A Brief Overview of Recent Neural Network Methods and Architectures

UCLA CS161

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Overview

1. Fully Connected Neural Networks
   - Multi-layer Preceptron (MLP)
   - Limitations of MLP
   - Inspirations from Visual Cortex
2. Convolutional Neural Networks (CNNs)
   - Basic Ideas of CNNs
   - Famous CNN Architectures
   - Visualizing CNNs
3. Recurrent Neural Networks (RNNs)
   - Handling Sequences as Input
   - RNN Applications
   - Basic Ideas of RNNs
4. TensorFlow Tutorial

Outline

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   - **Multi-layer Preceptron (MLP)**
   - **Limitations of MLP**
   - **Inspirations from Visual Cortex**
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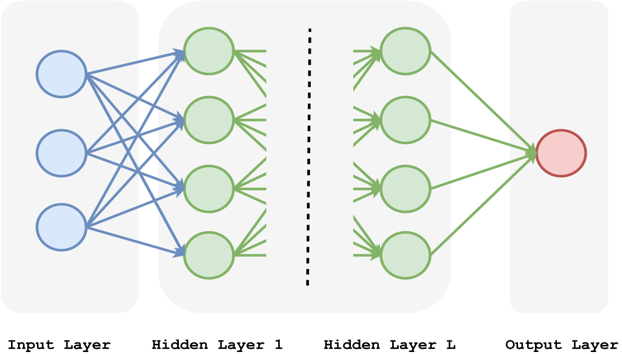
Multi-layer Preceptron (MLP) (1/2)

$$h_{i+1} = \sigma(h_i W_i + b_i)$$



Multi-layer Preceptron (MLP) (2/2)

- In a MLP, we have a few fully connected layers that are stacked with each other.
- There are three layer types: input layer, hidden layer, and output layer.
- Each layer takes the activation values of the previous layer as input, applies a linear transformation to it, and crates output activations by applying a non-linearity.
- The universal approximation theorem: theoretically, we can model any function using a neural network with a single hidden layer.

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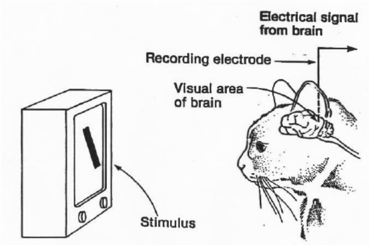
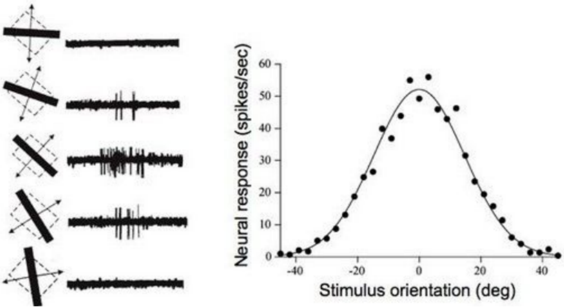
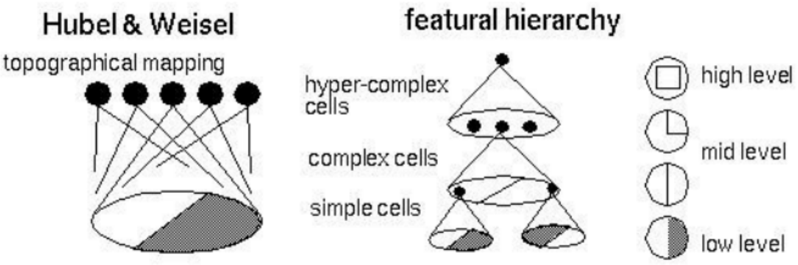
- Practically, training networks with more than a few layers is not easy.
- Finding the optimal number of layers and neurons inside each one is an open problem.
- The universal approximation theorem is not helping us that much because a huge number of hidden neurons needed to approximate a function using a shallow network.

