Introduction to Deep Learning

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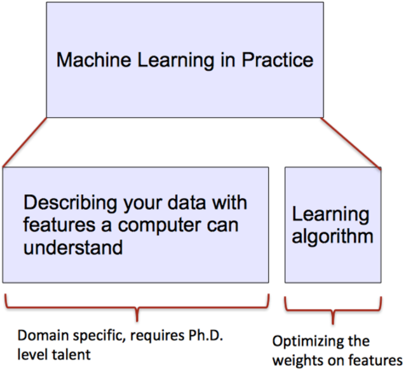
February 1, 2020

Introduction to Deep Learning

What is Deep Learning?

- Artificial Intelligence: mimicking human intelligence
- Machine Learning: Automating Learning with features.
- ML: human-designed representations and input features. So, its just optimizing weights to best make a final prediction
- There could be programmed (hand coded) AI, that's not Machine Learning
- Machine Learning could be for non AI activities, like automation
- Deep Learning: Neural network with no input features

ML vs DL: What's the difference?

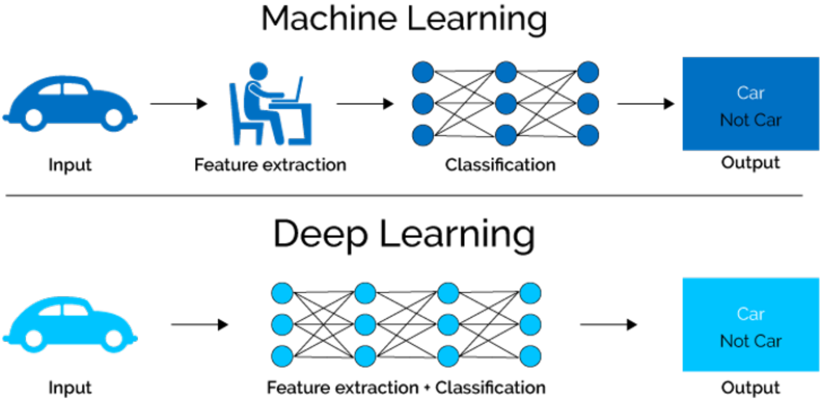


Feature	NER
Current Word	✓
Previous Word	✓
Next Word	✓
Current Word Character n-gram	all
Current POS Tag	✓
Surrounding POS Tag Sequence	✓
Current Word Shape	✓
Surrounding Word Shape Sequence	✓
Presence of Word in Left Window	size 4
Presence of Word in Right Window	size 4

(Reference: Introduction to Deep Learning - Ismini Lourentzou)

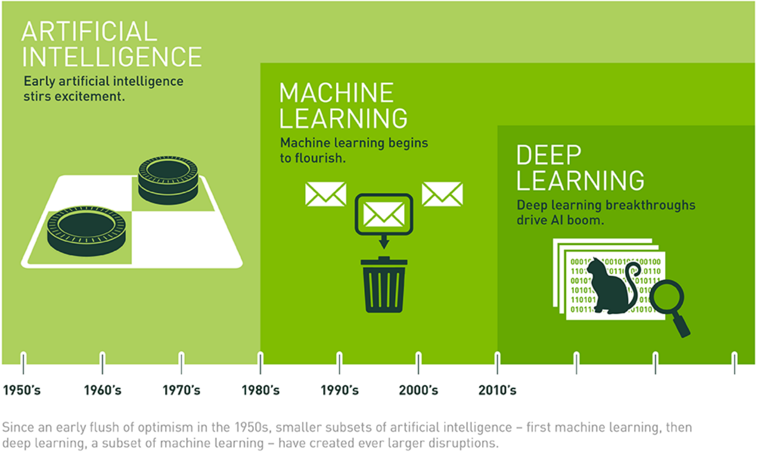
ML vs DL: What's the difference?

Deep learning algorithms attempt to learn (multiple levels of) representation by using a hierarchy of multiple layers



(Reference: https://www.xenonstack.com/blog/static/public/uploads/media/machine-learning-vs-deep-learning.png)

AI ML DL: What's the difference?



(Reference: The Difference Between AI, Machine Learning, and Deep Learning - NVIDIA Blog)

Use Deep Learning When ...

- You have lots of data (about 10k+ examples)
- The problem is "complex" - speech, vision, natural language
- The data is unstructured
- You need the absolute "best" model

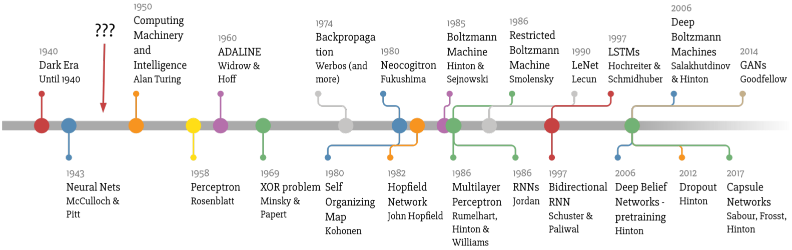
(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Don't use Deep Learning When ...

