Deep Learning with TensorFlow

Deep Learning — Units 7 & 8

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Slides available at jonkrohn.com/talks

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Outline

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Assessing

Your Deep Learning Project III

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Leading DL Libraries

	Caffe	**Torch**	**MXNet**	**TensorFlow**
Language	Python, Matlab	Lua, C	Python, R, C++ Julia, Matlab JavaScript, Go Scala, Perl	**Python, C**, C++ Java, Go, JS, Swift (*Haskell, Julia, R, Scala, Rust, C#)*
Programming Style	Symbolic	Imperative	Imperative	Imperative *(in 2.0)*
Parallel GPUs: Data	Yes	Yes	Yes	Yes
Parallel GPUs: Model		Yes	Yes	Yes
Pre-Trained Models	Model Zoo	Model Zoo	Model Zoo	github.com/tensorflow/models
High-Level APIs		PyTorch	in-built	Keras
Particular Strength	CNNs	interactivity		production deployment

Leading DL Libraries

PyTorch	TensorFlow
"NumPy", optimized for GPUs	ported to Python from C++
dynamic auto-differentiation (autodiff)	static computational graph
debugging is easier	
fast.ai API	Keras API
	more widely adopted
TorchScript Just-In-Time compilation	TensorFlow Serving, .js, Lite, tf.data, tf.io
better for interactively building models	**better for production deployments**