Hubel and Wiesel Experiments





Hierarchical Organization of Visual Cortex



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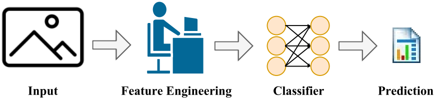
The Era of Deep Representations (1/2)

- Image recognition is a machine learning application in which the machine should predict objects that are present in the image.
- Before 2012, the major method in image recognition was using hand engineered features and classic machine learning classifiers.



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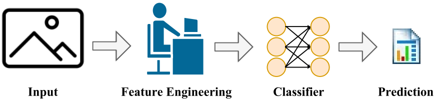
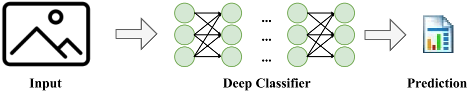
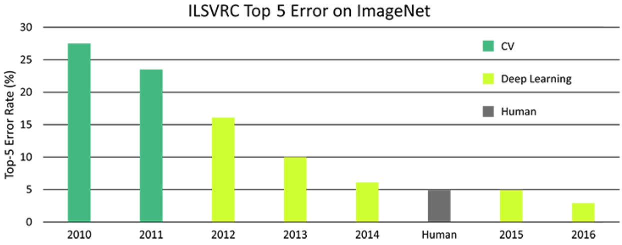


- Around 2012, three major factors changed the future landscape of recognition tasks from engineered features and shallow architectures to using automated feature extraction through deep neural networks.
  - Significantly bigger datasets such as ImageNet (10,000,000 labeled images depicting 10,000+ object categories)
  - More powerful computers and GPU accelerated computation.
  - Development of techniques and tricks for training deeper networks.



The Era of Deep Representations (2/2)



Model	Top-1	Top-5
Sparse coding [2]	*47.1%*	*28.2%*
SIFT + FVs [24]	*45.7%*	*25.7%*
CNN	**37.5%**	**17.0%**

Table 1: Comparison of results on ILSVRC-2010 test set. In *italics* are best results achieved by others.

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Is it possible to take the advantage of image characteristics in designing the network?

Basic Ideas of CNNs: Intuition

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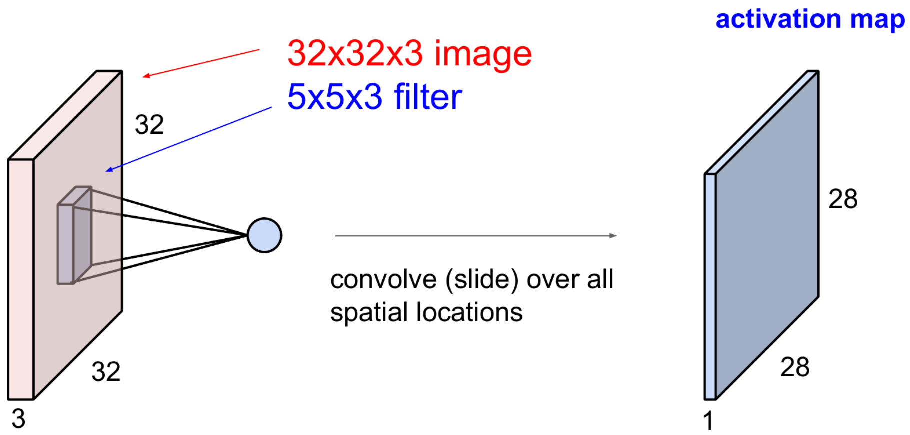
- It can be easily modeled as the 2D convolution operation.
- It is, basically, learning a set of filters and applying them at different image locations.