- You don't have a large dataset
- You are performing sufficiently well with traditional ML methods
- Your data is structured and you possess the proper domain knowledge
- Your model should be explainable

(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

History



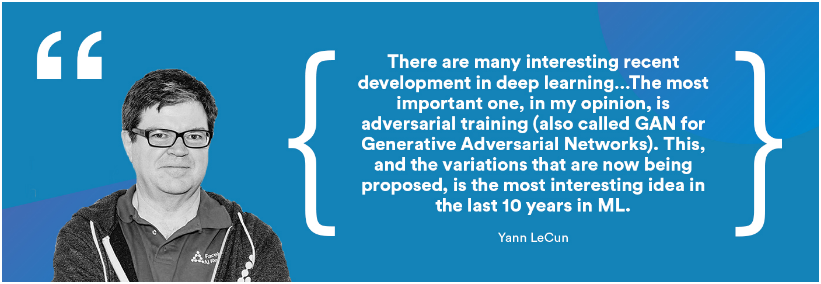
Made by Favio Vázquez

(Reference: Deep Learning basics - Rodrigo Agundez)

History

- 1958 - Percentron unit - Frank Rosenblatt
- 1986 - Backpropagation - Geoffrey Hinton
- 1986 - RNN - Schuster & Pallwal
- 1989 - LeNet Backpropagation to multi-layer perceptron - Yan LeCun
- 1997 - LSTM - Sepp Hochreiter and Jürgen Schmidhuber
- 1998 - LeNet-5 Convolutional neural networks - YanLecun
- 2007 - Fei Fei Li Princeton ImageNet competition
- 2009 - GPU for deep learning - Andrew Ng
- 2011 - Demonstration of ReLu for deep neural networks - Yoshua Bengio
- 2012 - AlexNet wins ImageNet 25% to 16% error
- 2012 - Dropout technique - Geoffrey Hinton
- 2014 - Generative adversarial networks - Ian Goodfellow & Yoshua Bengio
- 2015 - CNN beats human error in ImageNet 5% to 3%
- 2016 - AlphaGo - Goole DeepMind
- 2016 - Detectic cancer beats human pathologist .96 vs 0.99 AUC
- 2017 - Capsule networks - Geoffrey Hinton

History



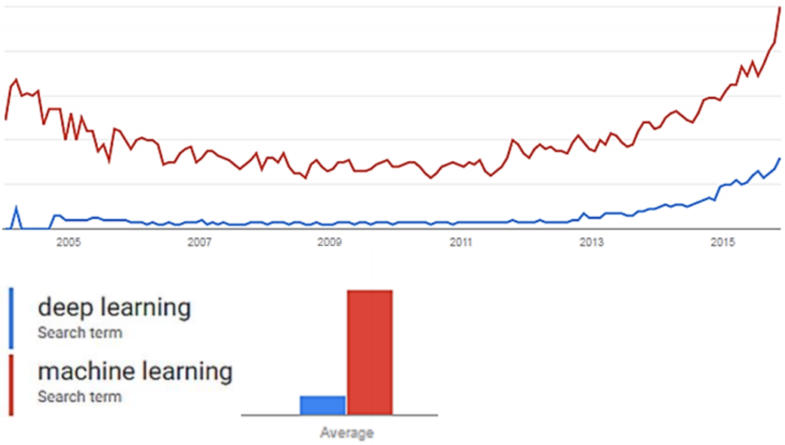
(Reference: Deep Learning basics - Rodrigo Agundez)

Why is DL useful?

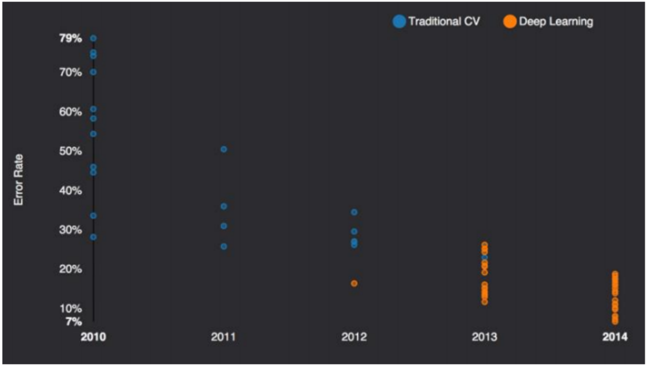
- ML features could be over-specified, incomplete and take longer to design
- DL "invents" features.
- Learned Features are easy to adapt, fast to learn
- Deep learning provides a very flexible, (almost?) universal, learnable framework for representing world, visual and linguistic information

Why is DL useful?

- In 2010 DL started outperforming other ML techniques
- First in speech and vision, then NLP

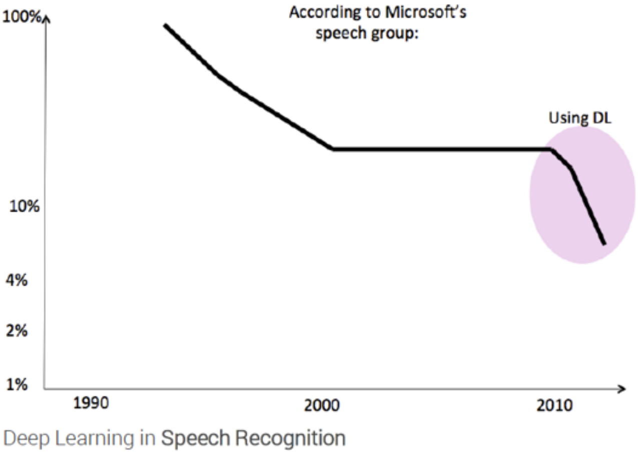


Big Break-through in Vision



(Reference: Introduction to Deep Learning - Ismini Lourentzou)

