Computation

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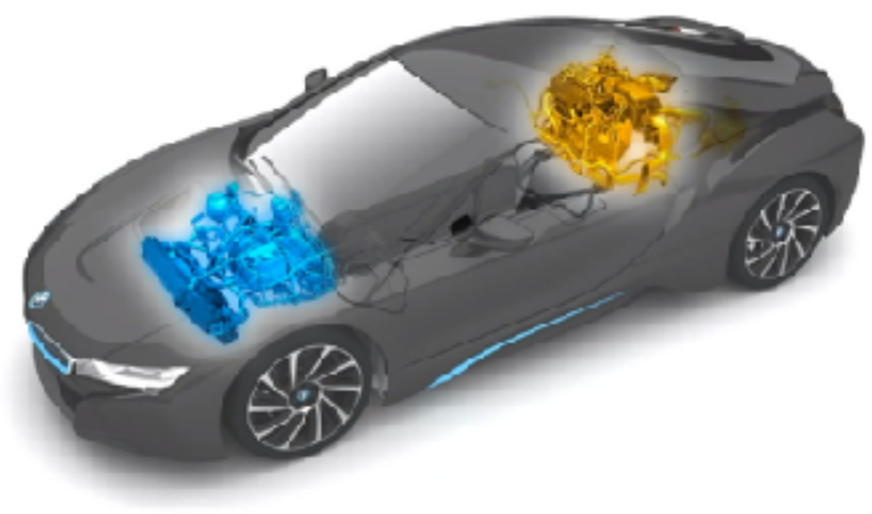
Outline

- Performance
  - Hybridization
  - Async-computation
  - Multi-GPU/machine training
- Computer Vision
  - Image augmentation
  - Fine tuning

A Hybrid of Imperative and Symbolic Programming



DIVE INTO DEEP LEARNING

Imperative Programming

- The common way to program in Python, Java, C/C++, …
- Straightforward, easy to debug
- Requires (Python) interpreter
  - Hard to deploy models (smart phones, browser, embedded)
  - Performance problems

Interpreter compiles into bytecode

Execute on virtual machine

```
a = 1
b = 2
c = a + b
```

3 calls in total

Symbolic Programming

- Define the program first, feed with data to execute later
- Math, SQL, …
- Easy to optimize, less frontend overhead, portable
- Hard to use

Know the whole program, easy to optimize

```
expr = "c = a + b"
exec = compile(expr)
exec(a=1, b=2)
```

May be used without Python interpreter

Single call

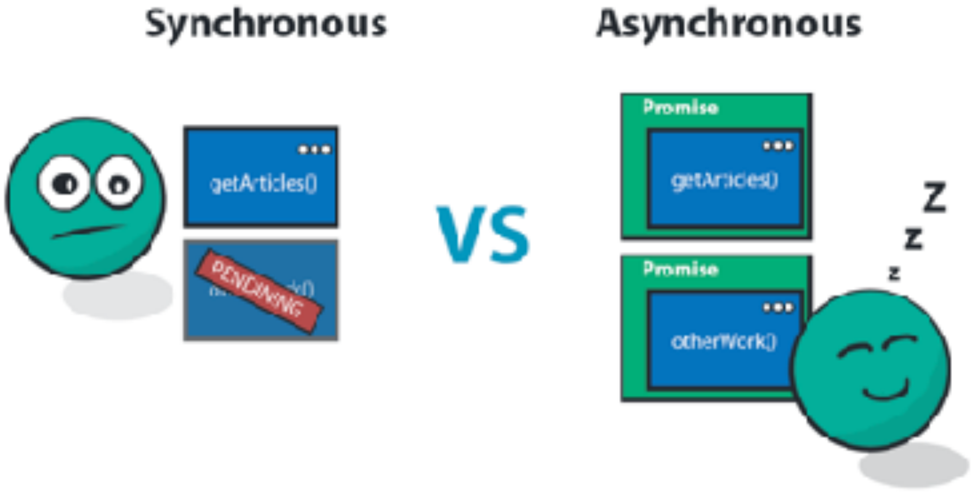
Hybridization in Gluon

- Define a model through nn.HybridSequential or nn.HybridBlock
- Call .hybridize() to switch from imperative execution to symbolic execution

```
net = nn.HybridSequential()
net.add(nn.Dense(256, activation='relu'),
        nn.Dense(10))
net.hybridize()
```

Hybridize Notebook

Asynchronous Computing



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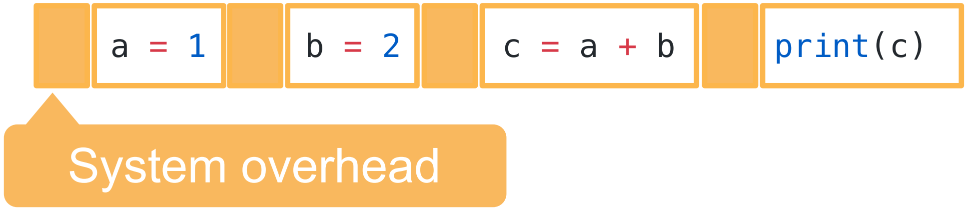
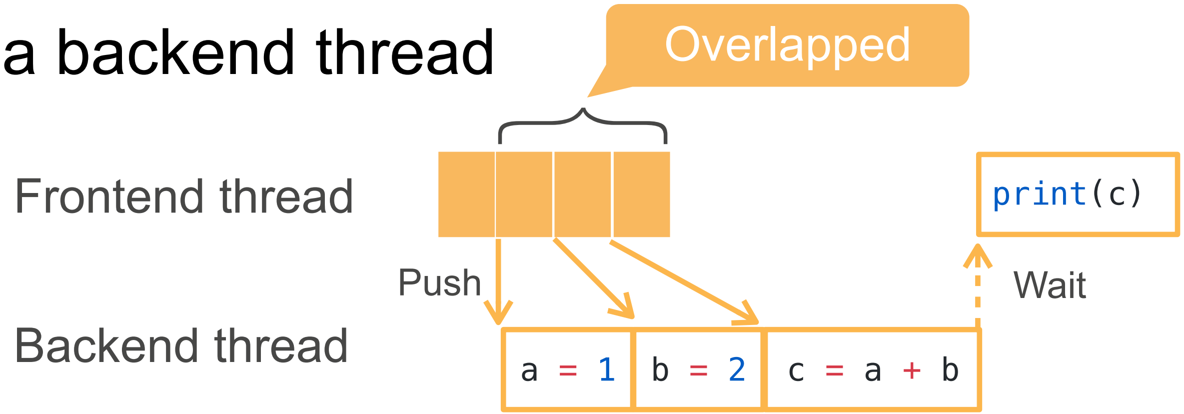
Asynchronous Execution