Basic Ideas of CNNs: Conv Layers (1/3)

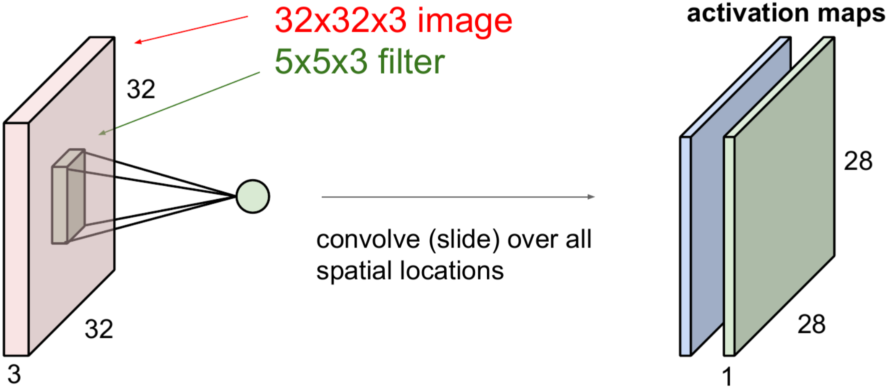
Applying a convolution filter on an image:



Fei-Fei Li, Andrej Karpathy, and Justin Johnson

Basic Ideas of CNNs: Conv Layers (2/3)

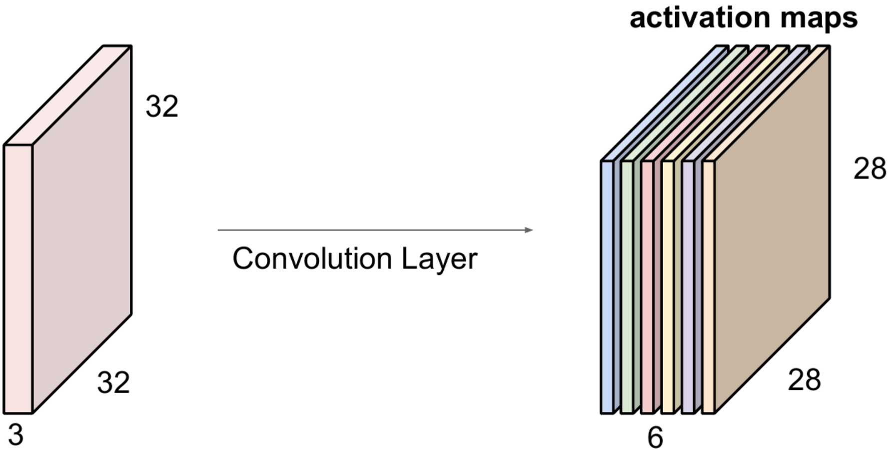
Applying two different convolution filters on an image:



Fei-Fei Li, Andrej Karpathy, and Justin Johnson

Basic Ideas of CNNs: Conv Layers (3/3)

Applying a set of different convolution filters on an image:



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- Lower complexity means ability to fit models faster, easier, and using fewer training samples.

Benefits of CNNs: Fast GPU Training

- Modern GPUs are optimized for fast and efficient convolution.

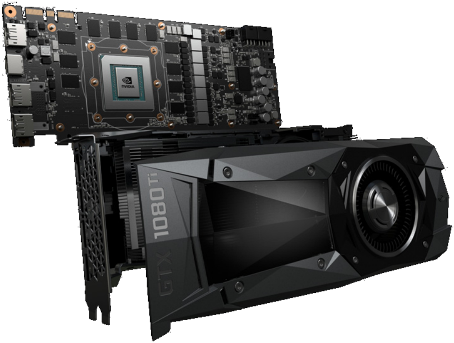

Figure: Nvidia GTX 1080Ti (3584 Cores, 11GB Memory). Source: nvidia.com

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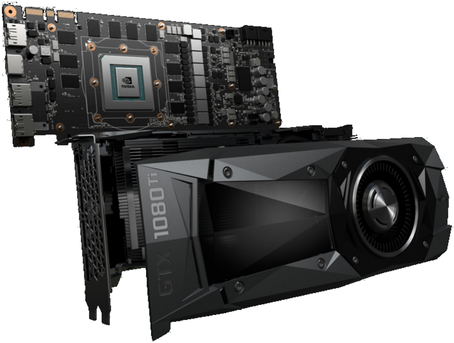

