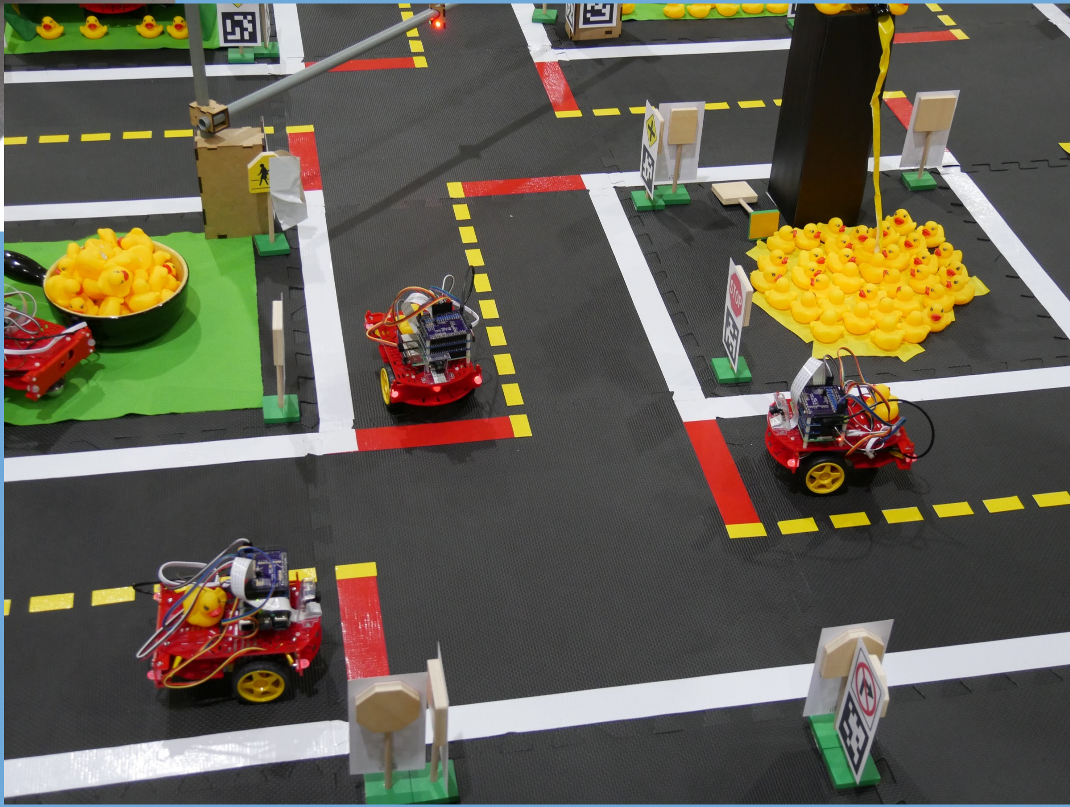
CS 3630!



Lecture 19:

Learning CNNs

Many slides adapted from Stanford's CS231N by Fei-Fei Li, Justin Johnson, Serena Yeung, as well as Slides by Marc'Aurelio Ranzato (NYU), Dhruv Batra & Devi Parikh (Georgia Tech)

Outline

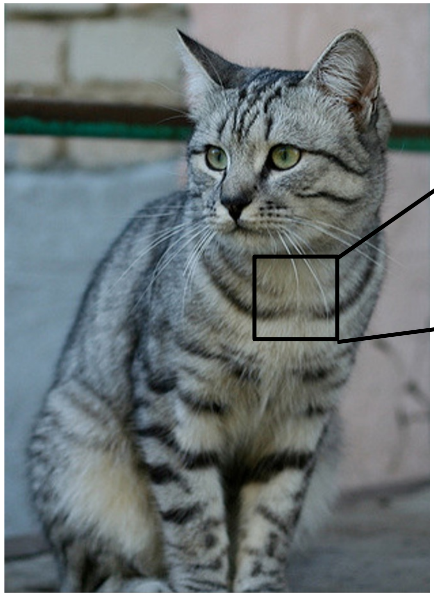
1. Intra-class variability
2. Supervised Learning
3. Regression and Classification Losses
4. Stochastic Gradient Descent
5. Calculating Gradients