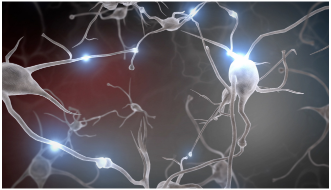
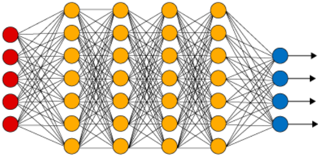
Big Break-through in Speech



(Reference: Introduction to Deep Learning - Ismini Lourentzou)

Deep Learning == Neural Nets

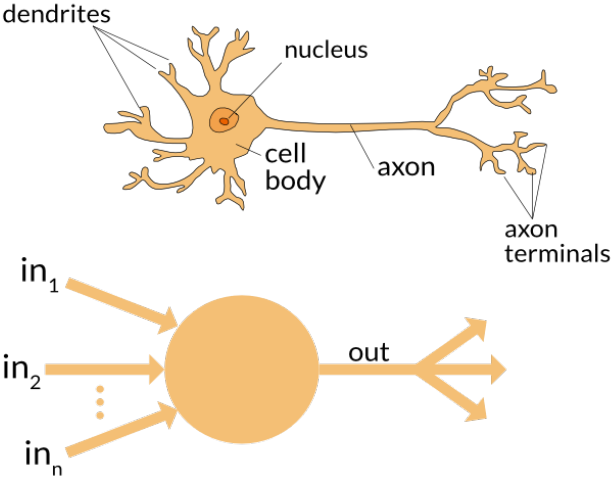
- Main idea of deep learning: transform the input space into outputs via higher level abstractions.
- Neural Net architectures are made up of perceptrons (similar to neurons)
- Each neuron carries certain transformations on inputs coming to it.
- Collection of such neurons with various types of transformations, can create desired overall transformation.

(Reference: Deep Learning basics - Rodrigo Agundez)

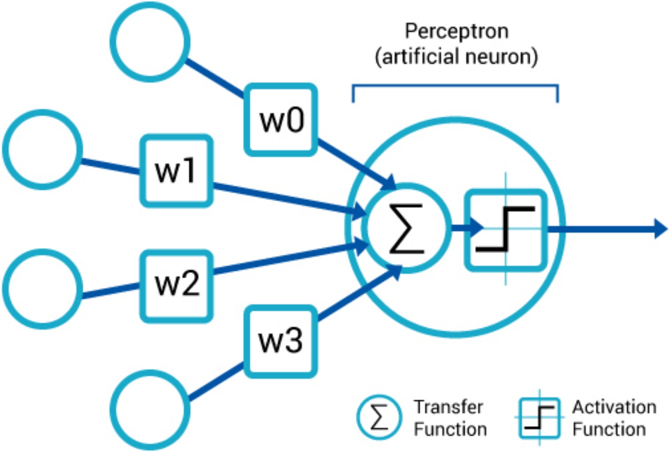
Deep Learning == Neural Nets

First artificial neuron proposed in 1943!



(Reference: Deep Learning basics - Rodrigo Agundez)

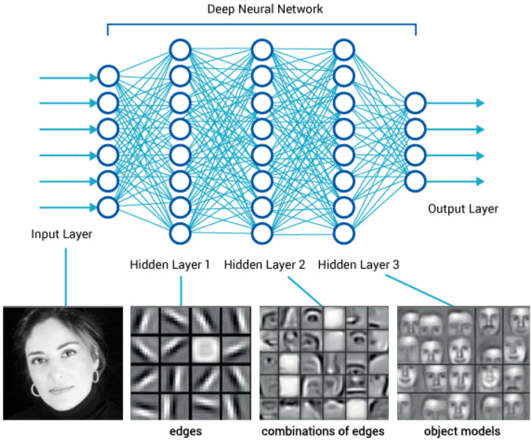
Artificial neuron



(Reference: Deep Learning basics - Rodrigo Agundez)

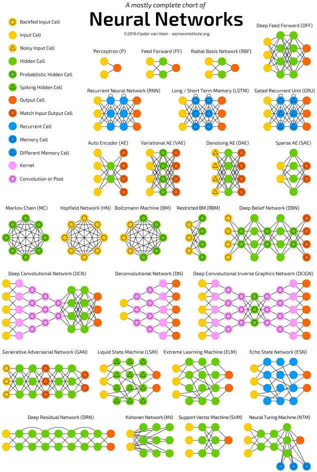
Layers

Hierarchical feature representations



(Reference: Deep Learning basics - Rodrigo Agundez)

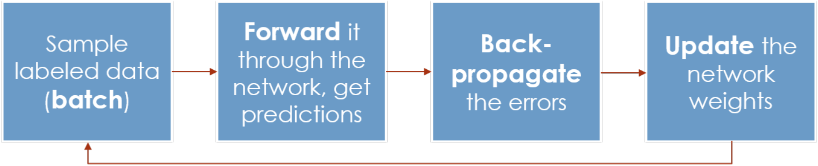
Neural Networks



(Reference: Deep Learning basics - Rodrigo Agundez)