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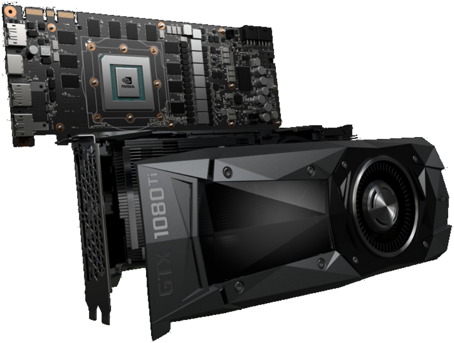

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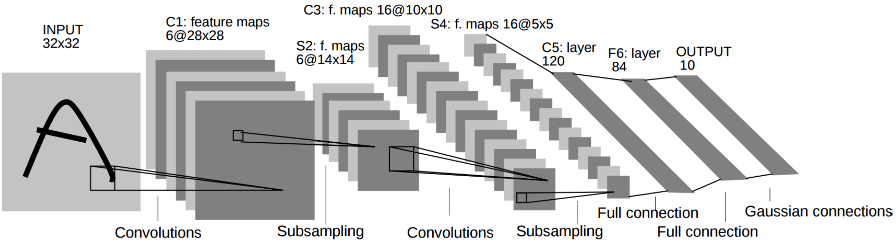
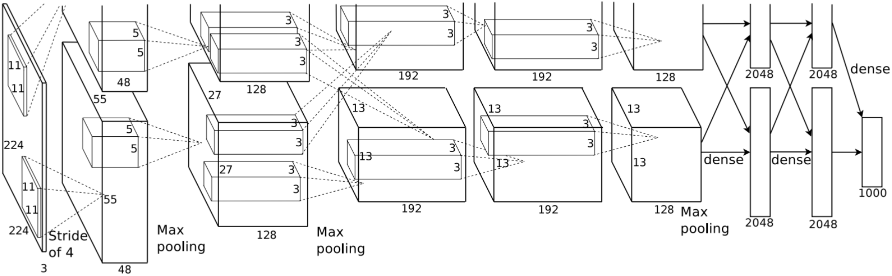
Famous CNN Architectures: LeNet 1998



LeCun, Yann, et al. "Gradient-based learning applied to document recognition." Proceedings of the IEEE 86.11 (1998): 2278-2324.

Famous CNN Architectures: ImageNet 2012 (AlexNet) (1/2)

About 8 weight layers and 50 million parameters.



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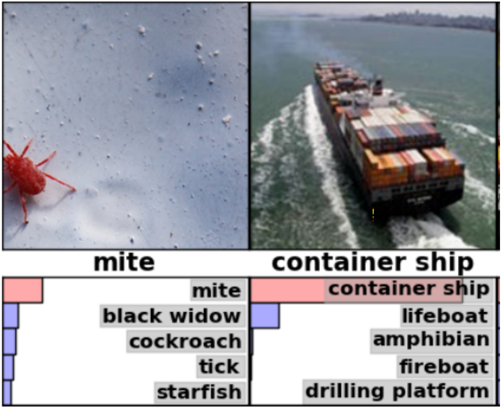
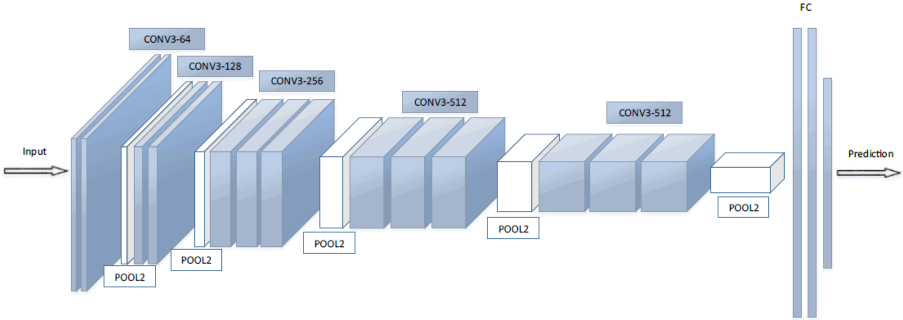


Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." Advances in neural information processing systems. 2012.