- Execute one-by-one



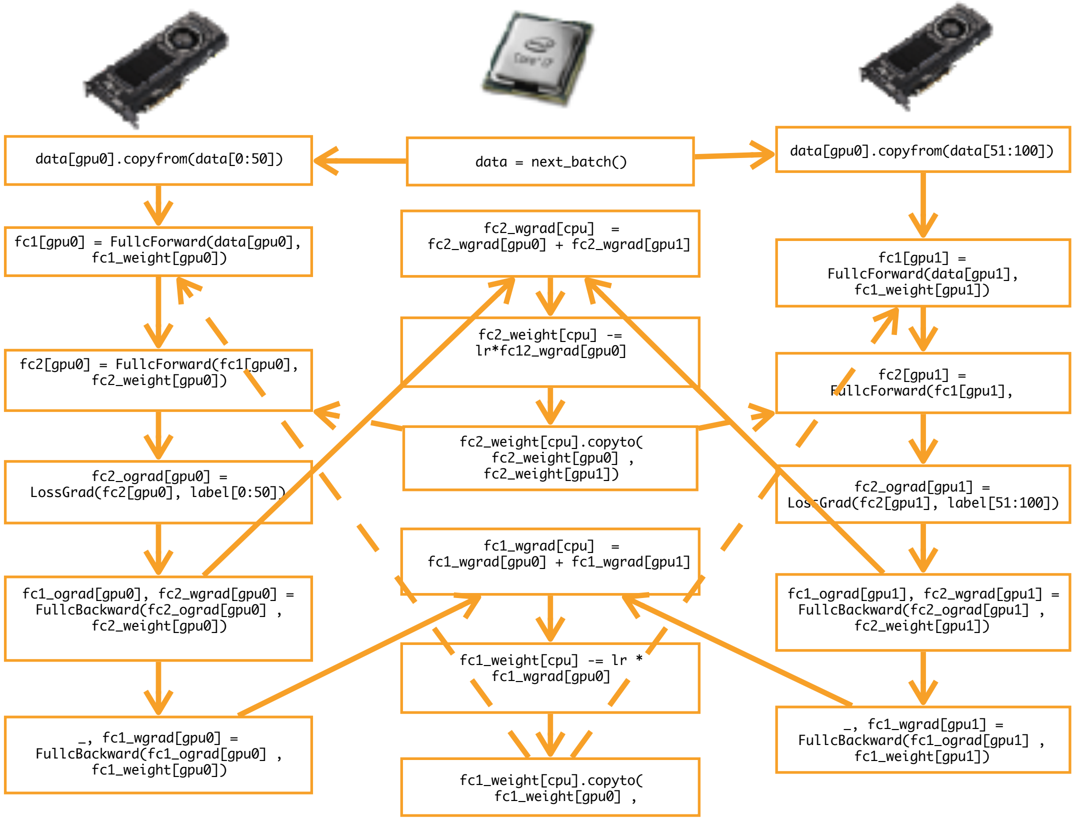

```
a = 1
b = 2
c = a + b
print(c)
```

- With a backend thread



Automatic Parallelism

Writing Parallel Program is Painful



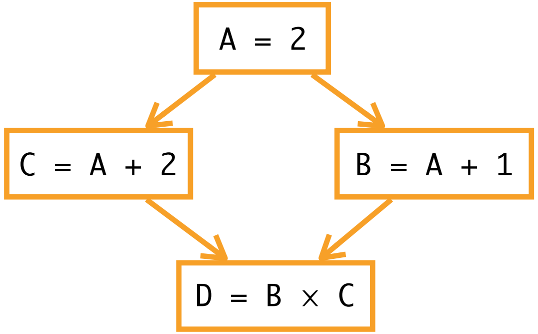
- Single hidden-layer MLP with 2 GPUs
- Scales to hundreds of layers and tens of GPUs

Auto Parallelization

Write serial programs

```
A = nd.ones((2,2)) * 2
C = A + 2
B = A + 1
D = B * C
```

Run in parallel



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Multi-GPU Training

(Lunar new year, 2014)

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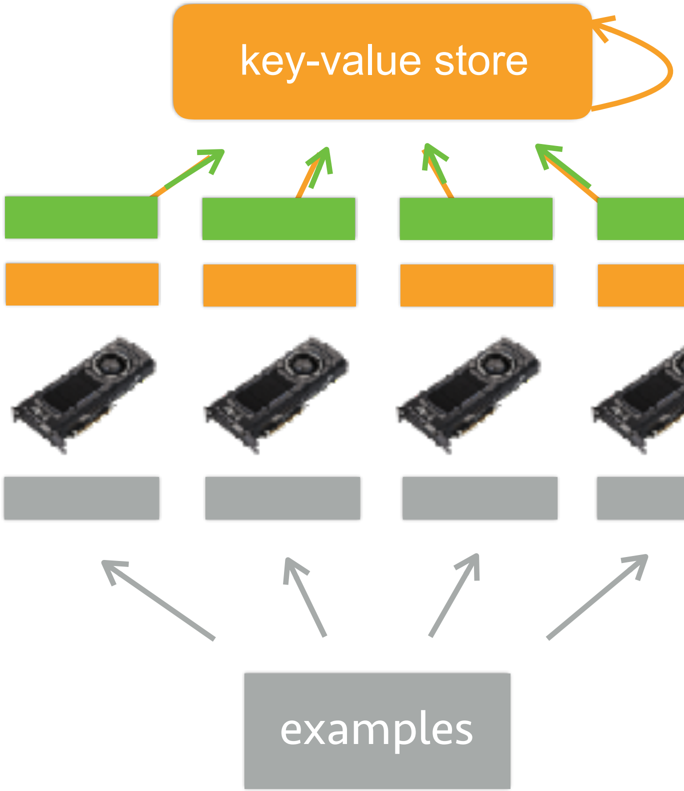
Data Parallelism

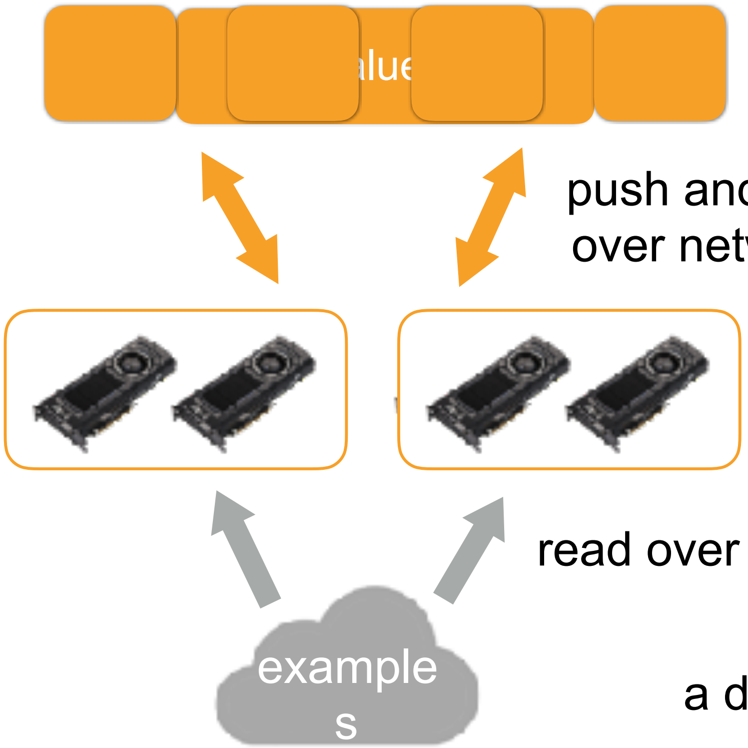


1. Read a data partition
2. Pull the parameters
3. Compute the gradient
4. Push the gradient
5. Update the parameters

Distributed Training

(Alex's frugal GPU cluster at CMU, 2015)