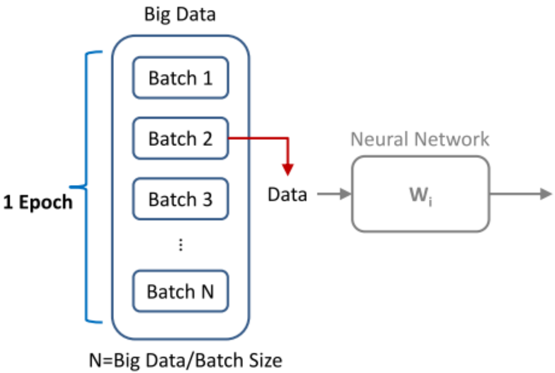
Neural Networks Training Process: Non Mathematical

Training Process: Non Mathematical



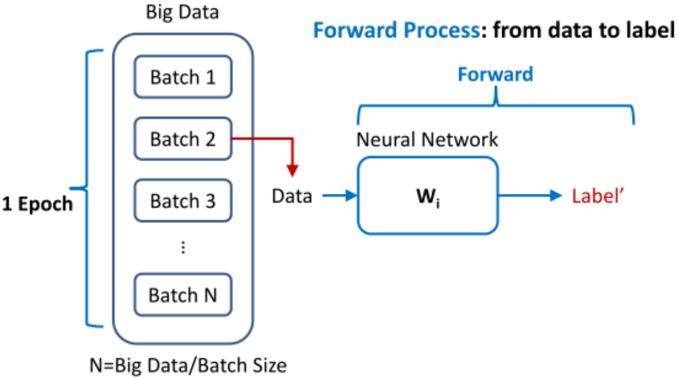
(Reference: Introduction to Deep Learning - Ismini Lourentzou)

Data Enters



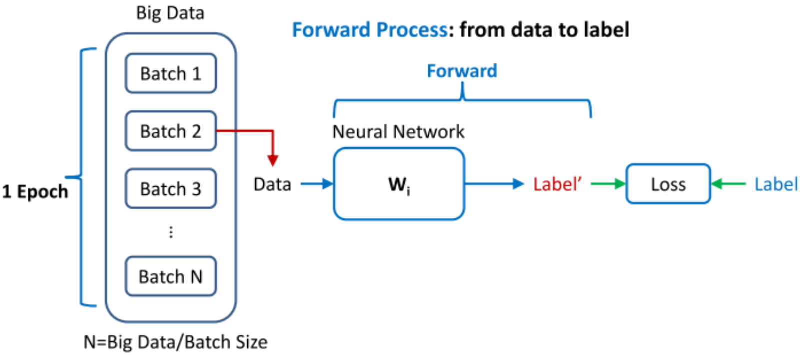
(Reference:PyTorch Tutorial-NTU Machine Learning Course-Lyman Lin)

Forward Pass



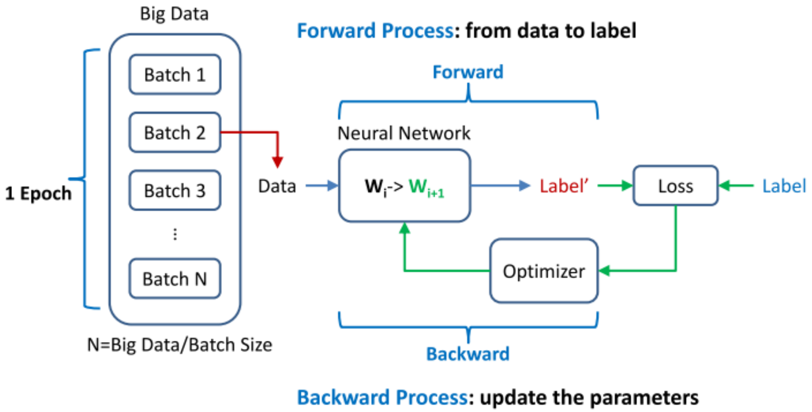
(Reference:PyTorch Tutorial-NTU Machine Learning Course-Lyman Lin)

Loss Calculations



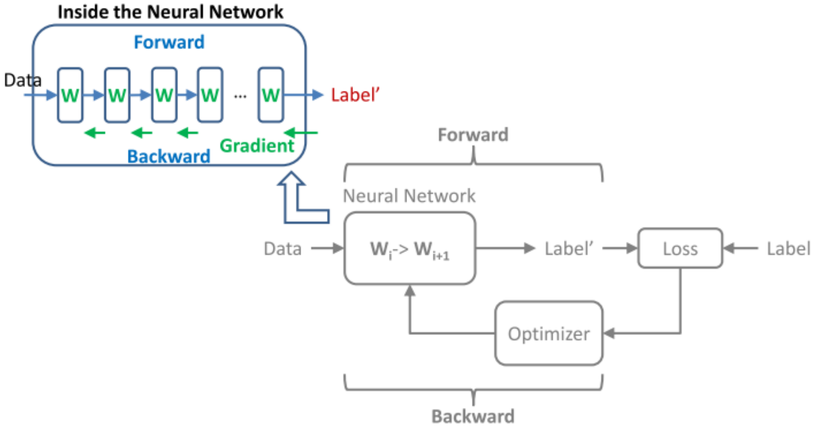
(Reference:PyTorch Tutorial-NTU Machine Learning Course-Lyman Lin)