Famous CNN Architectures: VGG (1/2)

About 20 weight layers and 130 million parameters.



Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." arXiv preprint arXiv:1409.1556 (2014).

Famous CNN Architectures: VGG (2/2)

Table 7: **Comparison with the state of the art in ILSVRC classification.** Our method is denoted as "VGG". Only the results obtained without outside training data are reported.

Method	top-1 val. error (%)	top-5 val. error (%)	top-5 test error (%)
VGG (2 nets, multi-crop & dense eval.)	**23.7**	**6.8**	**6.8**
VGG (1 net, multi-crop & dense eval.)	24.4	7.1	7.0
VGG (ILSVRC submission, 7 nets, dense eval.)	24.7	7.5	7.3
GoogLeNet (Szegedy et al., 2014) (1 net)	-	7.9	
GoogLeNet (Szegedy et al., 2014) (7 nets)	-	**6.7**	
MSRA (He et al., 2014) (11 nets)	-	-	8.1
MSRA (He et al., 2014) (1 net)	27.9	9.1	9.1
Clarifai (Russakovsky et al., 2014) (multiple nets)	-	-	11.7
Clarifai (Russakovsky et al., 2014) (1 net)	-	-	12.5
Zeiler & Fergus (Zeiler & Fergus, 2013) (6 nets)	36.0	14.7	14.8
Zeiler & Fergus (Zeiler & Fergus, 2013) (1 net)	37.5	16.0	16.1
OverFeat (Sermanet et al., 2014) (7 nets)	34.0	13.2	13.6
OverFeat (Sermanet et al., 2014) (1 net)	35.7	14.2	-
Krizhevsky et al. (Krizhevsky et al., 2012) (5 nets)	38.1	16.4	16.4
Krizhevsky et al. (Krizhevsky et al., 2012) (1 net)	40.7	18.2	-

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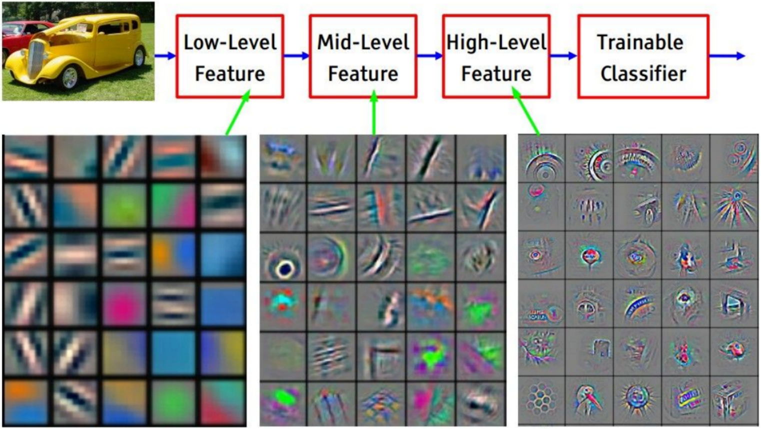
Visualizing CNNs



Zeiler, Matthew D., and Rob Fergus. "Visualizing and understanding convolutional networks." European conference on computer vision. Springer, Cham, 2014.