Distributed Computing



multiple
server machines

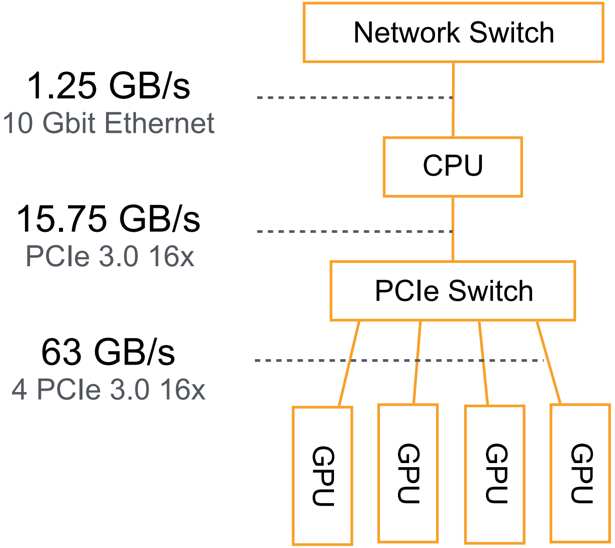
push and pull
over network

multiple
worker machines

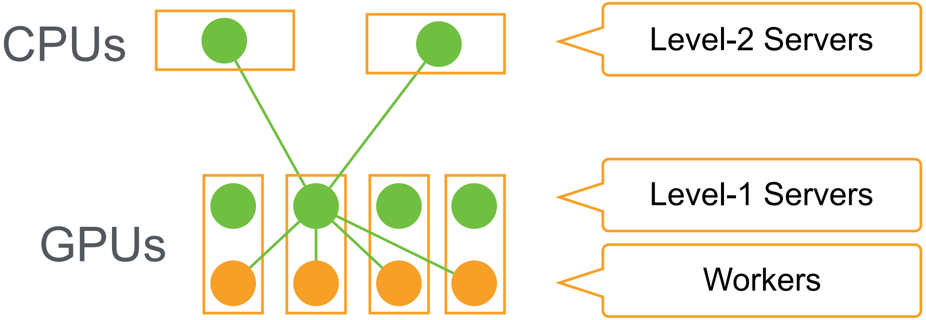
read over network

Store data in
a distributed filesystem

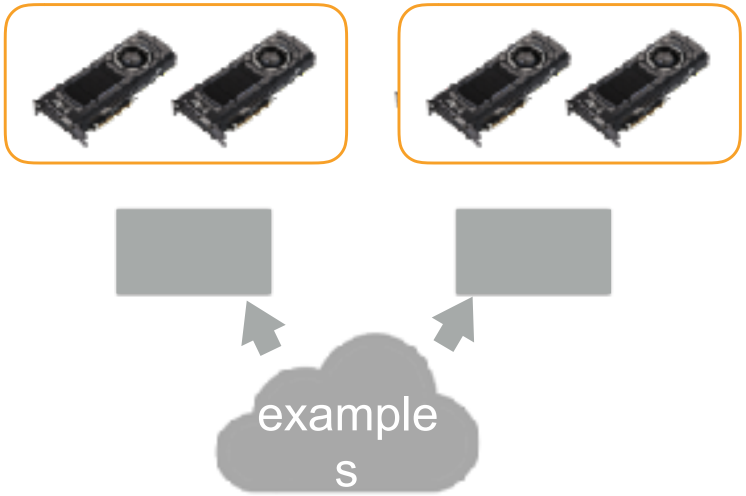
GPU Machine Hierarchy



Hierarchical parameter server

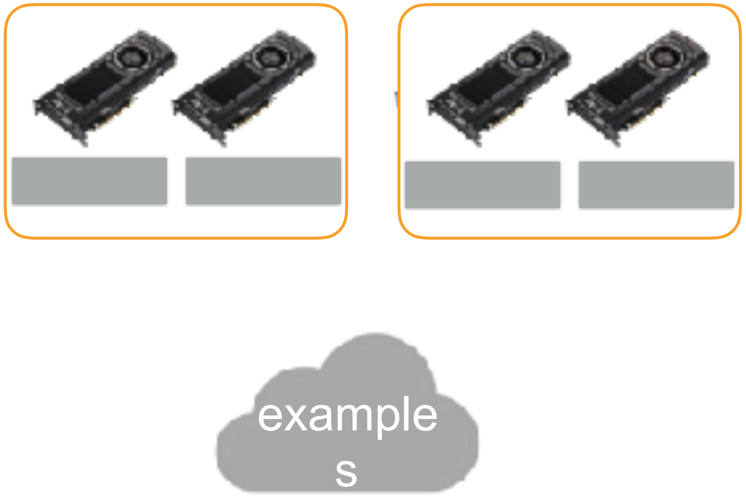


Iterating a Batch



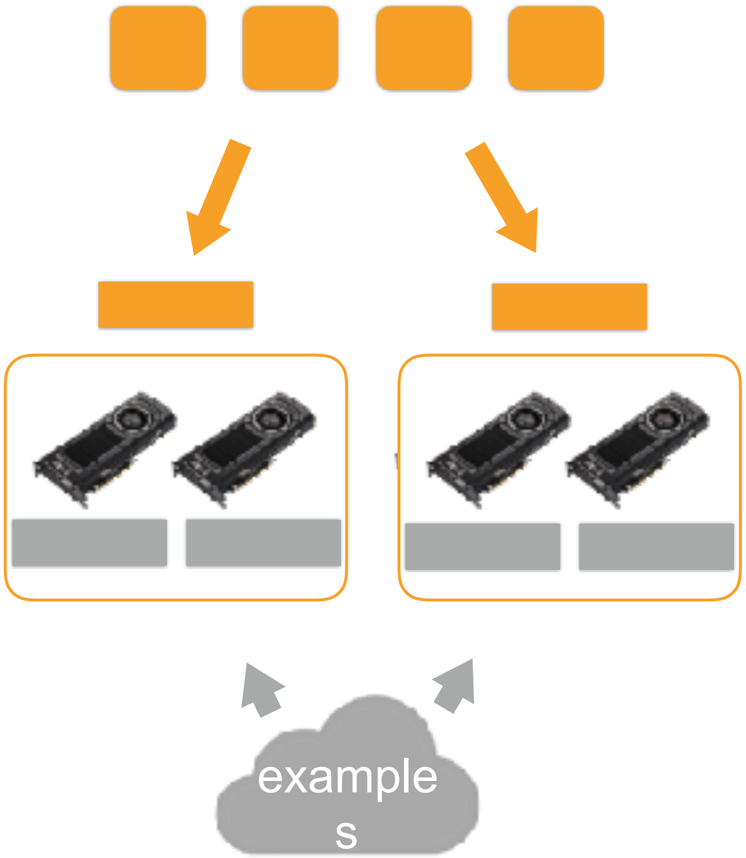
- Each worker machine read a part of the data batch

Iterating a Batch



- Further split and move to each GPU

Iterating a Batch



- Each server maintain a part of parameters
- Each worker pull the whole parameters from servers