Back Propagation



(Reference:PyTorch Tutorial-NTU Machine Learning Course-Lyman Lin)

Overall Process



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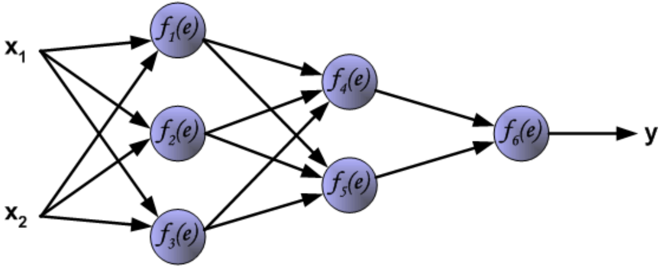
Neural Networks Training Process: Mathematical

Start



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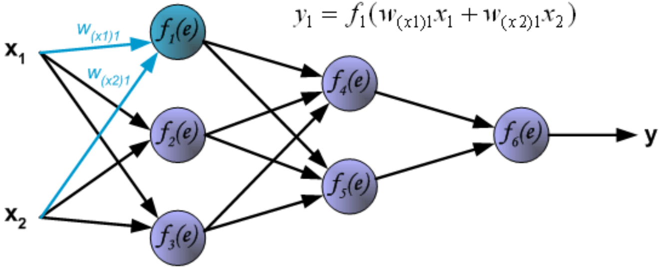
Forward pass



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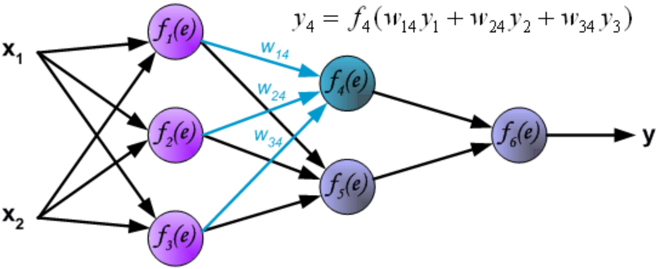
Forward pass



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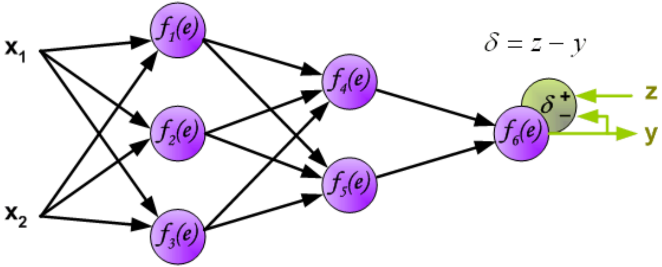
Forward pass



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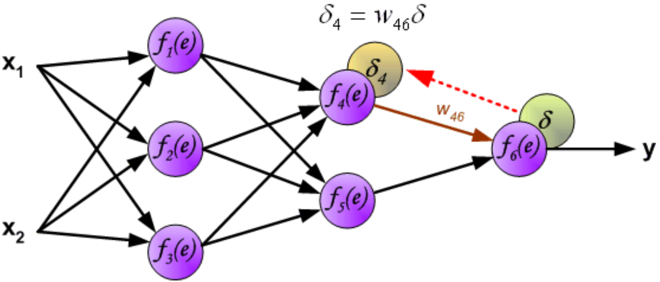
Backpropagation



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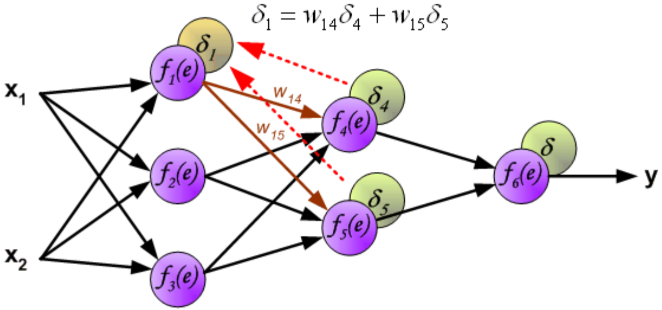
Backpropagation



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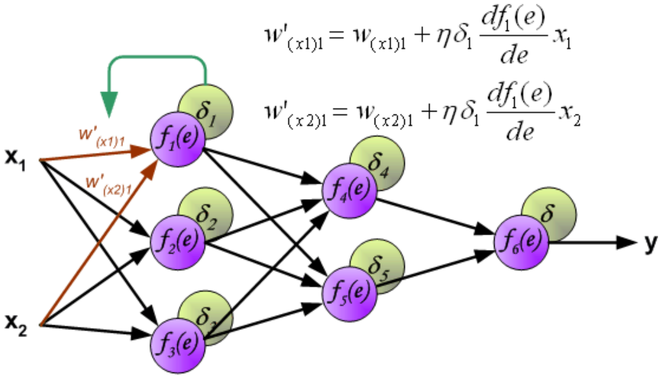
Backpropagation