Image Classification: A core task in Computer Vision

(assume given set of discrete labels)
{dog, cat, truck, plane, ...}

$\longrightarrow$ cat

The Problem: Semantic Gap




```
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 [ 76  85  90 105 128 105  87  96  95  99 115 112 106 103  99  85]
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 [122 121 102  80  82  86  94 117 145 148 153 102  58  78  92 107]
 [122 164 148 103  71  56  78  83  93 103 119 139 102  61  69  84]]
```
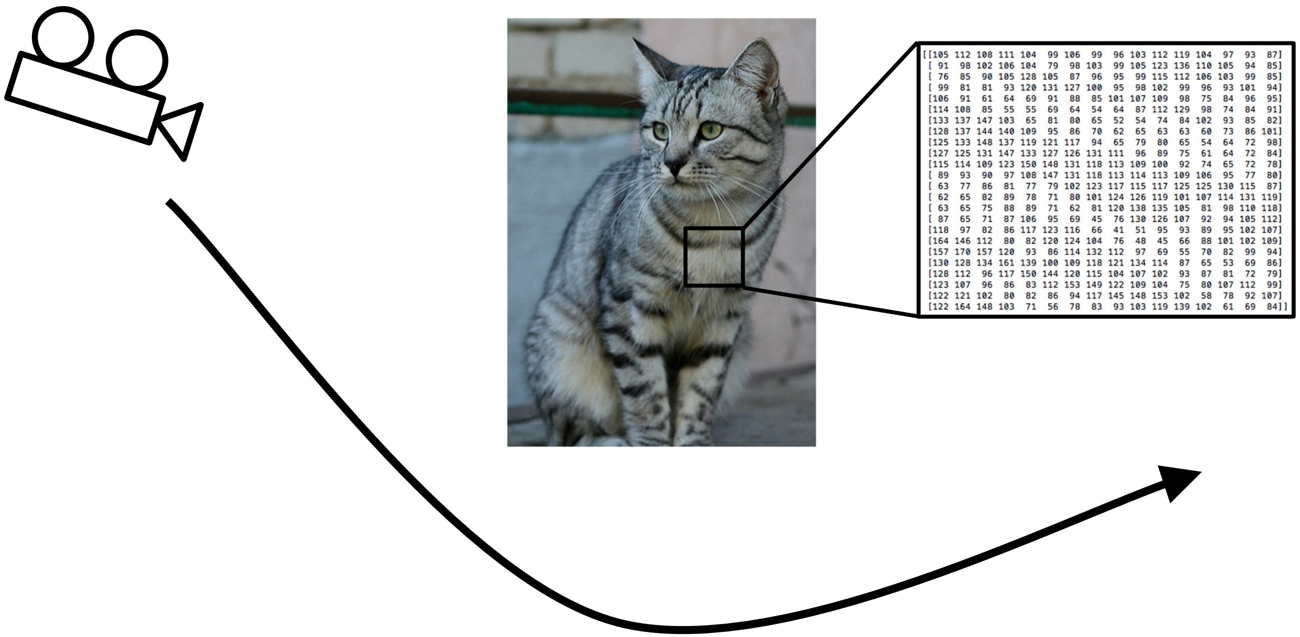

What the computer sees

An image is just a big grid of numbers between [0, 255]:

e.g. 800 x 600 x 3
(3 channels RGB)

Challenges: Viewpoint variation



All pixels change when the camera moves!

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Challenges: Illumination

This image is CC0 1.0 public domain

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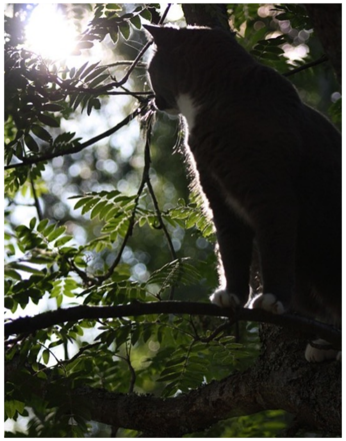

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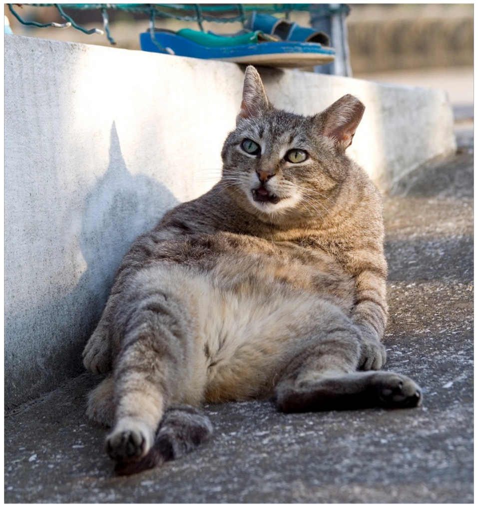
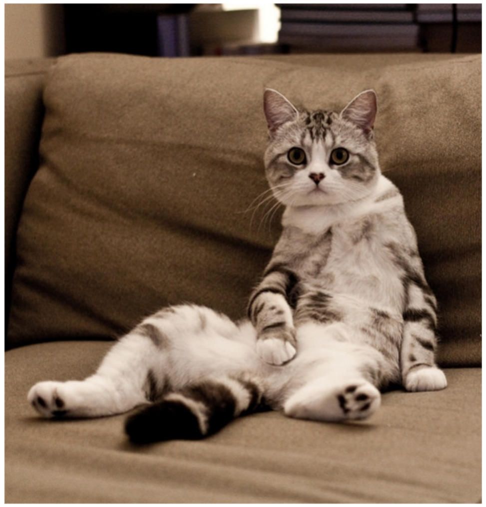
Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Challenges: Deformation