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Handling Sequences as Input

- We have a wide range of applications in which:
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  - The sequence length is not necessarily fixed.
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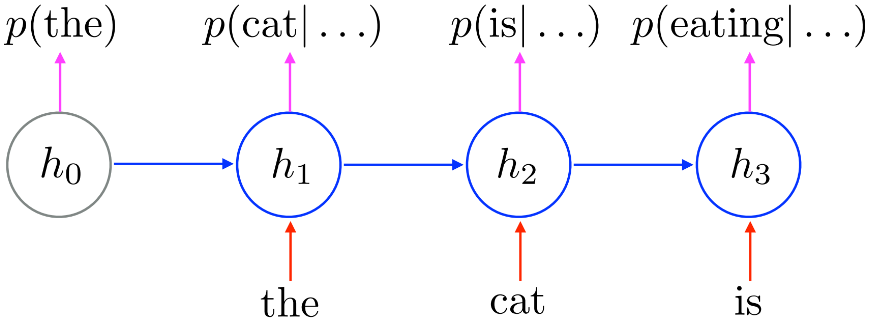
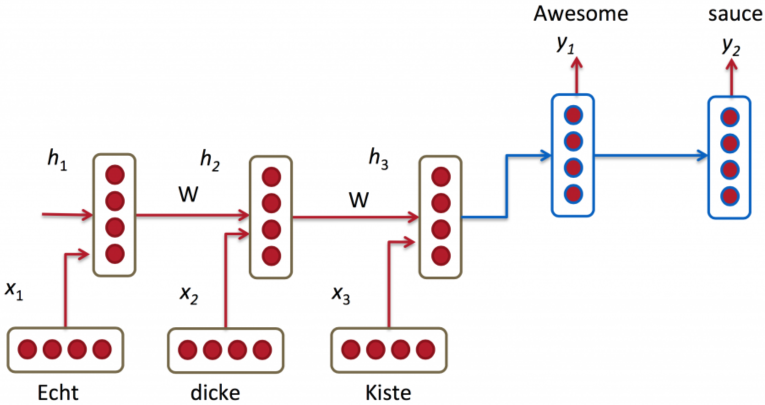
- For instance:
  - Predictive analysis in time series. e.g., predicting the expected future value of the stocks for a company.
  - Language modeling. e.g., designing an auto-complete engine which can predict and suggest the next work given the current incomplete sentence.
  - Sequence to sequence modeling. e.g., translating a speech from English to French in real-time.

RNN Applications: Language Modeling



Kyunghyun Cho, Natural Language Understanding

RNN Applications: Sentence Translation



Richard Socher, Recurrent Neural Networks

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- A more detailed discussion of RNNs is out of the scope of this lecture.

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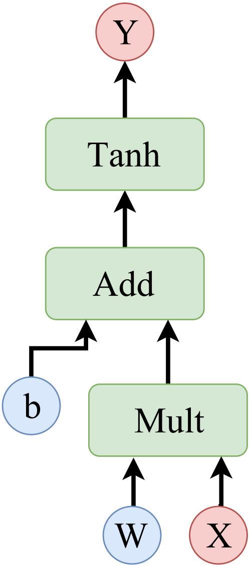
- Consider the computation of forward path in a simple one layer neural network:
  $Y = tanh(WX + b)$



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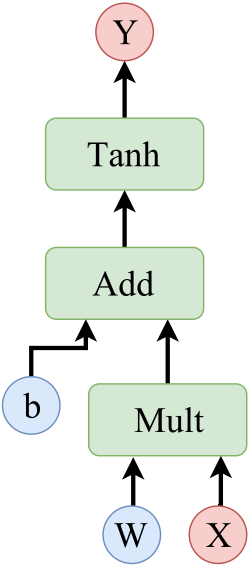
- A data flow graph is a computational graph that explains the processing that is happening to the flow of data.