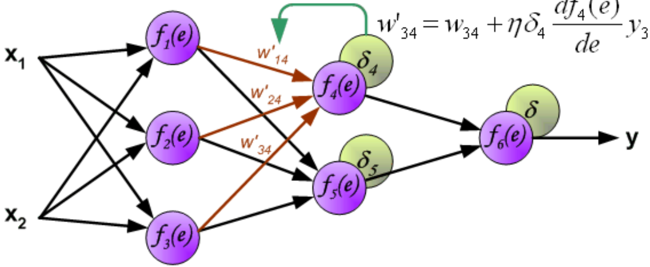
(Reference: Deep Learning basics - Rodrigo Agundez)

Backpropagation

$$w'_{14} = w_{14} + \eta \delta_4 \frac{df_4(e)}{de} y_1$$

$$w'_{24} = w_{24} + \eta \delta_4 \frac{df_4(e)}{de} y_2$$

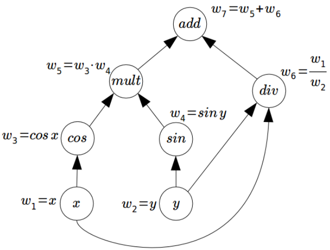
$$w'_{34} = w_{34} + \eta \delta_4 \frac{df_4(e)}{de} y_3$$



(Reference: Deep Learning basics - Rodrigo Agundez)

Backpropagation

- Starts at the end of the net and tunes each layer using the gradient of the loss function. Repeatedly applies the chain rule.
- Numeric approximation: $f'(x) \approx \frac{f(x+h)-f(x)}{h}$
- Symbolic differentiation: Symbolic, exact representation of the derivative.
- Reverse automatic differentiation



$$\frac{\partial w_7}{\partial w_1} = \frac{\partial w_3}{\partial w_1}\frac{\partial w_7}{\partial w_3} + \frac{\partial w_6}{\partial w_1}\frac{\partial w_7}{\partial w_6} = -\sin w_1 \frac{\partial w_7}{\partial w_3} + \frac{1}{w_2}\frac{\partial w_7}{\partial w_6}$$

$$\frac{\partial w_7}{\partial w_2} = \frac{\partial w_4}{\partial w_2}\frac{\partial w_7}{\partial w_4} + \frac{\partial w_6}{\partial w_2}\frac{\partial w_7}{\partial w_6} = \cos w_2 \frac{\partial w_7}{\partial w_4} - \frac{w_1}{w_2^2}\frac{\partial w_7}{\partial w_6}$$

$$\frac{\partial w_7}{\partial w_3} = \frac{\partial w_5}{\partial w_3}\frac{\partial w_7}{\partial w_5} = w_4 \frac{\partial w_7}{\partial w_5}$$

$$\frac{\partial w_7}{\partial w_4} = \frac{\partial w_5}{\partial w_4}\frac{\partial w_7}{\partial w_5} = w_3 \frac{\partial w_7}{\partial w_4}$$

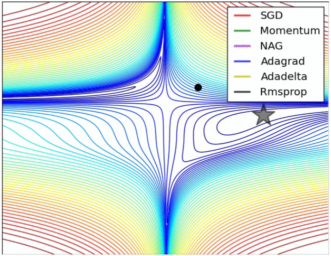
$$\frac{\partial w_7}{\partial w_5} = 1$$

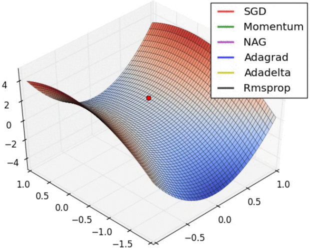
$$\frac{\partial w_7}{\partial w_6} = 1$$

(Reference: Deep Learning basics - Rodrigo Agundez)

Optimization by backpropagation

- Loss/cost function
- Gradient descent





(Reference: Deep Learning basics - Rodrigo Agundez)

Other Aspects

Challenges of Deep Learning

- Explain-ability - How do you learn what you learn?
- Debugging - What has gone wrong?
- Why is this not converging?

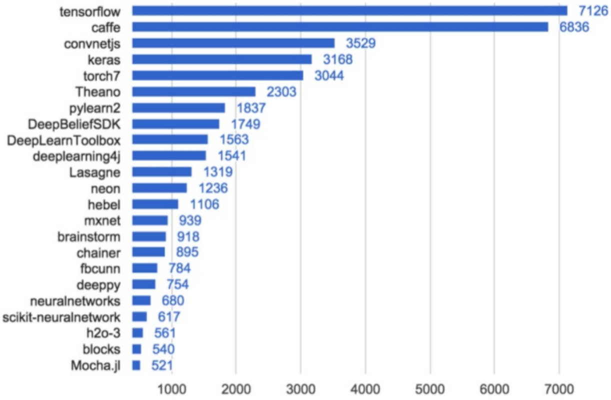
(Reference: AI and Deep Learning - Subrat Panda)

Usage Requirements

- Large data set with good quality (input-output mappings)
- Measurable and describable goals (define the cost)
- Enough computing power (AWS GPU Instance)
- Excels in tasks where the basic unit (pixel, word) has very little meaning in itself, but the combination of such units has a useful meaning.