Challenges: Occlusion

Challenges: Background Clutter

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Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Challenges: Intraclass variation

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Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

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1. Intra-class variability
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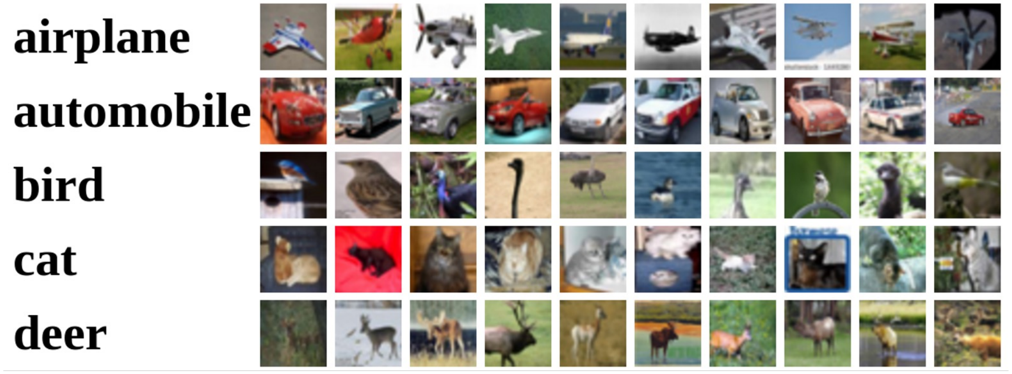
ML: A Data-Driven Approach

1. Collect a dataset of images x and labels y
2. Use Machine Learning to train a classifier
3. Evaluate the classifier on new images

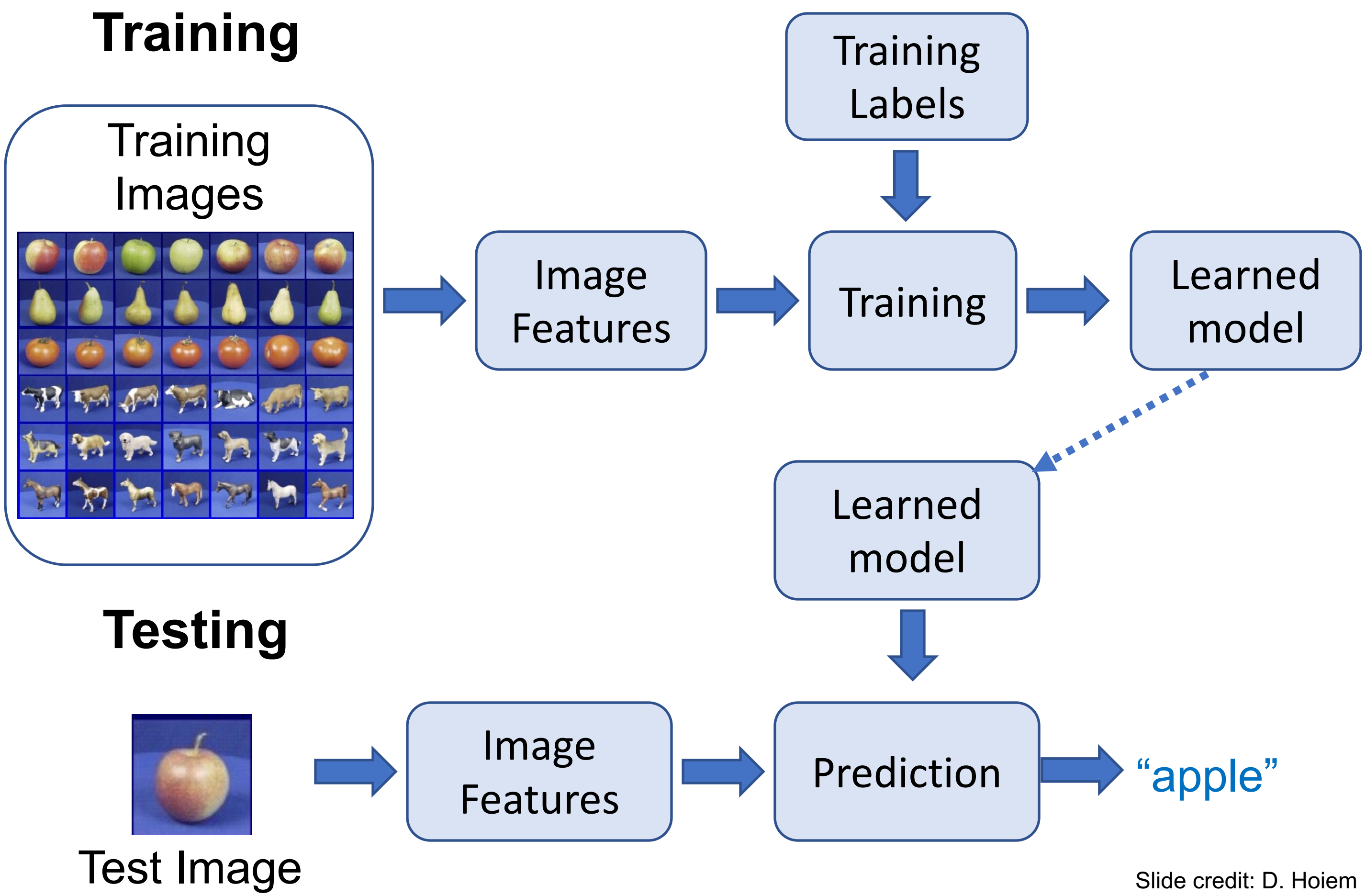
```python
def train(images, labels):
  # Machine learning!
  return model
```

```python
def predict(model, test_images):
  # Use model to predict labels
  return test_labels
```

