

# Tensorflow, Part A

MSAIL 2017

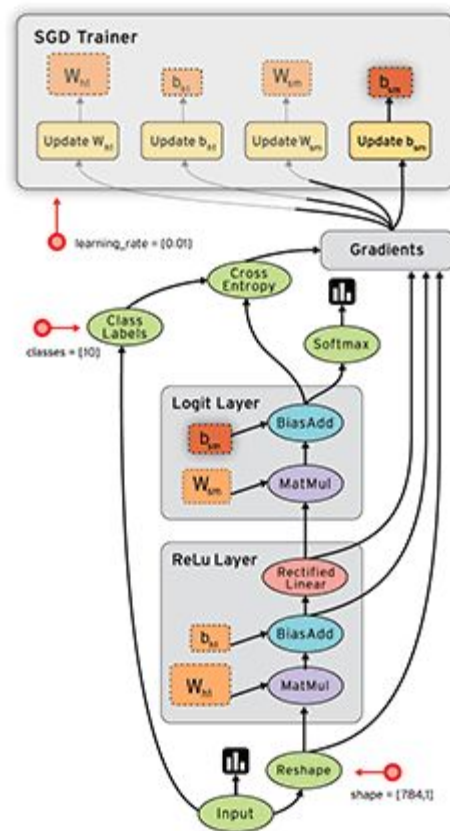
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# What is Tensorflow?

- a less interpreted, more compiled version of numpy
- Google's "library for ... computation using ... graphs"
- See [www.tensorflow.org/tutorials/](http://www.tensorflow.org/tutorials/)

## Why use Tensorflow?

- fast: supports GPU computation if available
- makes experimenting with deep neural networks easy



# Basics: Graphs, Sessions, Ops, Variables

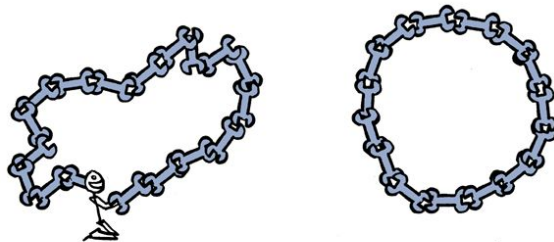
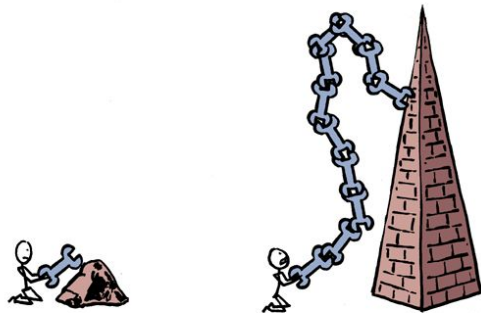
A brief history of automation:

0. Manually do X
1. Manually write program to automatically do X
2. Manually write program  
to automatically write program  
to automatically do X