(Deep Learning - The Past, Present and Future of Artificial Intelligence - Lukas Masuch)

Deep Learning Tools



(Reference: Introduction to Deep Learning - Ismini Lourentzou)

Deep Learning Outlook

- Significant advances in deep reinforcement and unsupervised learning
- Bigger and more complex architectures
- Harder problems being attempted

Introduction to TensorFlow 2.0

TensorFlow is

- Open source, Free library, with Python bindings, by Google Brain team
- Other libraries are: Caffe (Berkeley), Torch (Facebook), Cntk (Microsoft),
- Can deploy computation to one or more CPUs or GPUs in a desktop, server, or mobile device with a single API
- Flexibility: from Raspberry Pi, Android, Windows, iOS, Linux to server farms
- Till 2019 Keras was popular as a separate library (with back-end as Tensorflow) but with Tensorflow 2.0, Keras as become its default front end API.
- TensorFlow 2.0 merges keras as "tf.keras". It allows you to design, fit, evaluate deep learning models.

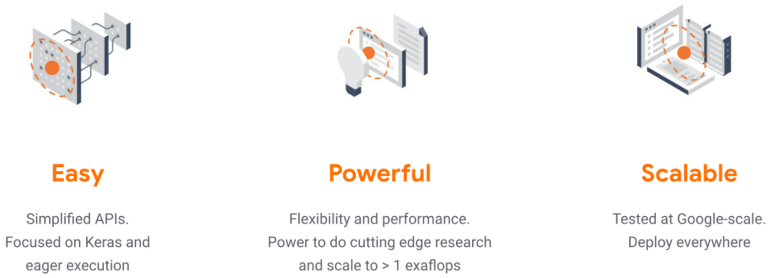
Open Source Community

41,000,000+	69,000+	12,000+	2,200+
downloads	commits	pull requests	contributors

As of Oct 2019 . . .

(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Tensorflow 2.0

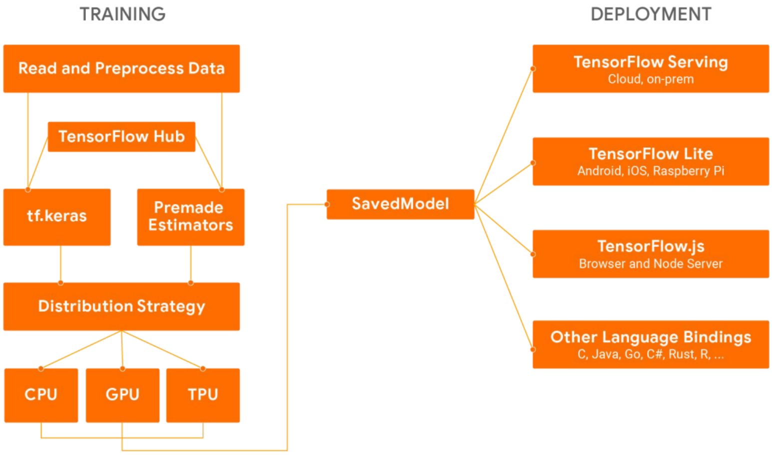


(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Deploy Anywhere

(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Training and Deployment



(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Ecosystem/Verticals

TF Probability

TF Agents

Tensor2Tensor

TF Ranking

TF Text

TF Federated

TF Privacy

...

Ecosystem/Verticals

```
import tensorflow as tf # Assuming TF 2.0 is installed
a = tf.constant([[1, 2],[3, 4]])
b = tf.matmul(a, a)
print(b)
# tf.Tensor( [[ 7 10] [15 22]], shape=(2, 2), dtype=int32)
print(type(b.numpy()))
# <class 'numpy.ndarray'>
```

(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Compared to TF 1.0

What's Gone

- `Session.run`
- `tf.control_dependencies`
- `tf.global_variables_initializer`
- `tf.cond, tf.while_loop`
- `tf.contrib`

(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

What's New

- Eager execution by default
- `tf.function`
- Keras as main high-level api

tf.keras

(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Installation

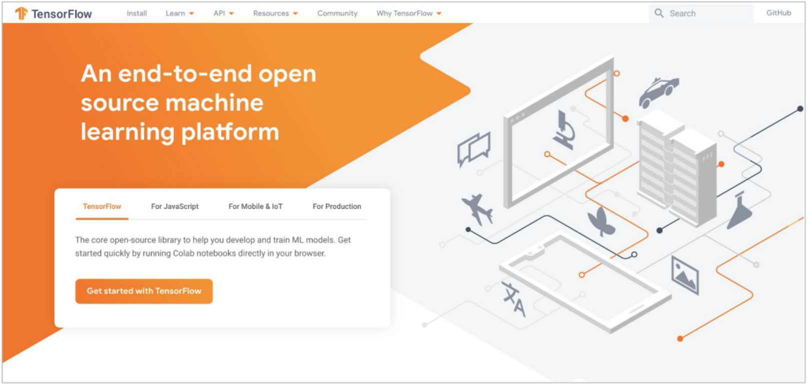
- Have Python installed, such as Python 3.6 or higher.
- Easy way to install TensorFlow
- Linux:

```
sudo pip install tensorflow
```