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TensorFlow Graphs

1. build graph
2. initialize session
3. fetch and feed data

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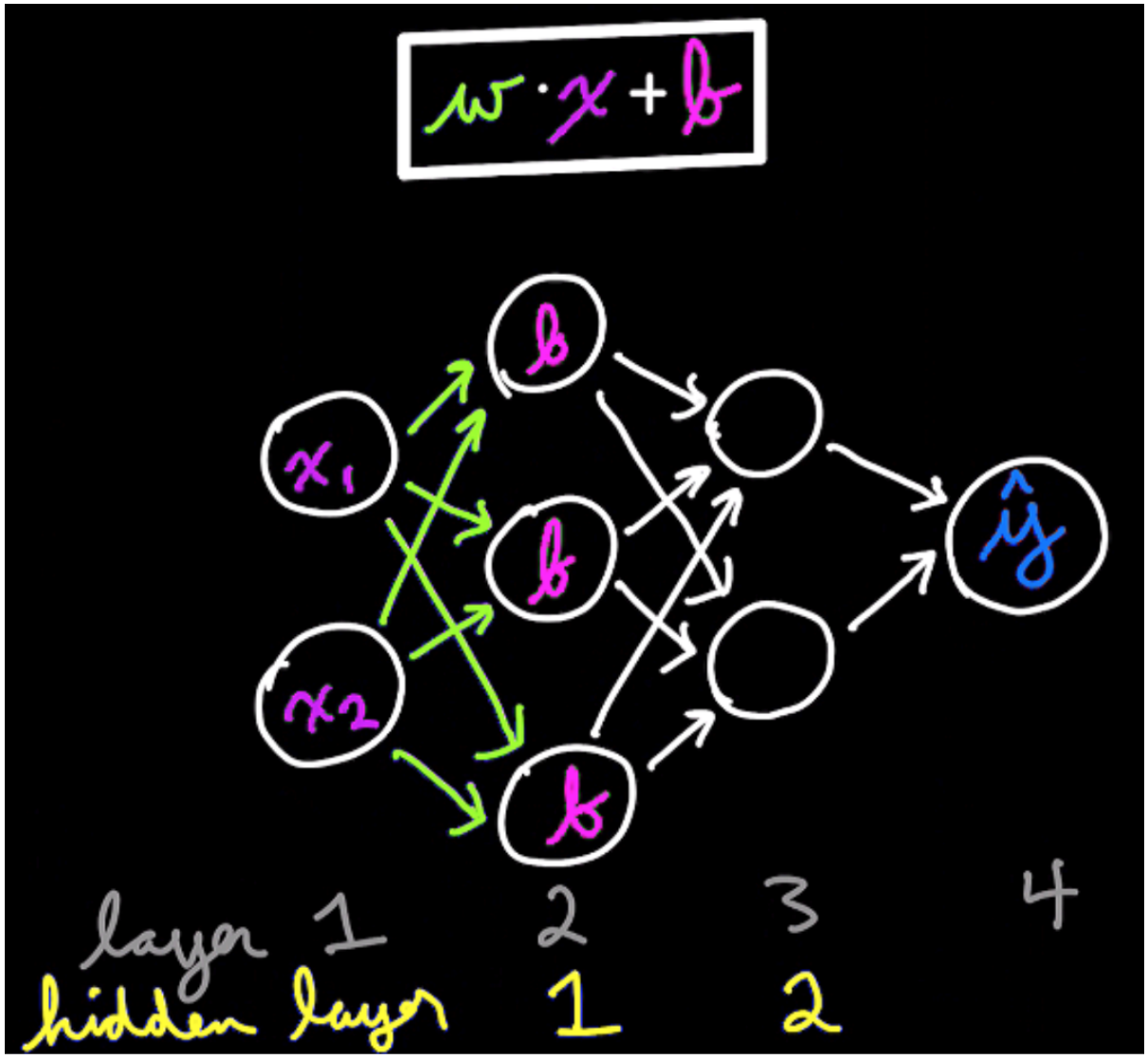
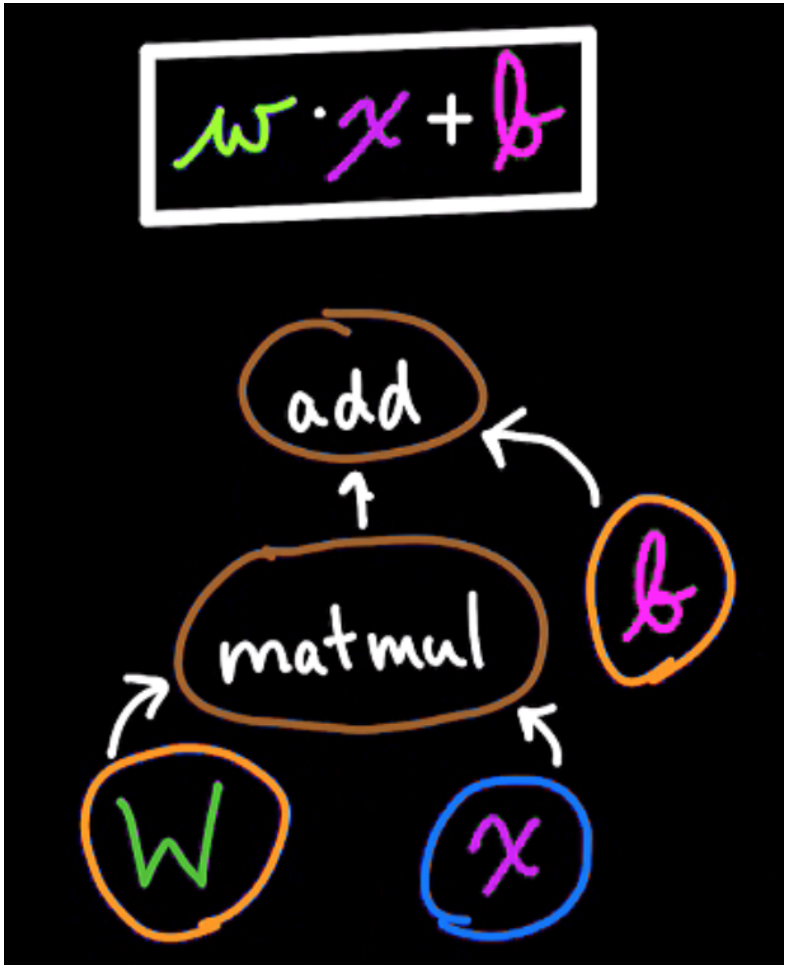
A Familiar Equation



TensorFlow Graphs



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TensorFlow Graph

Programming

[*first TensorFlow graphs* notebook]