Example training set



Steps



Slide credit: D. Hoiem

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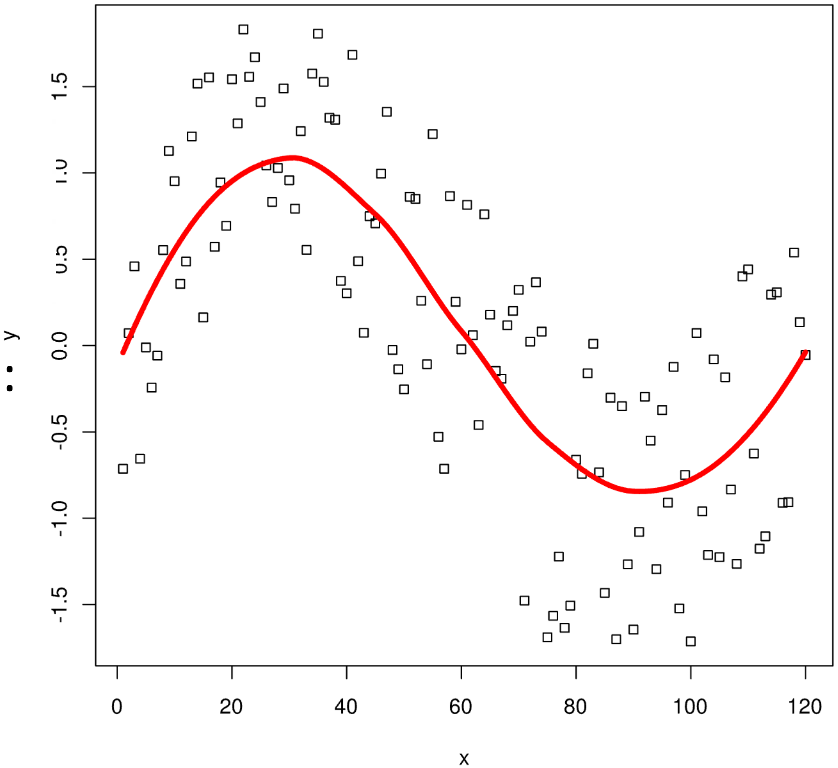
Two different learning problems are classification and regression

- **Regression**: continuous labels y
- Sum-square-difference loss:

$$L_{\mathrm{SSD}}(W;D) \doteq \sum_{(x,y)\in D} |f(x;W) - y|^2$$

- Example: direct 3D pose regression:

https://paperswithcode.com/task/6d-pose-estimation



By Kierano - Own work, CC BY-SA 3.0,
https://commons.wikimedia.org/w/index.php?curid=7034448

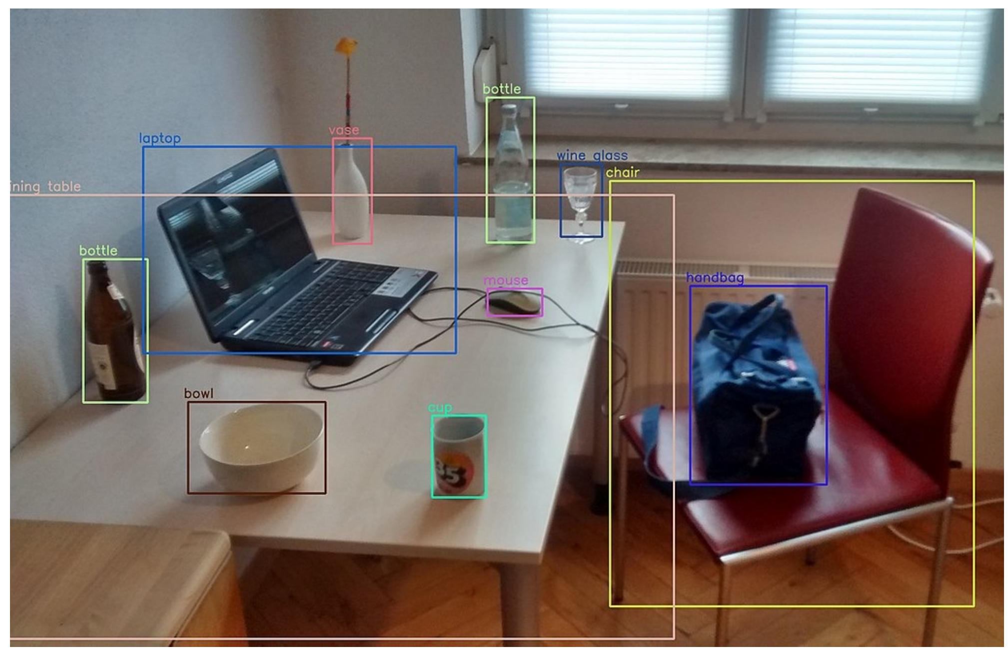
Two different learning problems are classification and regression

