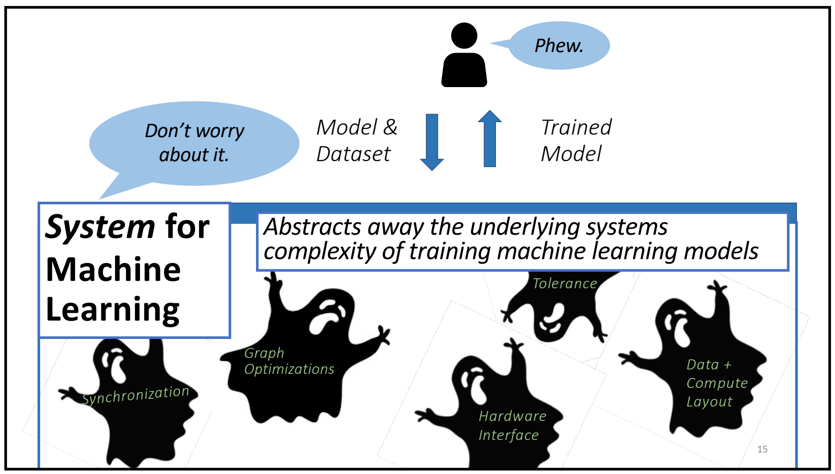

System for Machine Learning

- Abstracts away the underlying systems complexities of executing the training of machine learning models
- Design Considerations
  - Main
    - How to handle distributed computation?
    - How to support execution in different environments and on heterogeneous hardware?
    - What's the right interface for users that still supports customizations?
  - Others
    - How to support different non deterministic control flows (eg recurrent neural networks?)

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Design Consideration #1: How to handle distributed computation?

- Why perform distributed machine learning in the first place?

- Trends
  - Increasingly large datasets
    - millions/billions of images/samples

    Too slow to process on a single machine
  - Increasingly large DNNs
    - more layers, more parameters

    The entirety of a DNN (and its weights/gradients) cannot fit on a single machine!
  - For example,
    - GPT-3 is a language model with about 175 billion parameters
    - Is trained on 45 Terabytes of text data

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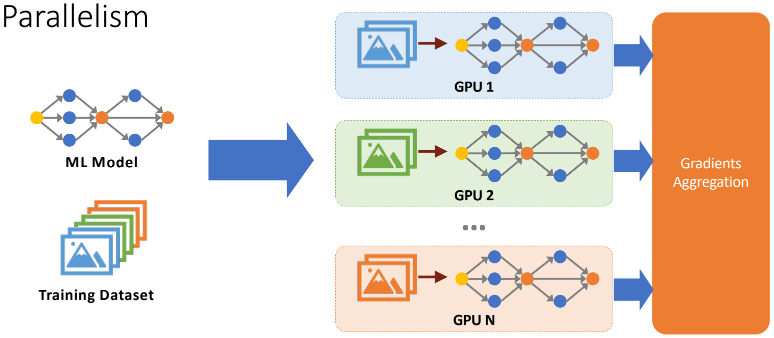
Distributed ML: Data Parallelism

Challenge: All the workers must communicate with the centralized server for weight updates.



1. Partition training data into batches

2. Compute the gradients of each batch on a GPU

3. Aggregate gradients across GPUs

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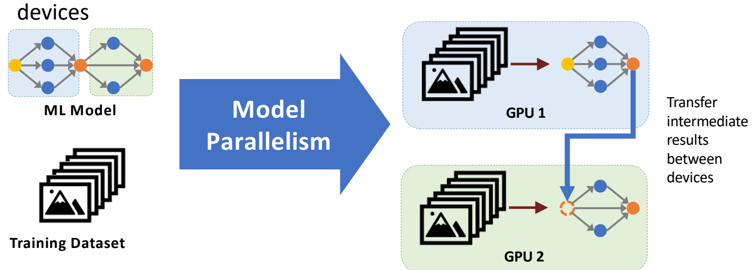
Distributed ML: Model Parallelism

Challenge: How split model across machines?

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



Adapted from Zhihao Jia

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Distributed ML Considerations

- Placement of computation across machines
- Communication of intermediate data between machines
- Fault tolerance! What happens if a machine crashes?
- Synchronization

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Design Consideration #**2**: How to support execution in different environments and on heterogeneous hardware?