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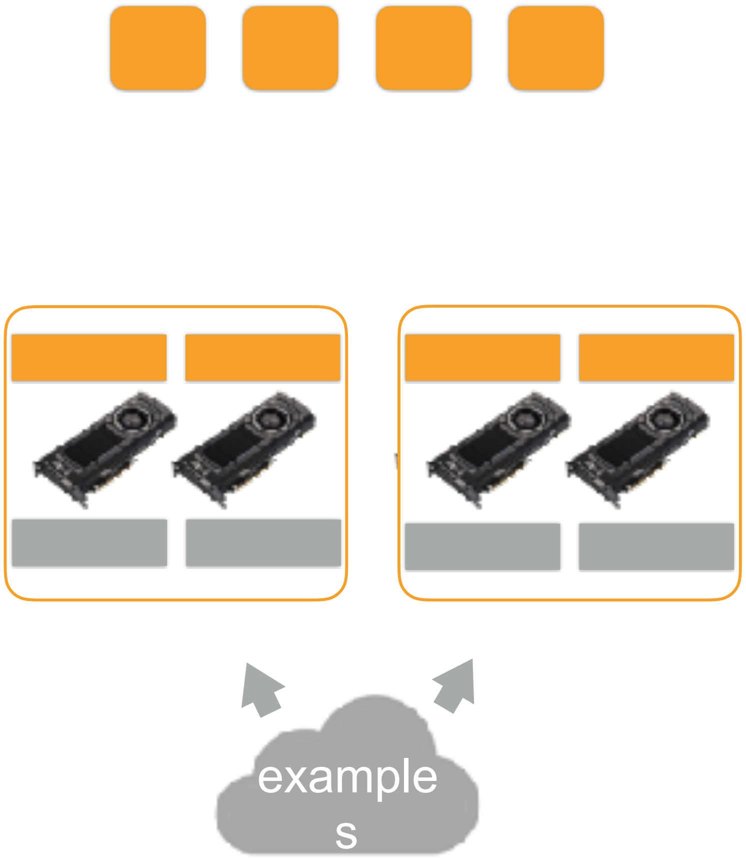
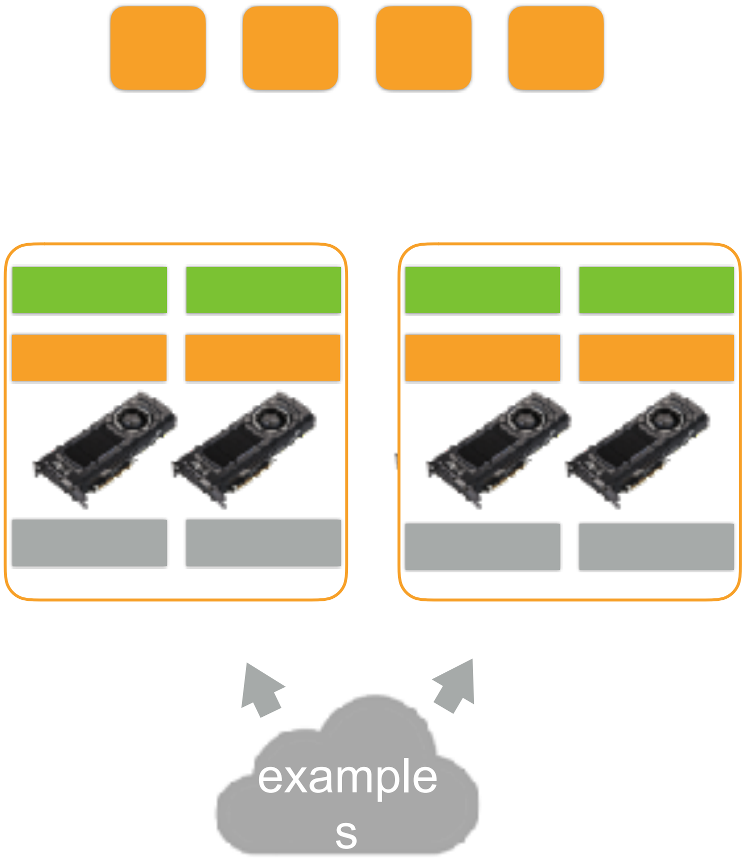
Iterating a Batch