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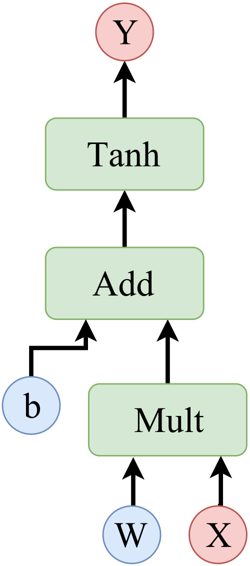
- Data flow model is in contrast to the control flow model.



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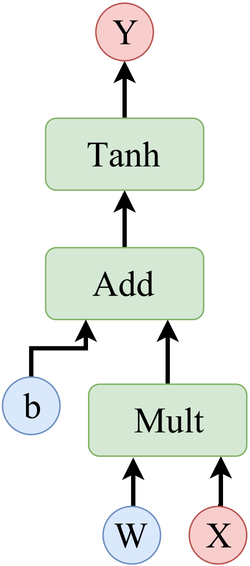
- Data flow model is in contrast to the control flow model.
- TensorFlow is a computational library by Google that is designed for fast and scalable computing based on data flow graphs.



TensorFlow: Introduction (2/2)

- In a typical computational library, we call functions on data sequentially.
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  - It adds the overhead of function call, argument pass, and return to the actual processing time.
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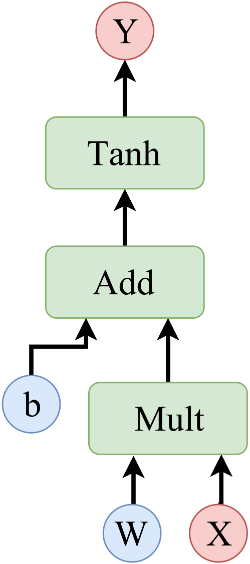
- In TensorFlow, we create a complete computational graph. Then we feed our data to the graph and every process takes place in background.



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- Defined variables are by default trainable and need to be initialized before usage.

```
# import tensorflow package
import tensorflow as tf
# create a constant tensor of ones
C = tf.ones((2,2))
# create a tensor variable initialized with zeros, name it
    weights
W = tf.Variable(tf.zeros((2,2)), name="weights")
# define a multiplication tensor (Y) which is the result of
    multiplying C by W
Y = tf.matmul(C, W, name='op_matmul_CW')
```

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Basics: Placeholders

- Placeholder variables are input ports to the TensorFlow graph.
- The Python program can feed data into and get information from the computational graph through placeholders.
- We define placeholders and use them as regular tensor variables inside our graph code.
- before running the graph, we assign values to the placeholders in our Python code.

```

# create a place holder of type float and shape 2x2
P = tf.placeholder(dtype=tf.float32, shape=(2,2), name='ph_input')
# create a tensor variable initialized with zeros, name it weights
W = tf.Variable(tf.zeros((2,2)), name="weights")
# define a multiplication tensor (Y) which is the result of multiplying P by W
Y = tf.matmul(P, W, name='op_matmul_CW')
```

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- However, before using a graph, we need to create a session in which the graph evaluation will take place.
- In TensorFlow we do this by creating a session object and running it while feeding the placeholders.

```
# the next three lines are similar to the previous example
P = tf.placeholder(dtype=tf.float32, shape=(2,2), name='ph_input')
W = tf.Variable(tf.zeros((2,2)), name="weights")
Y = tf.matmul(P, W, name='op_matmul_CW')
# create a session
sess = tf.Session()
# create a dummy feed data
feed_data = {P: np.ones((2,2), dtype=np.float32)}
# run the Y graph using the session and feed the dummy data
res = sess.run(Y, feed_dict=feed_data)
# print the result
print(res)
```

Training and Optimization

- TensorFlow supports automatic differentiation.
- For training a neural net, we need to:
  - Define forward path.
  - Define a cost function.
  - Create an optimizer.
  - Run the optimization operation to update network weights.