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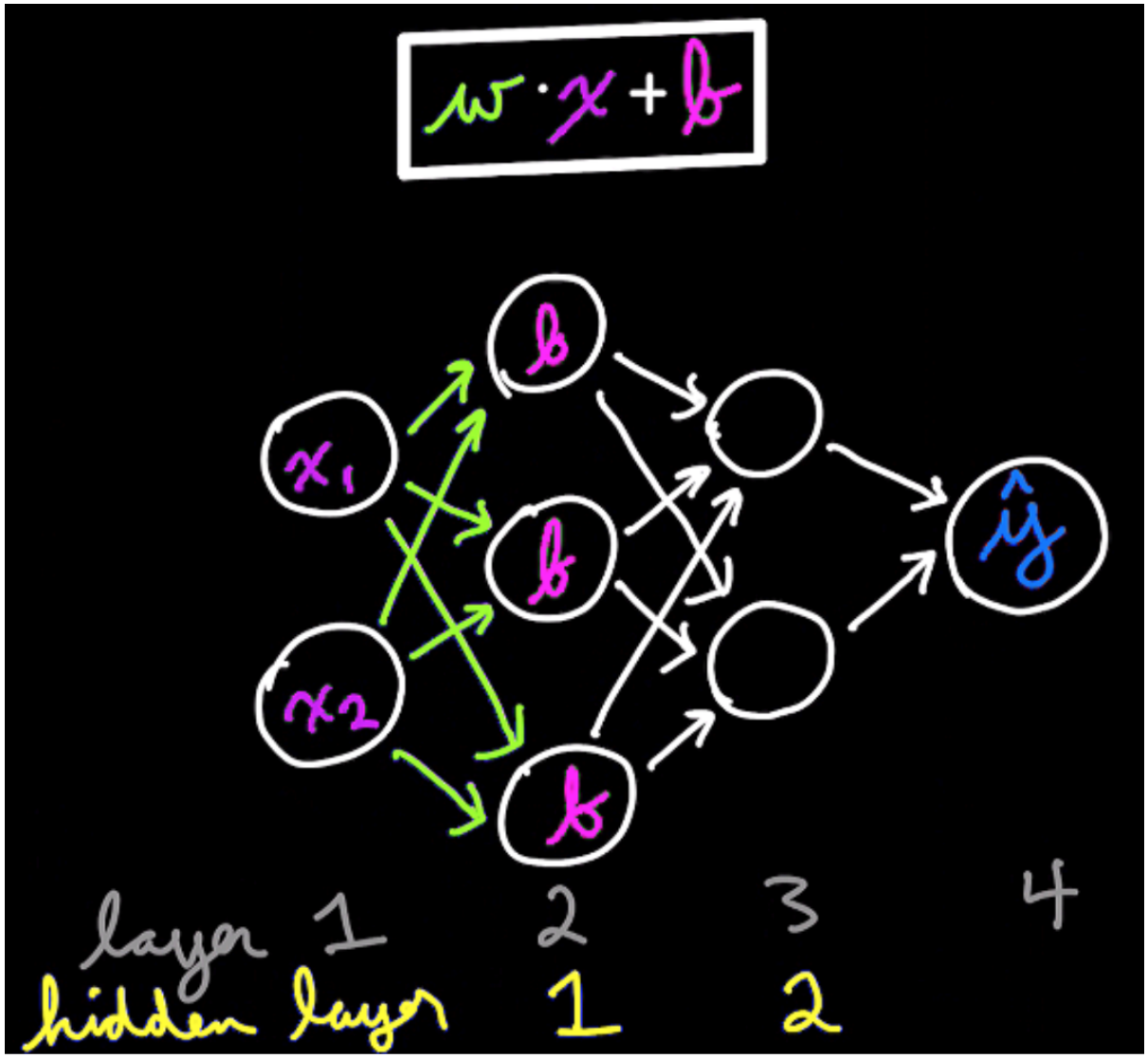

Neurons in TensorFlow

Programming

[*first TensorFlow neurons* notebook]

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Fitting Eight Points

[*point by point intro to TensorFlow* notebook]

Fitting Eight Points

with Tensors

[*tensor-fied intro to TensorFlow* notebook]

Outline

Fitting Eight Million Points

[*intro to TensorFlow times a million* notebook]

Outline

Dense Nets

[*intermediate net in TensorFlow* notebook] [*deep net in TensorFlow* notebook]