- Copy parameters into each GPU

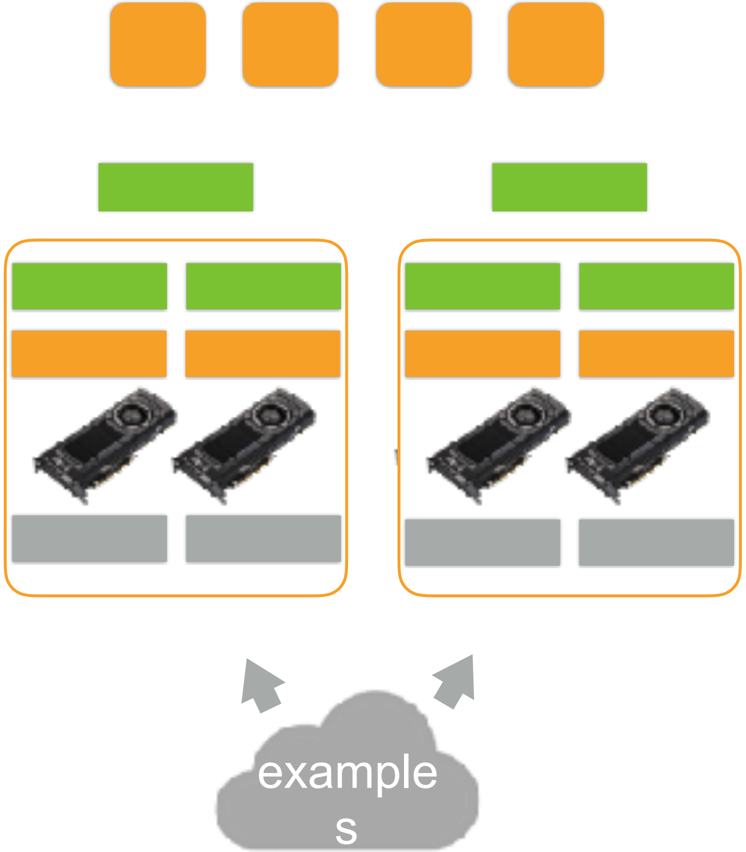
DIVE INTO
DEEP LEARNING

Iterating a Batch



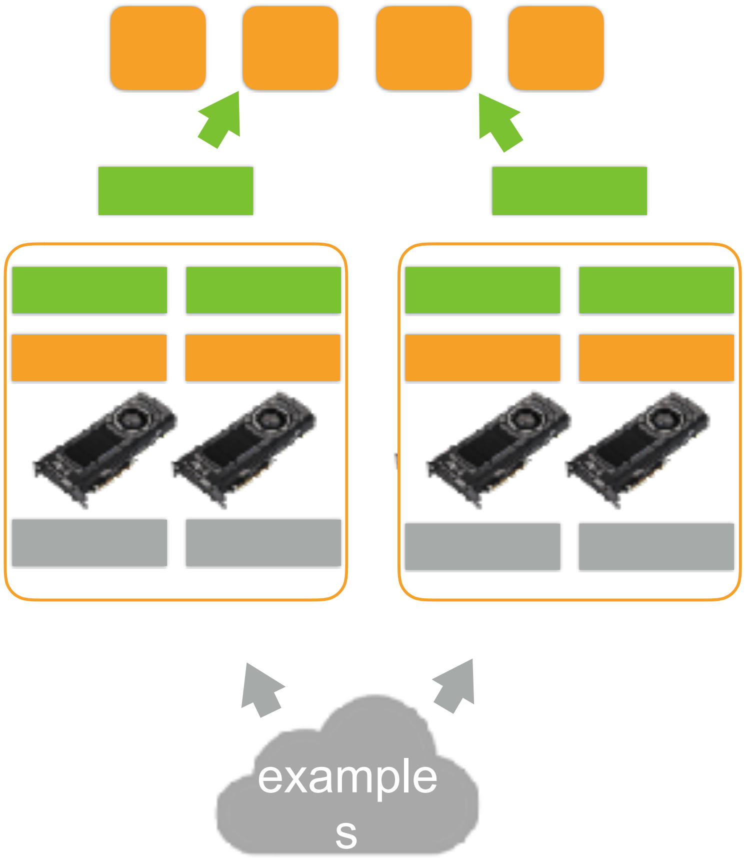
- Each GPU computes gradients

Iterating a Batch



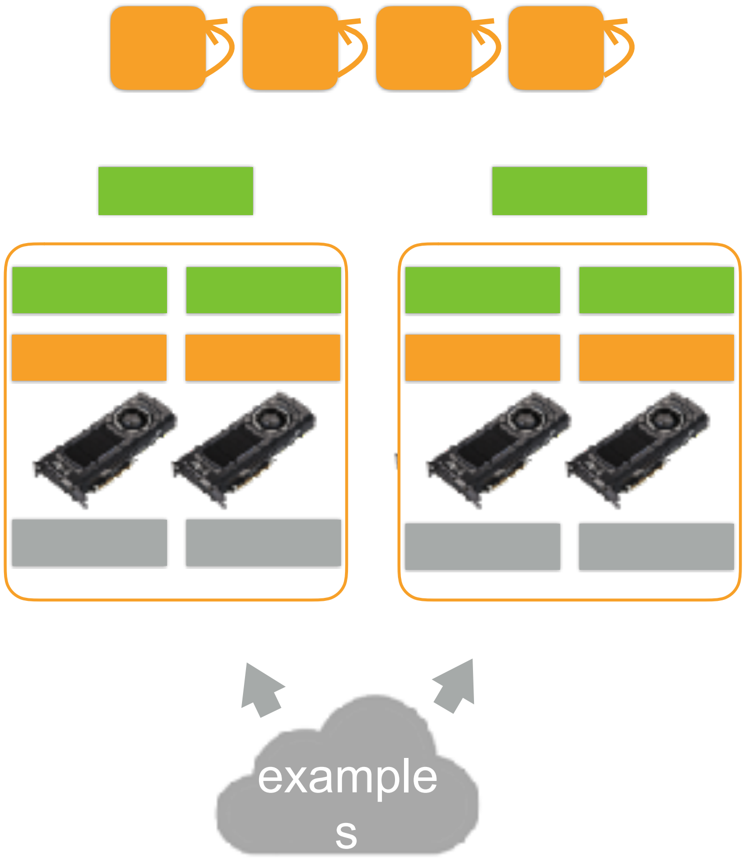
- Sum the gradients over all GPU

Iterating a Batch



- Push gradients into servers

Iterating a Batch



- Each server sum gradients from all workers, then updates its parameters

Synchronized SGD

- Each worker run synchronically
- If *n* GPUs and each GPU process *b* examples per time
    - Synchronized SGD equals to mini-batch SGD on a single GPU with a *nb* batch size
- In the ideal case, training with *n* GPUs will lead to a n times speedup compared to a single GPU training

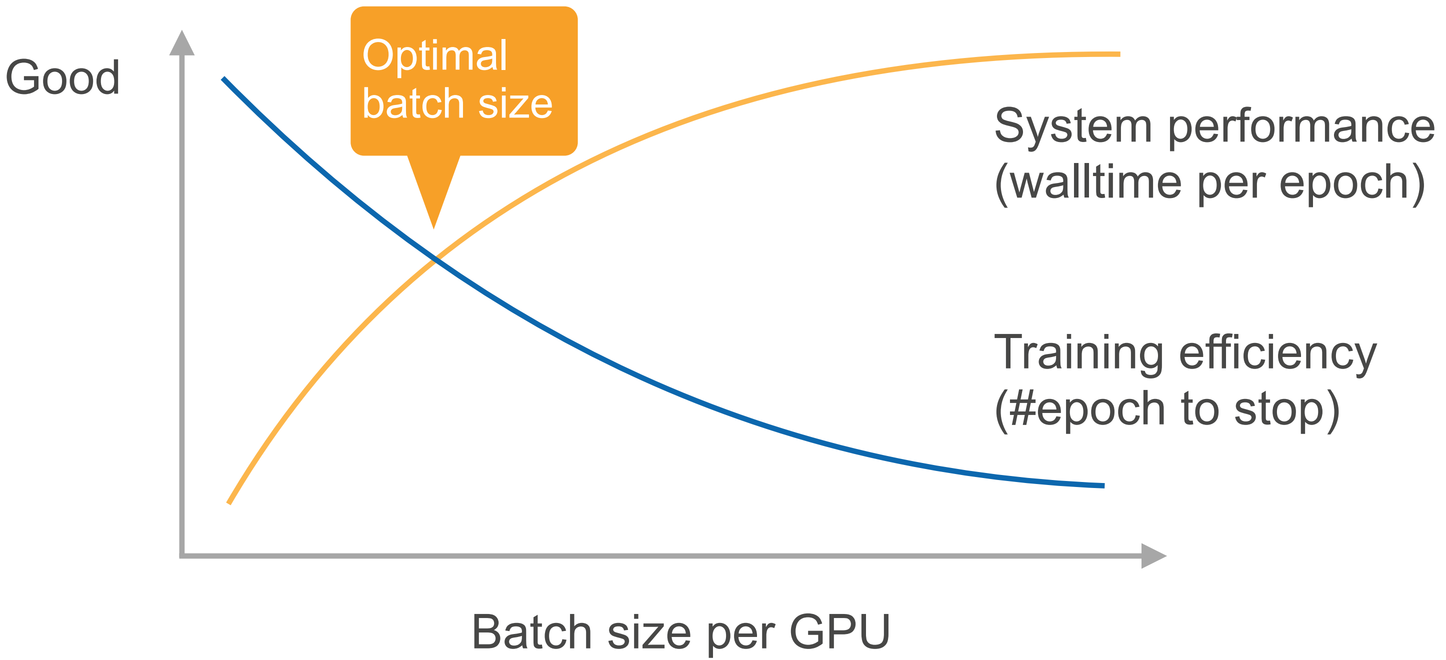
DIVE INTO DEEP LEARNING

Performance

- T1 = O(*b*): time to compute gradients for *b* example in a GPU
- T2 = O(*m*): time to send and receive *m* parameters/gradients for a worker
- Wall-time for each batch is max(T1, T2)
    - Idea case: T1 > T2, namely using large enough *b*
- A too large *b* needs more data epochs to reach a desired model quality