- **Classification**: discrete labels y
- Cross-entropy loss:

$$L_{\mathrm{CE}}(W;D) \doteq \sum_{c} \sum_{(x,y=c)\in D} \frac{1}{\log\{p_c(x;W)\}}$$

- Average surprise!

- Example: object detection:



How to get probabilities? **Softmax** converts a set of C class "scores" into "probabilities"

- If we need to classify inputs into C different classes, we put C units in the last layer to produce C *one-vs.-others* scores $f_1, f_2, \ldots, f_C$
- Apply *softmax* function to convert these scores to probabilities:

$$\text{softmax}(f_1, \ldots, f_c) = \left(\frac{\exp(f_1)}{\sum_j \exp(f_j)}, \ldots, \frac{\exp(f_C)}{\sum_j \exp(f_j)}\right)$$

If one of the inputs is much larger than the others, then the corresponding softmax value will be close to 1 and others will be close to 0

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How to minimize the loss by changing the weights?
Strategy: **Follow the slope of the loss function**

Strategy: **Follow the slope**

In 1-dimension, the derivative of a function:

$$\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

In multiple dimensions, the **gradient** is the vector of (partial derivatives) along each dimension

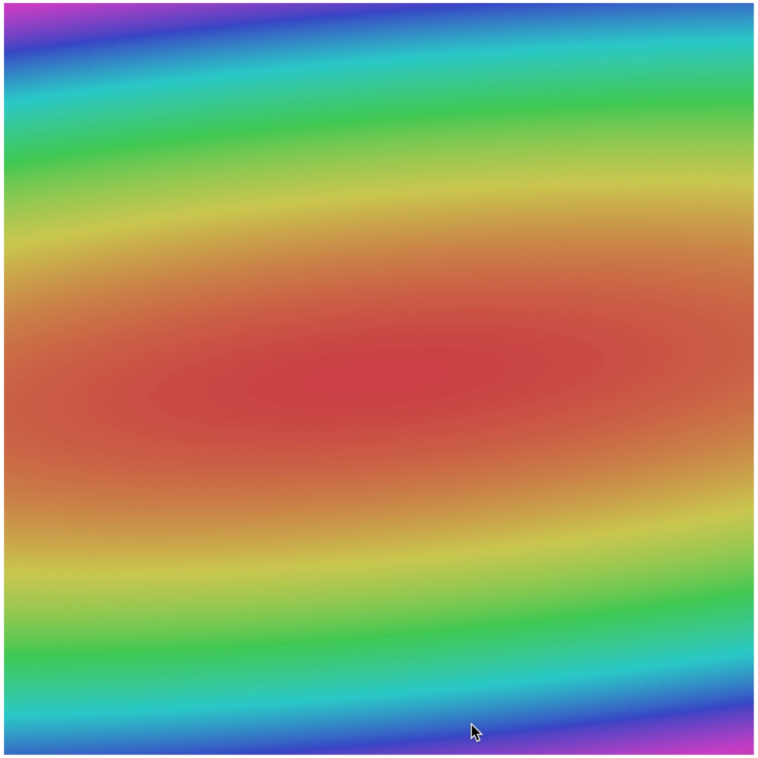
The slope in any direction is the **dot product** of the direction with the gradient