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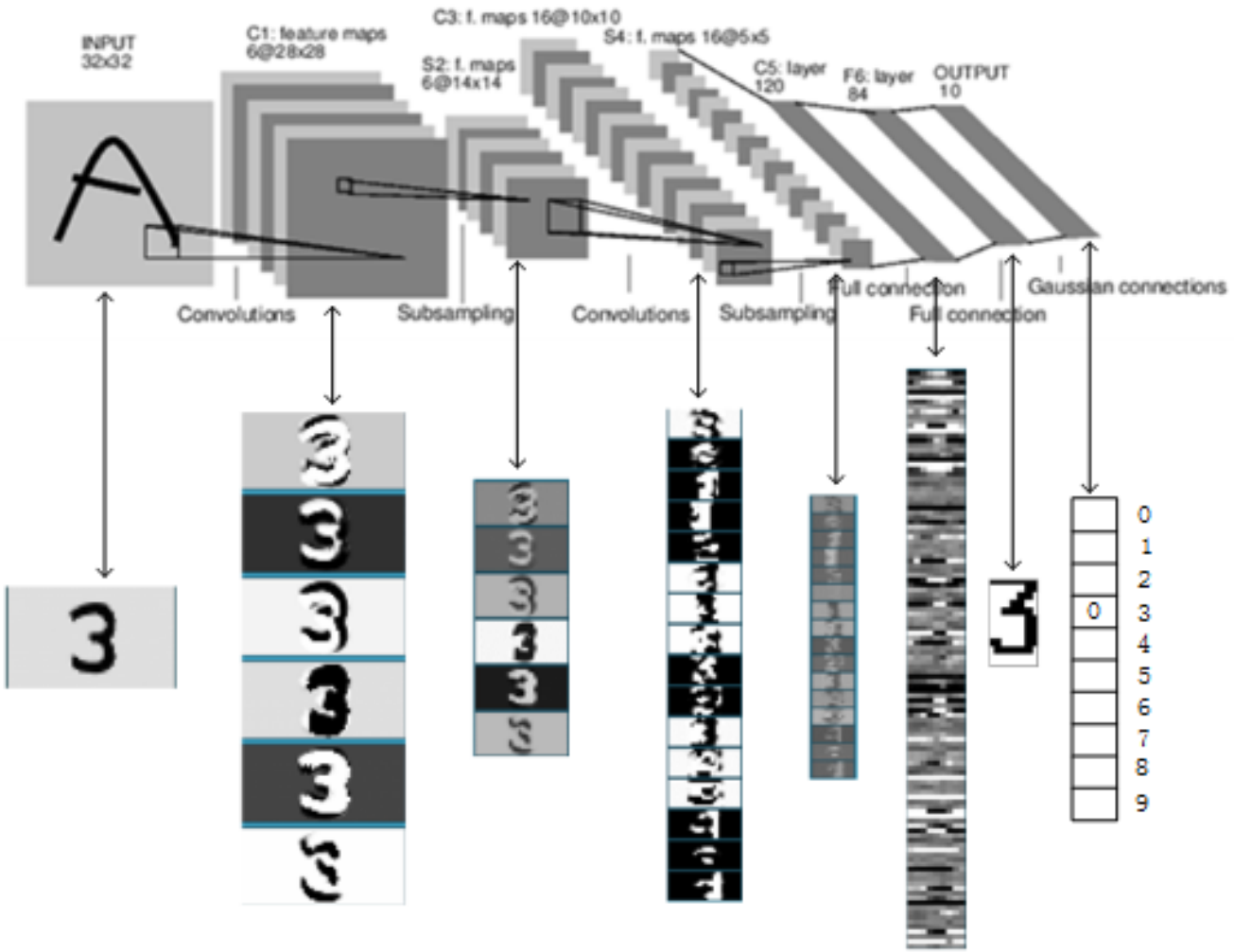
LeNet-5

LeCun et al. (1998)



LeNet-5

LeCun et al. (1998)

[*LeNet in TensorFlow* notebook]

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- use layers (Keras) by default
- autodiff Eager execution by default
- JIT compiler for optimization, especially across devices
- subclassing for unlimited flexibility, e.g.:
  - custom loss, optimizers, layers, training loops
  - repeating layers, blocks of layers
- data pipelines & processing with tf.data & tf.io
- portability with:
  - *TensorFlow Serving*
  - *TensorFlow Lite* for mobile/embedded
  - *TensorFlow.js*
- [to update from TF 1.x]

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[shallow net in PyTorch]
[deep net in PyTorch]

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GANs

Deep RL