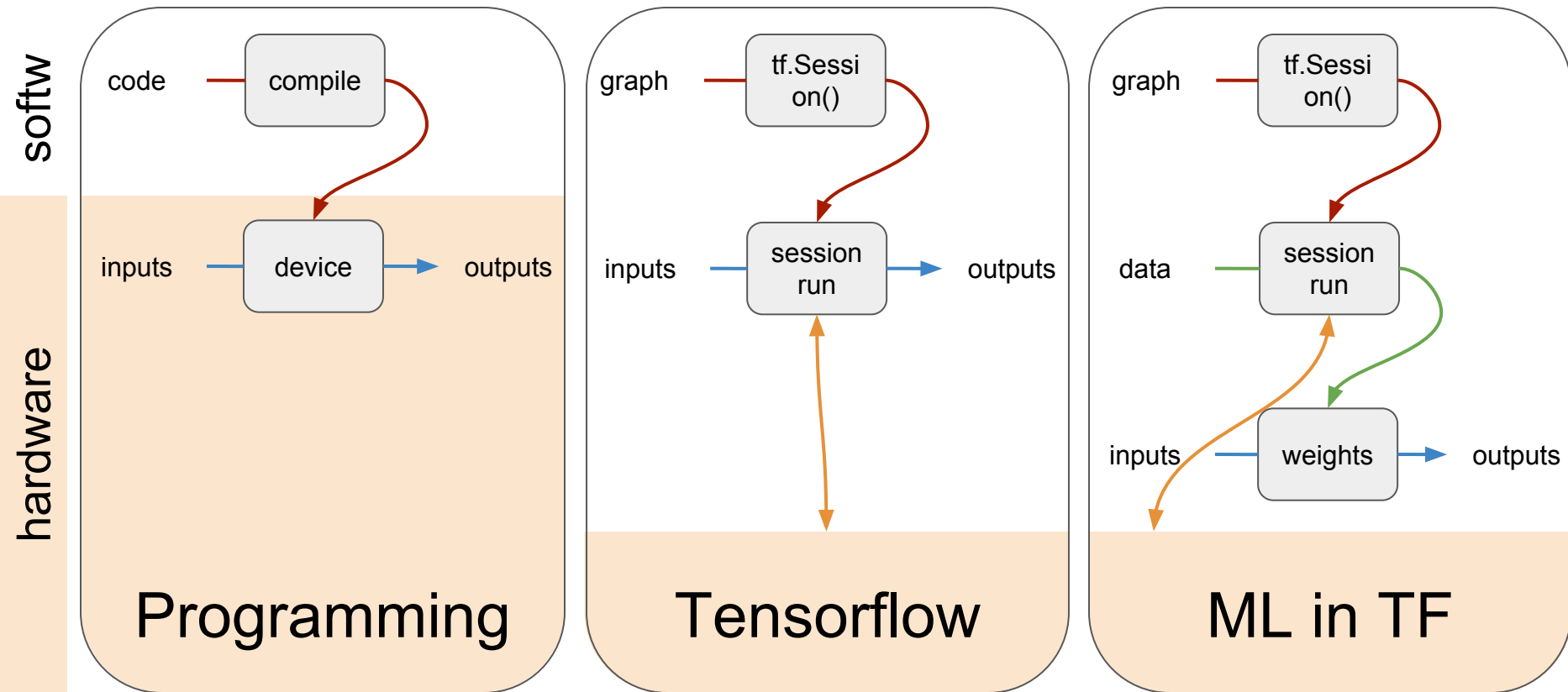
Machine learning is meta-programming!

**Graphs** are the level-2 programs. Graphs are realized in **Sessions**, which execute the level-2 programs to construct the level-1 programs.

A SHORT HISTORY OF TOOL USE



# Basics: Graphs, Sessions, Ops, Variables



# Basics: Manual Gradient Descent

Now we create our first Machine Learning model: linear regression!

**Data:**  $((x[i], y[i]) \text{ for } i \text{ in } I)$  with each  $x[i]$  of a length-D vector and each  $y[i]$  a scalar.

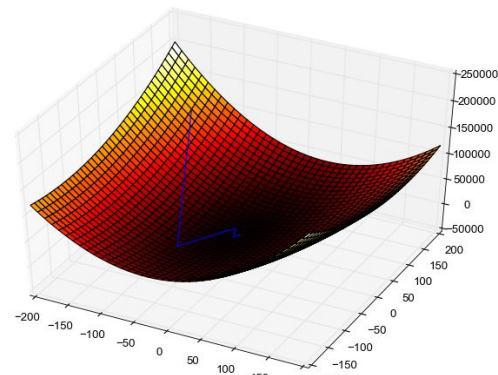
**Model:** Estimate  $y[i] \sim \mathbf{w} \cdot x[i]$ . Our goal is to determine a good  $\mathbf{w}$ .

**Loss:** Try to minimize mean square error:  $L = \text{average}((\mathbf{w} \cdot x[i] - y[i])^2 \text{ for } i \text{ in } I)$ .

We randomly initialize  $\mathbf{w}$ . Then we repeatedly adjust  $\mathbf{w}$  to become more accurate on the data. This is stochastic gradient descent (SGD):

While unsatisfied:

$$\mathbf{w} \leftarrow \mathbf{w} + 0.001 * \text{average}((y[i] - \mathbf{w} \cdot x[i]) * x[i] \text{ for } i \text{ in RandomSubset}(I))$$



# Basics: Automatic Gradient Descent

Two essential time-savers for deep learning experiments:

We manually differentiated, but Tensorflow can differentiate automatically.

We used vanilla SGD, but Tensorflow comes with some smarter optimizers.

**#OLD:**

```
GradPredictedOutputs = 2 * (PredictedOutputs - TrueOu...  
GradWeights = tf.reduce_mean(tf.multiply(TrueInputs, ...  
Update = tf.assign(Weights, Weights - LearningRate*GradWeights)
```

**#NEW:**

```
Update =  
tf.train.GradientDescentOptimizer(LearningRate).minimize(Loss)
```

We now have the complete structure of a Tensorflow deep learning program. We just need to replace the linear regressor with a deep neural network! Let us do shallow networks first...