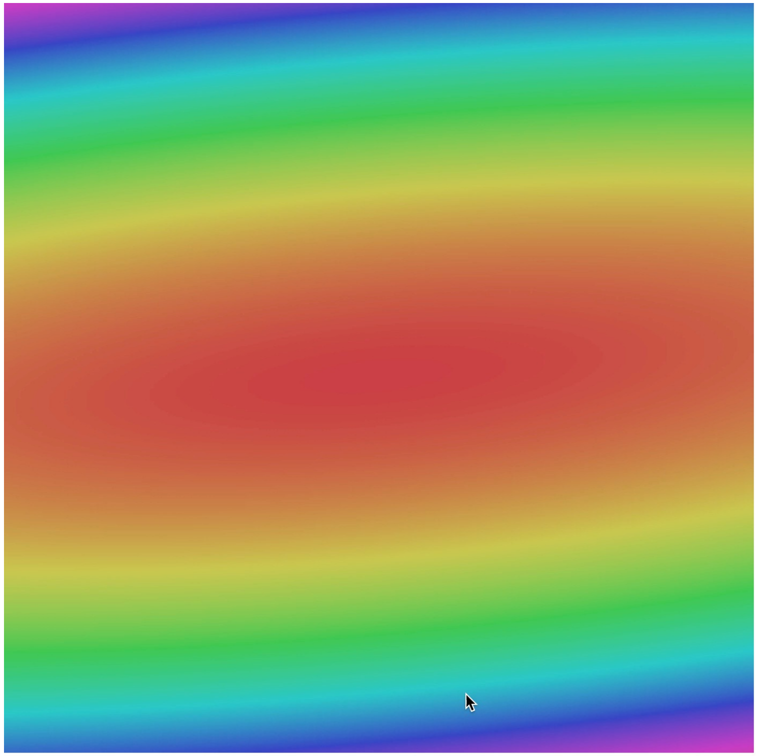
The direction of steepest descent is the **negative gradient**

Gradient Descent

```
# Vanilla Gradient Descent

while True:
  weights_grad = evaluate_gradient(loss_fun, data, weights)
  weights += - step_size * weights_grad # perform parameter update
```





Stochastic Gradient Descent (SGD)

$$L(W) = \frac{1}{N} \sum_{i=1}^{N} L_i(x_i, y_i, W) + \lambda R(W)$$

$$\nabla_W L(W) = \frac{1}{N} \sum_{i=1}^{N} \nabla_W L_i(x_i, y_i, W) + \lambda \nabla_W R(W)$$

Full sum expensive when N is large!

Approximate sum using a **minibatch** of examples
32 / 64 / 128 common

```
# Vanilla Minibatch Gradient Descent

while True:
  data_batch = sample_training_data(data, 256) # sample 256 examples
  weights_grad = evaluate_gradient(loss_fun, data_batch, weights)
  weights += - step_size * weights_grad # perform parameter update
```

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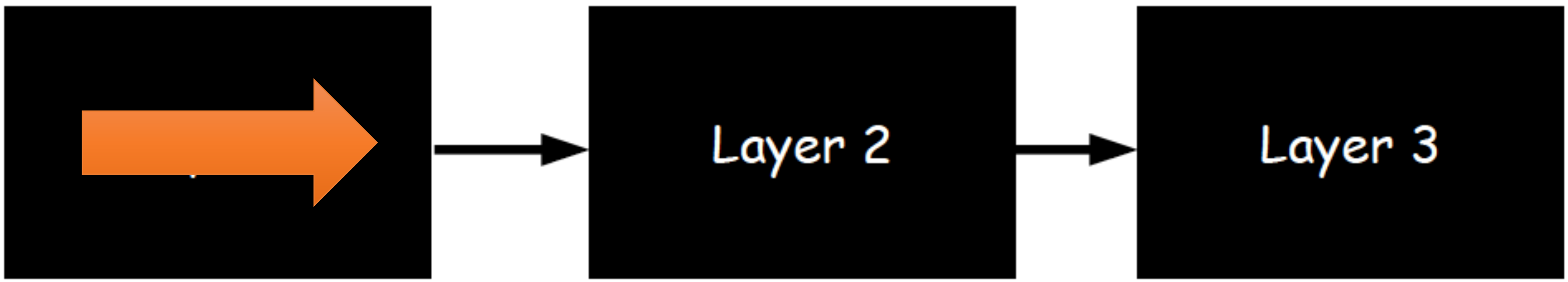
How do we *really* compute gradients?

- Analytic or “Manual” Differentiation
- Symbolic Differentiation
- Numerical Differentiation
- Automatic Differentiation!
    - Forward mode AD
    - Reverse mode AD
        - aka “backpropagation”
    - Implemented in specialized frameworks:
        - pytorch (Facebook)
        - TensorFlow (Google) frameworks
    - Main computation, mainly done on GPU (or TPU)