DIVE INTO DEEP LEARNING

Performance Trade-off

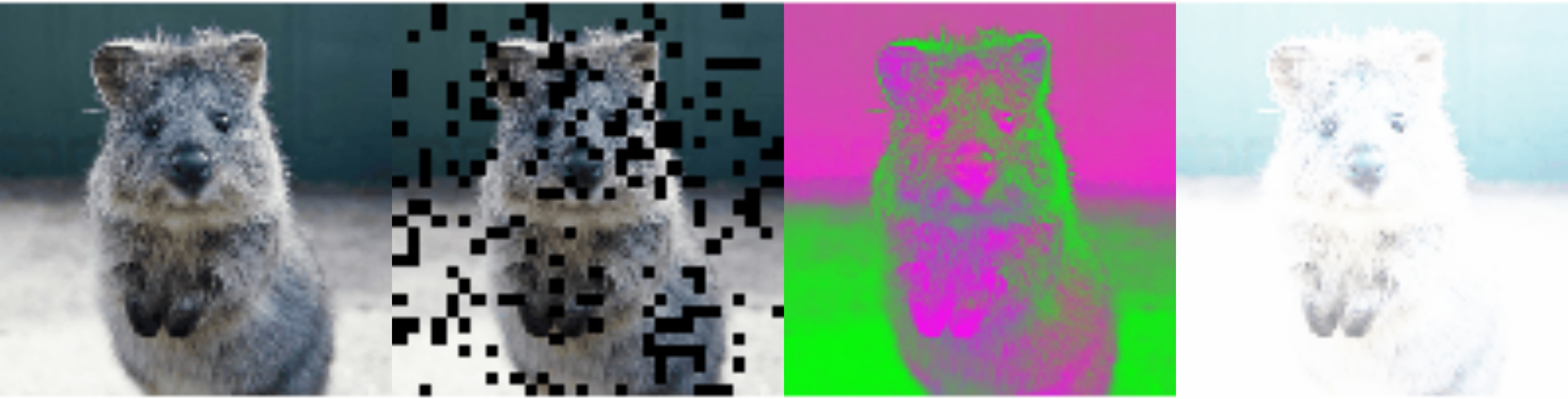


Practical Suggestions

- A large dataset
- Good GPU-GPU and machine-machine bandwidth
- Efficient data loading/preprocessing
- A model with good computation (FLOP) vs communication (model size) ratio
  - ResNet > AlexNet
- A large enough batch size for good system performance
- Tricks for efficiency optimization with a large batch size

Multi-GPU Notebooks

Image Augmentation



p=1.0 size_percent=0.30 p=0.50 cutoff=0.00

DEEP LEARNING

Real Story from CES'19

- Startup with smart vending machine demo that identifies purchases via a camera
- Demo at CES failed
  - Different light temperature
  - Light reflection from table
- The fix
  - Collect new data
  - Buy tablecloth
  - Retrain all night

Data Augmentation

- Use prior knowledge about invariances to augment data
  - Add background noise to speech
  - Transform / augment image by altering colors, noise, cropping, distortions

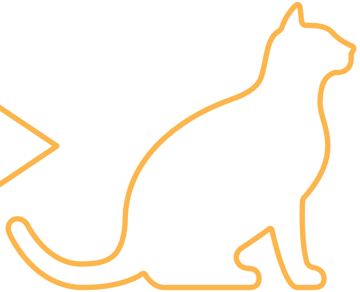
Training with Augmented Data

Original

Augmented Dataset

Generate on the fly

Model



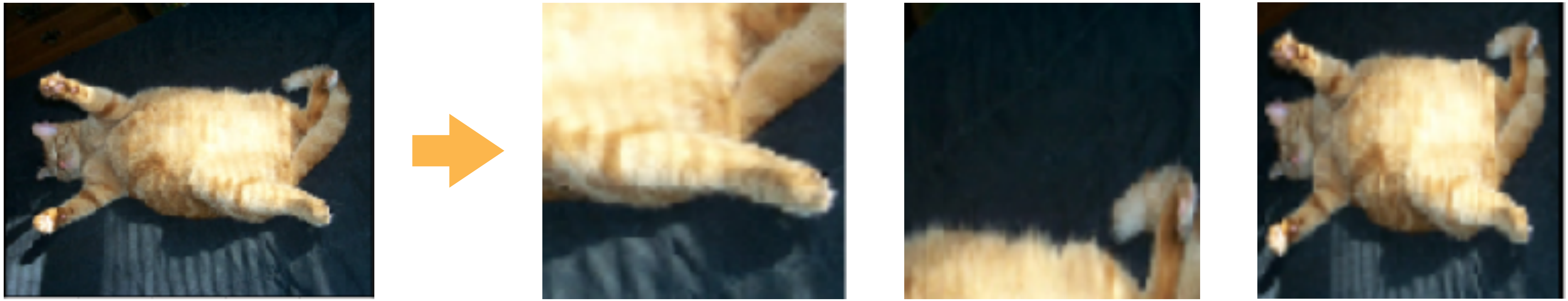
Flip

vertical

horizontal

Crop

- Crop an area from the image and resize it
    - Random aspect ratio (e.g. [3:4, 4:3])
    - Random area size (e.g. [8%, 100%])
    - Random position