- Various types of compute settings:
  - datacenter (thousands of CPUs, GPUs)
  - workstation set up (single CPU, few GPUs)
  - laptop

Define Once + Run Everywhere

- Heterogeneous Hardware: GPUs, TPUs, FPGAs
  - Each is optimized for different tasks
  - Optimal memory placement/computation configuration depends on type

Design Consideration #**3**: What's the right interface/programming model for users that still supports customizations?

- Support different user requirements
  - novice user: uses several default settings
  - expert user:
    - define new layers
    - try new training algorithms
    - introduce new optimizations
- Want easy-to-use interface while still being customizable

System for Machine Learning Recap

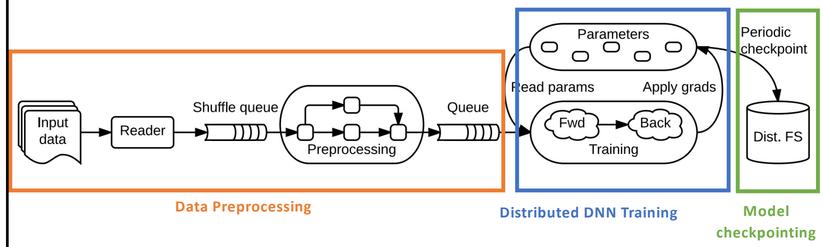
- Abstracts away the underlying systems complexities of executing the training of machine learning models
- Design Considerations
  - How to handle distributed computation?
  - How to support execution in different environments and on heterogeneous hardware?
  - What's the right interface for users that still supports customizations?

Case Study: TensorFlow

TensorFlow

- Developed by Google Brain
  - successor to DistBelief
- A system widely used in industry/academia for distributed machine learning!
- Main Contributions
  - Support for large-scale distributed training
  - Modular architecture that decouples optimizations of the machine learning model from the infrastructure itself
    - supports diverse compute environments, heterogeneous hardware
  - Very user-friendly: Python interface that enables customizability across the stack

TensorFlow System Design



Adapted from Zhihao Jia

TensorFlow: Example

Phase 1: Define an ML model as a dataflow graph

```
# 1. Construct a graph representing the model.
x = tf.placeholder(tf.float32, [BATCH_SIZE, 784])   # Placeholder for input.
y = tf.placeholder(tf.float32, [BATCH_SIZE, 10])    # Placeholder for labels.

W_1 = tf.Variable(tf.random_uniform([784, 100]))    # 784x100 weight matrix.
b_1 = tf.Variable(tf.zeros([100]))                  # 100-element bias vector.
layer_1 = tf.nn.relu(tf.matmul(x, W_1) + b_2)       # Output of hidden layer.

W_2 = tf.Variable(tf.random_uniform([100, 10]))     # 100x10 weight matrix.
b_2 = tf.Variable(tf.zeros([10]))                   # 10-element bias vector.
layer_2 = tf.matmul(layer_1, W_2) + b_2             # Output of linear layer.

# 2. Add nodes that represent the optimization algorithm.
loss = tf.nn.softmax_cross_entropy_with_logits(layer_2, y)
train_op = tf.train.AdagradOptimizer(0.01).minimize(loss)
```

Phase 2: Execute an optimized version of the graph

```
# 3. Execute the graph on batches of input data.
with tf.Session() as sess:                          # Connect to the TF runtime.
  sess.run(tf.initialize_all_variables())           # Randomly initialize weights.
  for step in range(NUM_STEPS):                     # Train iteratively for NUM_STEPS.
    x_data, y_data = ...                            # Load one batch of input data.
    sess.run(train_op, {x: x_data, y: y_data})      # Perform one training step.
```

Adapted from Zhihao Jia

Systems for Machine Learning *Inference*

- Application/customer facing: stringent latency targets
- Deal with interactions with network
- Caching opportunities
- Model compression/pruning
  - tradeoff between speed and accuracy
- Edge deployments

Active Research Areas in ML+Systems

- Application-specific optimizations for machine learning (e.g., video analytics)
- ML for systems (e.g., learned databases, compilation optimizations)
- New computation models (spot instances, serverless computing, programmable networks)

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Takeaways

- **Systems for machine learning** are critical to the success of machine learning
- Handle the systems challenges involved in running large-scale distributed machine learning
  - e.g., fault tolerance, consistency, heterogeneous hardware, communication
- Provide an easy-to-use interface for developers while still enabling significant levels of customizability

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