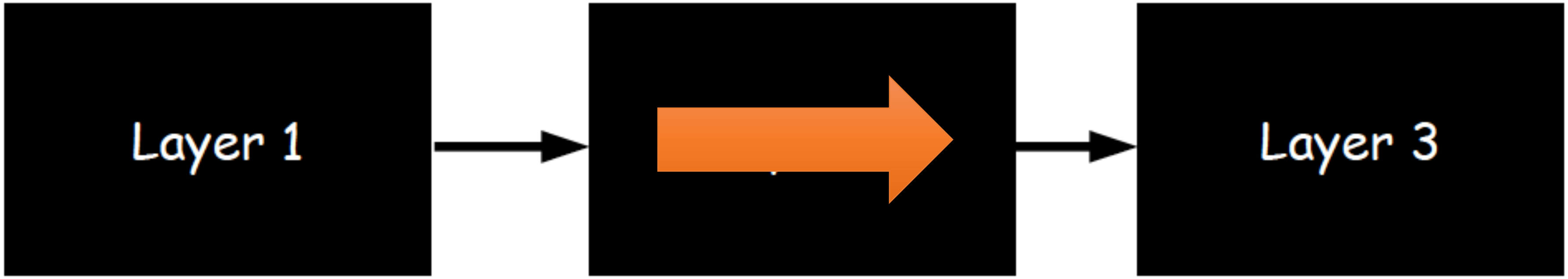
Neural Network Training

- Step 1: Compute Loss on mini-batch [F-Pass]



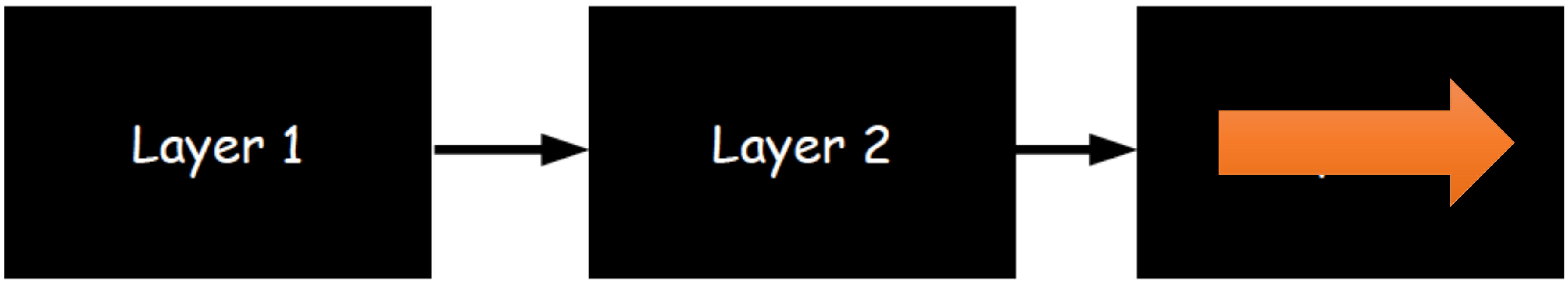
Neural Network Training

- Step 1: Compute Loss on mini-batch [F-Pass]



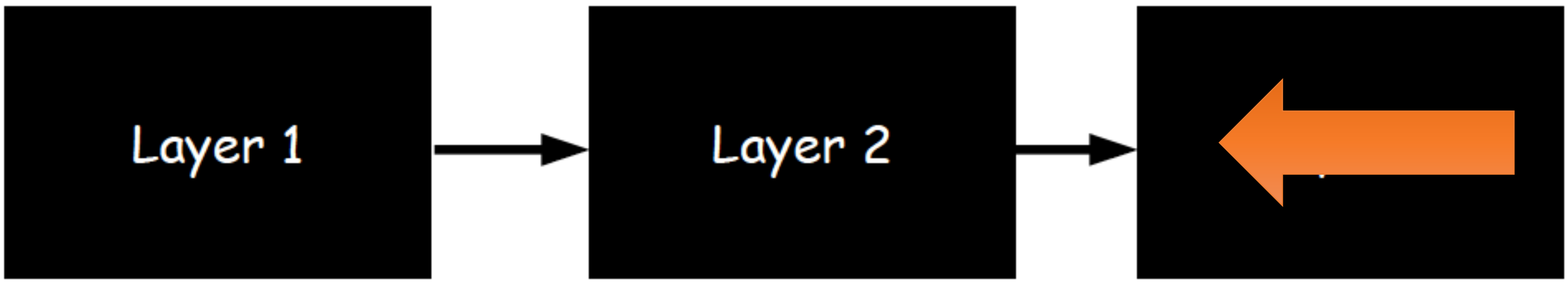
Neural Network Training

- Step 1: Compute Loss on mini-batch [F-Pass]