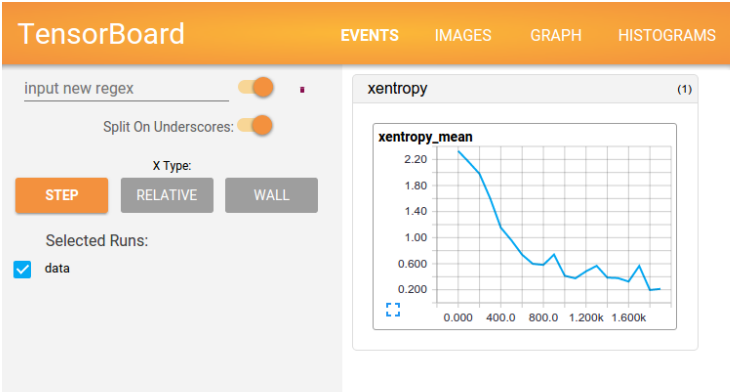
```
# define a train step
train_step = tf.train.GradientDescentOptimizer(0.5).minimize(
    cross_entropy)
# training for 1000 iterations
for _ in range(1000):
  # load a dataset batch
  batch_xs, batch_ys = mnist.train.next_batch(100)
  # run the train step
  sess.run(train_step, feed_dict={x: batch_xs, y_: batch_ys})
```

Linear Regression using TensorFlow

```python
# define placeholders
X = tf.placeholder(dtype=tf.float32, shape=(None,1), name='ph_input')
Y = tf.placeholder(dtype=tf.float32, shape=(None,1), name='ph_output')
# create variable tensors
W = tf.Variable(0.0, dtype=tf.float32, name="weight")
b = tf.Variable(0.0, dtype=tf.float32, name="bias")
# define a cost function
errors = Y - X * W + b
cost_mse = tf.reduce_mean(errors ** 2.0)
# define a train step
train_step = tf.train.GradientDescentOptimizer(0.01).minimize(cost_mse)
# training for 1000 iterations
for iter_trn in range(1000):
    # load a dataset batch
    batch_xs, batch_ys = train_dataset.next_batch(100)
    # run the train step
    sess.run(train_step, feed_dict={X: batch_xs, Y: batch_ys})
    # test the model
    batch_xs, batch_ys = test_dataset.next_batch(100)
    cost = sess.run(cost_mse, feed_dict={X: batch_xs, Y: batch_ys})
    print('Iter: ', iter_trn, ' Test cost:', cost)
```

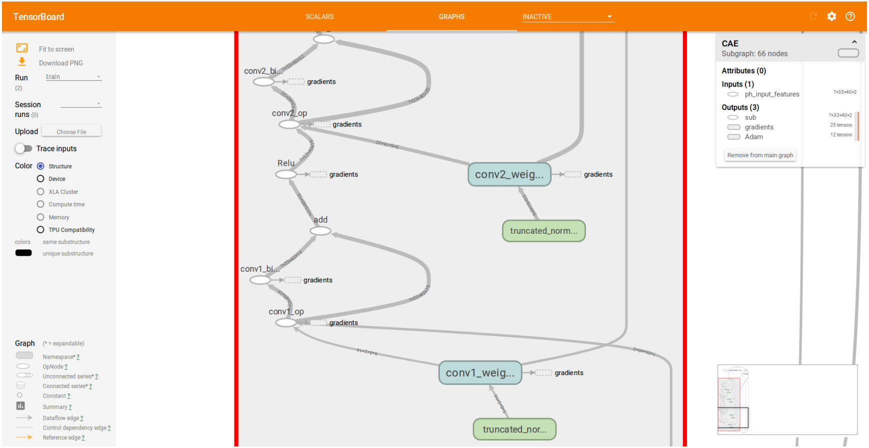
TensorBoard (1/2)

- TensorBoard is a web application by TensorFlow that offers visualization tools for graph visualization, drawing learning curves and histograms, etc.



tensorflow.org

TensorBoard (2/2)



The End