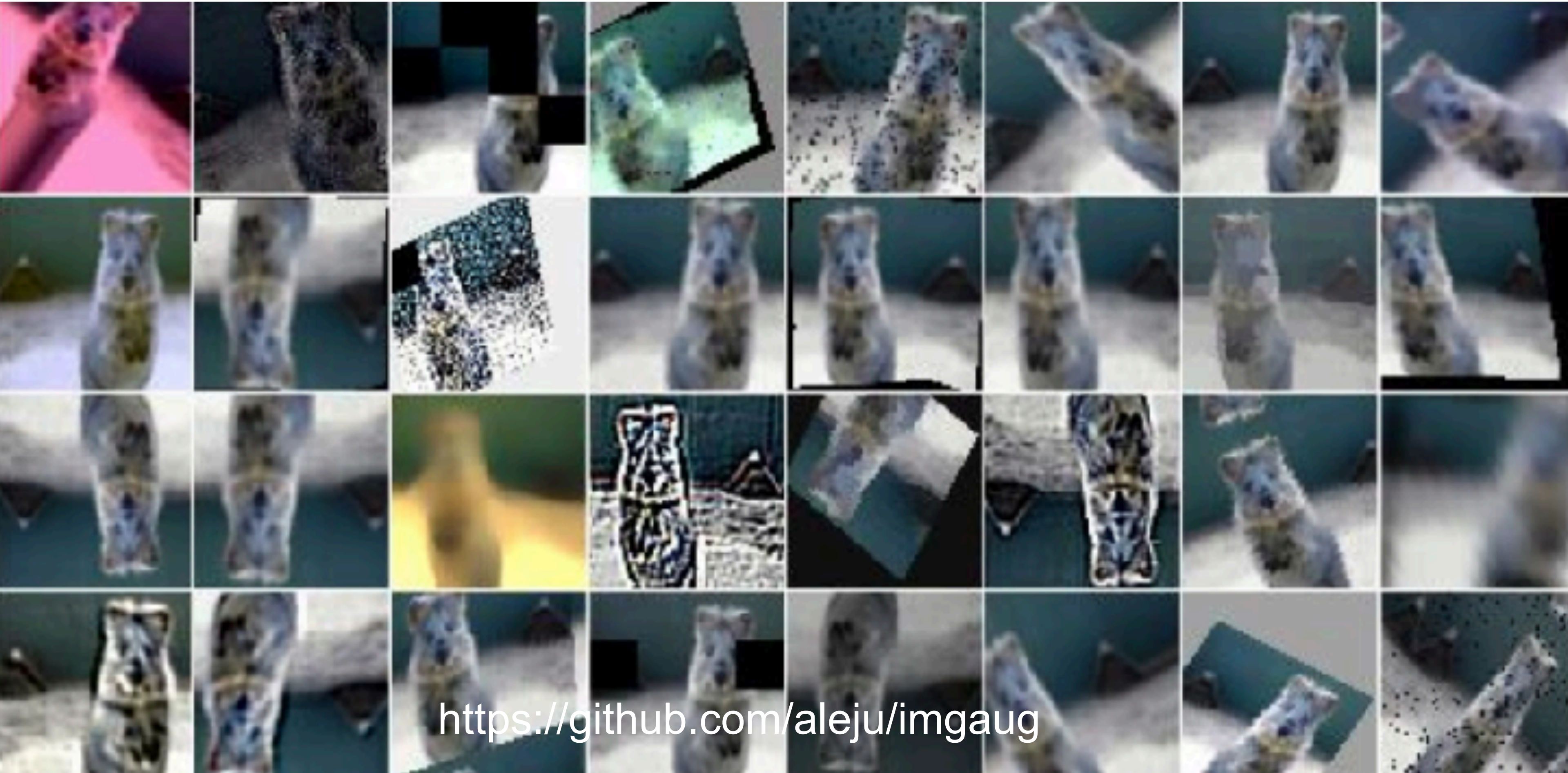
Color

Scale hue, saturation, and brightness (e.g. [0.5, 1.5])

Brightness

Hue

Many Other Augmentations

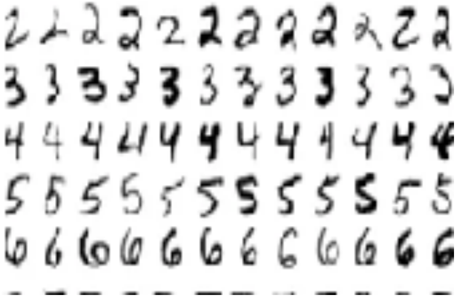


Fine Tuning

Labelling a Dataset is Expensive

# examples	1.2M	50K	60K
# classes	1,000	100	10





Can we reuse this?

My dataset

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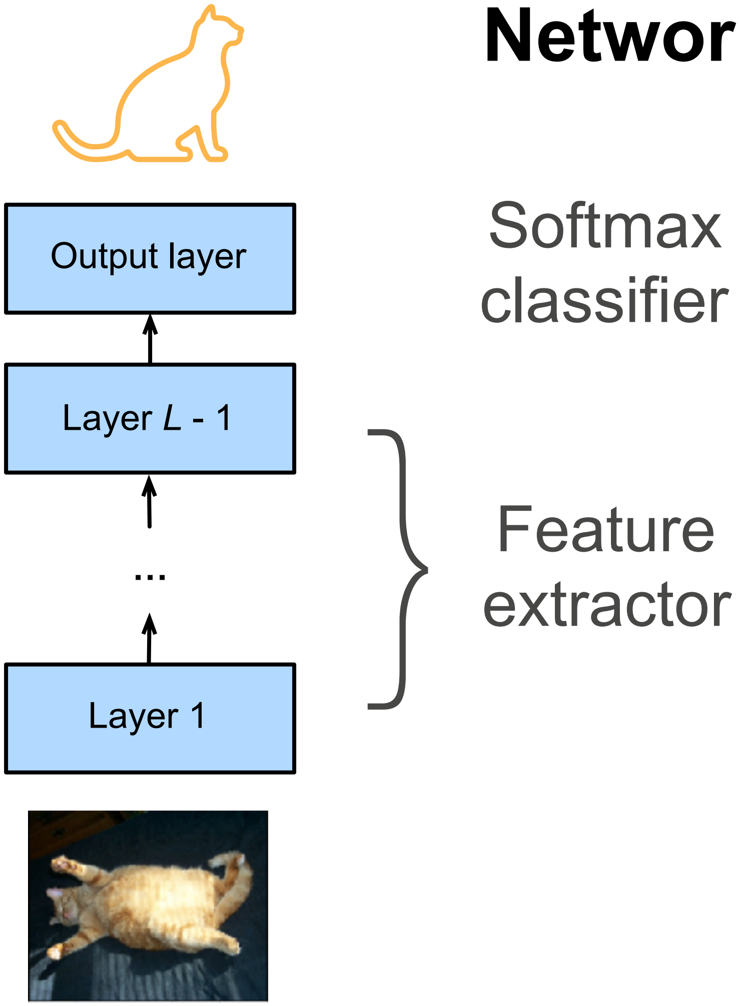
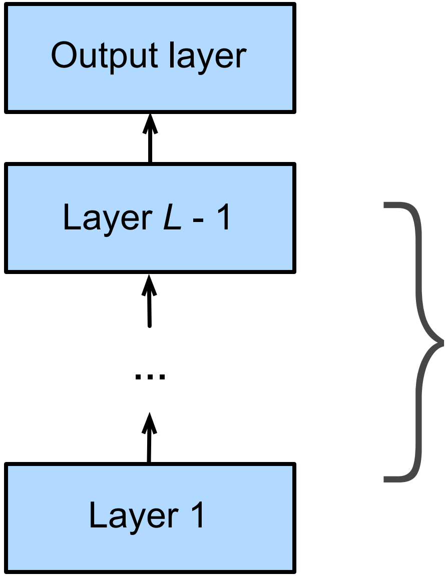
Network Structure



Two components in deep network

- **Feature extractor to map raw pixels into linearly separable features.**
- Linear classifier for decisions