# Deep Learning: A Fully Connected Classifier

Two essential time-savers for deep learning experiments:

- Automatic Differentiation

- Built-In Optimizers

Let us use the above to classify images!

**Data:**  $((x[i], y[i]) \text{ for } i \text{ in } I)$

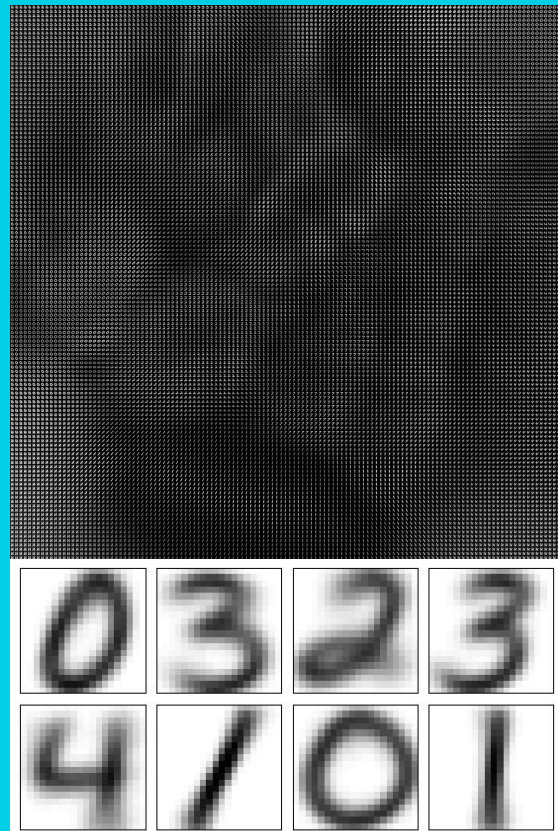
$x[i]$  has shape  $(28*28)$  and  $y[i]$  has shape  $(10,)$

**Model:** Estimate  $y[i] \sim \text{Normalize}(\exp(\mathbf{w} \cdot x[i]))$ .

$\mathbf{w}$  has shape  $(10, 28*28)$ .

**Loss:** Minimize cross-entropy:

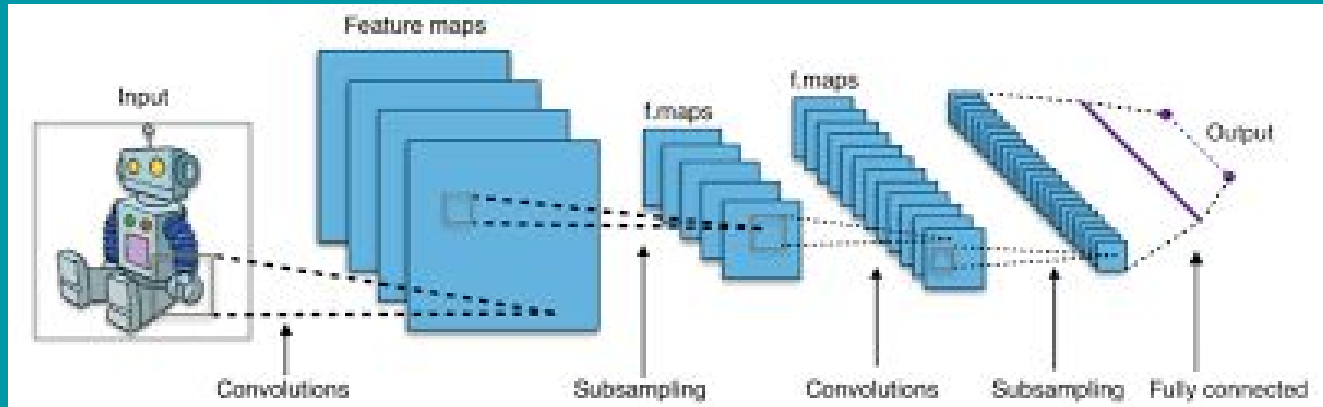
$L = - \text{average}(\log(\text{guess}[i]) \cdot y[i] \text{ for } i \text{ in } I)$ .



# Deep Learning: A Convolutional Classifier

Hmm... around 91% accuracy isn't bad: compare to the don't-look-at-the-data baseline of only 10% accuracy.

But can we do better? Let us build a convolutional classifier...





# Questions?

- Check out the exercises in README.markdown. Is it clear how to approach them?