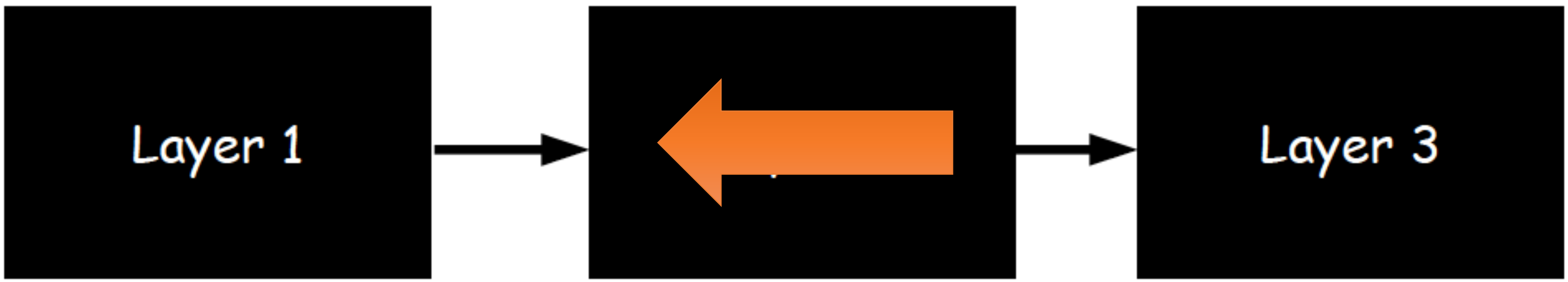
Neural Network Training

- Step 1: Compute Loss on mini-batch [F-Pass]
- Step 2: Compute gradients wrt parameters [B-Pass]



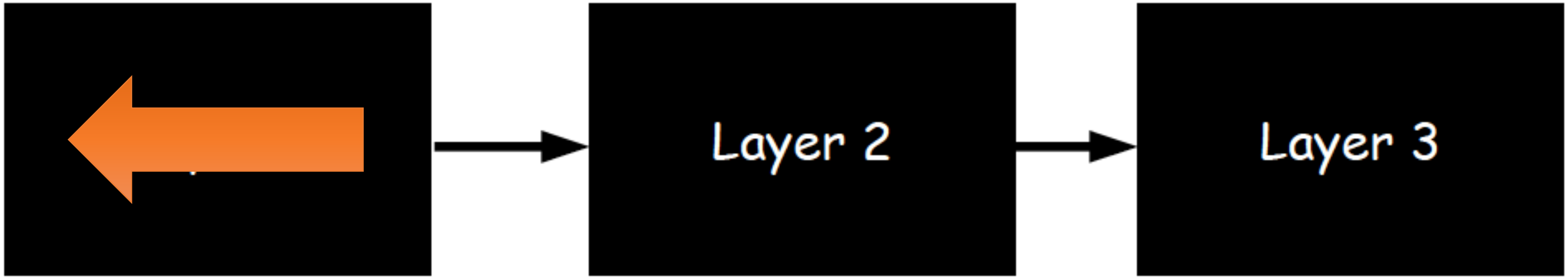
Neural Network Training

- Step 1: Compute Loss on mini-batch [F-Pass]
- Step 2: Compute gradients wrt parameters [B-Pass]



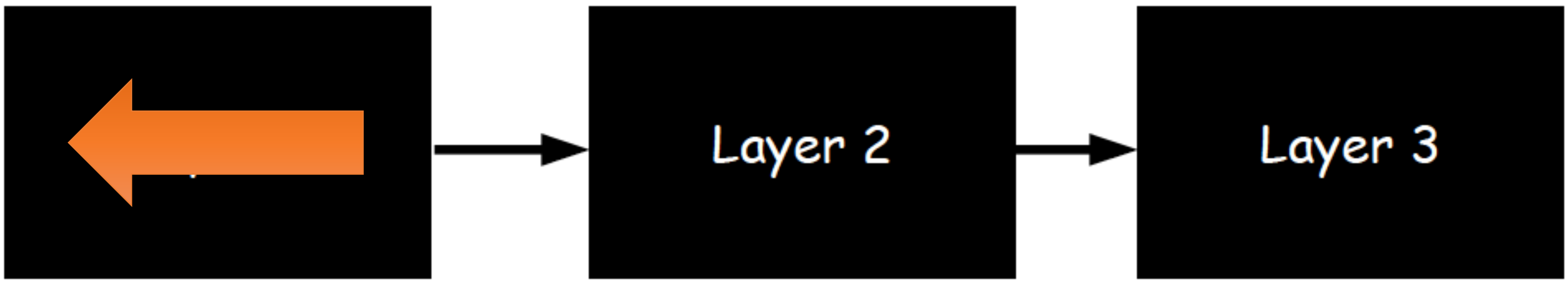
Neural Network Training

- Step 1: Compute Loss on mini-batch [F-Pass]
- Step 2: Compute gradients wrt parameters [B-Pass]



Neural Network Training

- Step 1: Compute Loss on mini-batch [F-Pass]
- Step 2: Compute gradients wrt parameters [B-Pass]
- Step 3: Use gradient to update parameters



$$\theta \leftarrow \theta - \eta \frac{dL}{d\theta}$$

Outline

1. Intra-class variability: viewpoint, lighting, instance
2. Supervised Learning: label + optimization
3. Regression and Classification: SSD + CE
4. Stochastic Gradient Descent: mini-batches
5. Calculating Gradients: back-propagation