Fine Tuning



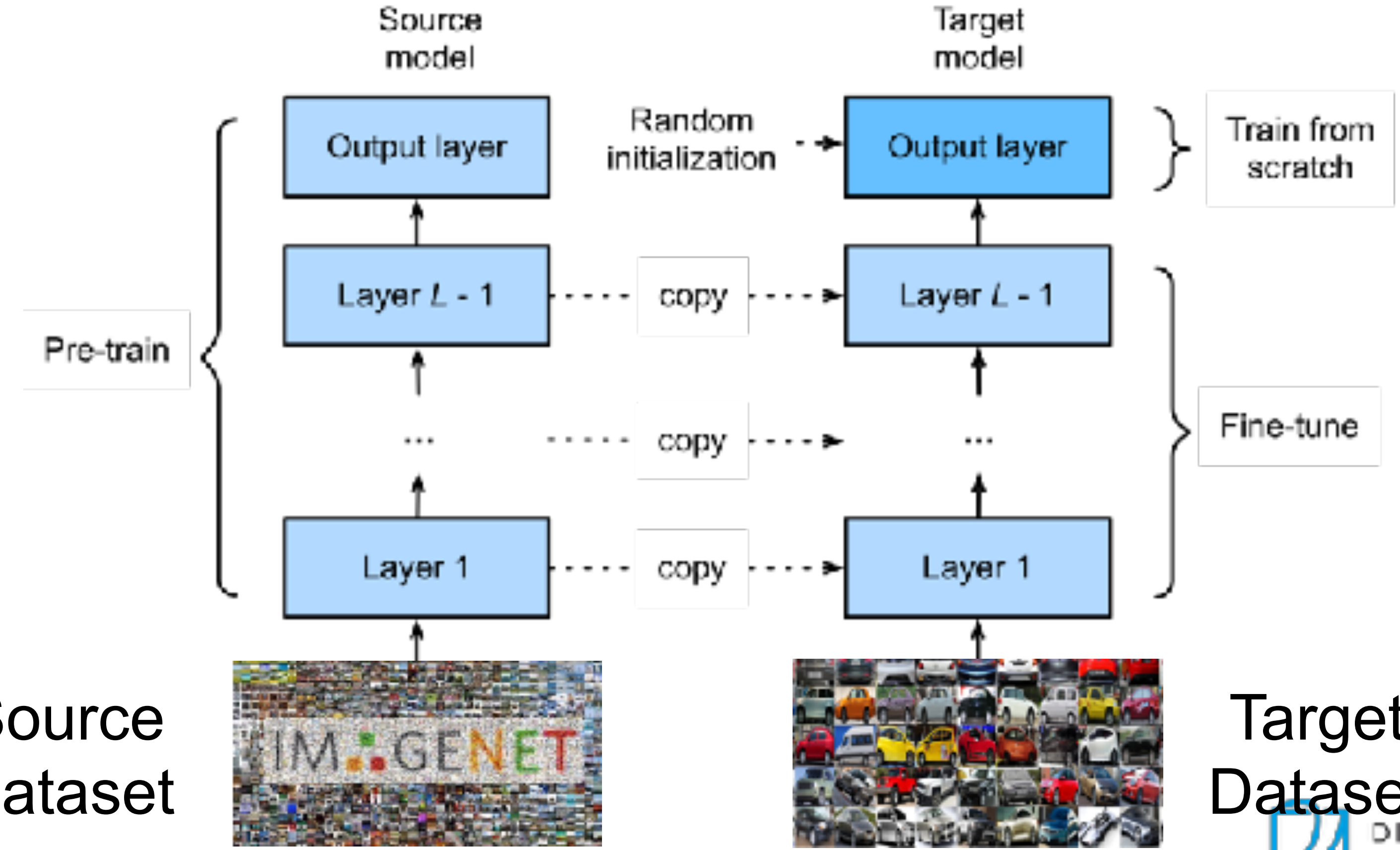
Don’t use last layer since classification problem is different

Likely good feature extractor for target

Source Dataset

Target Dataset

Weight Initialization for Fine Turning

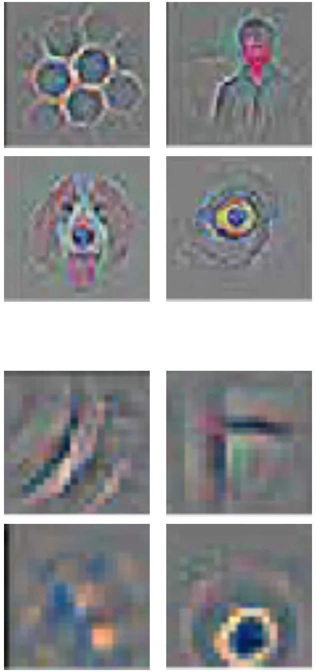


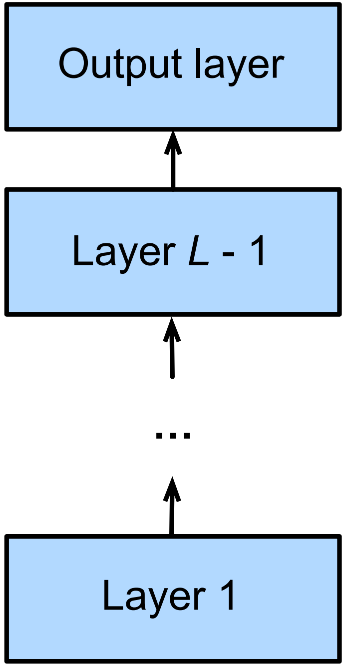
Source Dataset

Target Dataset

Fix Lower Layers

- Neural networks learn hierarchical feature representations
    - Low-level features are universal
    - High-level features are more related to objects in the dataset
- **Fix the bottom layer parameters during fine tuning**
  (useful for regularization)



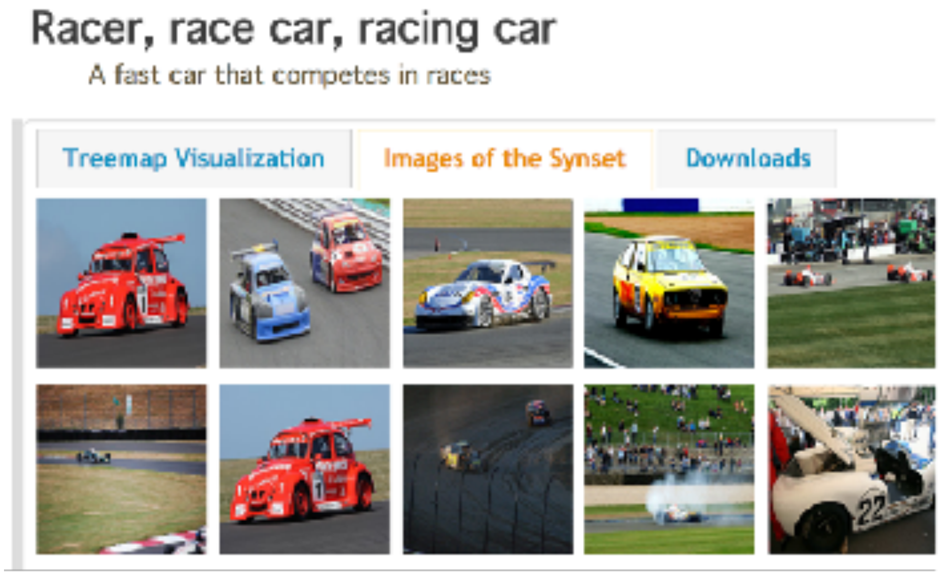


Re-use Classifier Parameters

Lucky break

- Source dataset may contain some of the target categories
- Use the according weight vectors from the pre-trained model during initialization

IMAGENET



Fine-tuning Training Recipe

- Train on the target dataset as normal but with strong regularization
  - Small learning rate
  - Fewer epochs
- If source dataset is more complex than the target dataset, fine-tuning can lead to better models (source model is a good prior)

Fine-tuning Notebook

Summary

- To get good performance:
  - Optimize codes through hybridization
  - Use multiple GPUs/machines
- Augment image data by transformations
- Train with pre-trained models