- Windows:

```
pip install tensorflow
```

Installation



(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Installation Check

- Confirm the installation by:

```python
# check version
import tensorflow
print(tensorflow.__version__)
```

- It must be 2.0 onwards
- If you get warning like below, Don't worry, just IGNORE.

```
Your CPU supports instructions that this TensorFlow binary was not
     compiled to use: AVX2 FMA
XLA service 0x7fde3f2e6180 executing computations on platform Host.
     Devices:
StreamExecutor device (0): Host, Default Version
```

tf.keras

(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Keras and tf .keras

- Fast prototyping, advanced research, and production
- keras.io = reference implementation `import keras`
- tf .keras = TensorFlow's implementation (a superset, built-in to TF, no need to install Keras separately) `from tensorflow import keras`

(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Steps to use tf.Keras

- Define the model.
- Compile the model.
- Fit the model.
- Evaluate the model.
- Make predictions.

Define the Model

- First, select the type of the model.
- Choose architecture or network topology.
- Meaning, define layers, its parameters.
- There are multiple API ways to define the model (will look at later)

```
...
# define the model
model = ...
```

Compile the Model

- Select loss function that you want to optimize, eg Cross Entropy or Mean Squared Error
- Select Optimization method, eg Adam, Stochastic Gradient Descent
- Select performance metrics to be used during Training

```
...
# compile the model
opt = SGD(learning_rate=0.01, momentum=0.9)
model.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
```

Fit the Model

- Select Training configuration (epochs, batch size, etc)
- *Epochs: number of full cycles (forward + backward) during training
- *Batch Size: Number of samples used to estimate model error, or update the weights
- Can take minutes to hours to days depending on complexity, hardware, training samples size.
- Progress bar shows status of each epoch, performance, etc.

```
...
# fit the model
model.fit(X, y, epochs=100, batch_size=32)
```

Evaluate the Model

- Select a holdout dataset (cross validation)
- This is not used for training but just for evaluation as it has correct answers as well.

```
...
# evaluate the model
loss = model.evaluate(X, y, verbose=0)
```

Making Predictions

- Get Test set for which answers have to be found out.
- Better to save the model and later load it to make predictions.
- May choose to fit a model on all of the available data before you start using it.

```
...
# make a prediction
yhat = model.predict(X)
```

Model Definition

API styles

- The Sequential Model
  - Dead simple
  - Only for single-input, single-output, sequential layer stacks
  - Good for 70+% of use cases
- The functional API
  - Like playing with Lego bricks
  - Multi-input, multi-output, arbitrary static graph topologies
  - Good for 95% of use cases
- Model subclassing
  - Maximum flexibility
  - Larger potential error surface

Sequential Model API (Simple)

- Called "Sequential" because it involves using Sequential class and adding layers to it one-by-one, in a sequence.
- E.g. 8 inputs, one hidden layer with 10 nodes, and one output layer with one node to predict numerical value would look:

```
# example of a model defined with the sequential api
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense
# define the model
model = Sequential()
model.add(Dense(10, input_shape=(8,)))
model.add(Dense(1))
```

Note:

- Input layer, per say, is NOT added. Its an argument for the first HIDDEN layer.
- Here 'input_shape' of (8,) means one sample/row is of 8 values. And such, many samples/rows can come, so left blank.

Functional Model API (Advanced)

- Need to explicitly connections between layers.
- Models may have multiple input/output paths (a word and a number)
- Input layer needs to be defined explicitly, like:

```
x_in = Input(shape=(8,))
```

- Next, a fully connected layer can be connected to the input by calling the layer and passing the input layer. This will return a reference to the output connection in this new layer.

```
x = Dense(10)(x_in)
```

- Once connected, we define a Model object and specify the input and output layers.

```
x_in = Input(shape=(8,))
x = Dense(10)(x_in)
x_out = Dense(1)(x)
# define the model
model = Model(inputs=x_in, outputs=x_out)
```

Sub-classing Model API (Very Advanced)

```python
class MyModel(tf.keras.Model):
  def __init__(self, num_classes=10):
    super(MyModel, self).__init__(name='my_model')
    self.dense_1 = layers.Dense(32, activation='relu')
    self.dense_2 = layers.Dense(num_classes, activation='sigmoid')

  def call(self, inputs):
    # Define your forward pass here,
    x = self.dense_1(inputs)
    return self.dense_2(x)
```

Understanding deferred (symbolic) vs. eager (imperative)

- Deferred: Build a computation graph that gets compiled first and then once values are filled, executed later
- Eager: Model is a python exe,Execution is runtime (like Numpy)
- Deferred: Symbolic tensors don't have a value in your Python code (yet)
- Eager: tensors have a value in your Python code
- Eager: can use value-dependent dynamic topologies (tree-RNNs)

Sample eager execution code

```
lstm_cell = tf.keras.layers.LSTMCell(10)

def fn(input, state):
  return lstm_cell(input, state)

input = tf.zeros([10, 10]); state = [tf.zeros([10, 10])] * 2
lstm_cell(input, state); fn(input, state) # warm up
# benchmark
timeit.timeit(lambda: lstm_cell(input, state), number=10) # 0.03
```

Let's make this faster

```python
lstm_cell = tf.keras.layers.LSTMCell(10)

@tf.function
def fn(input, state):
  return lstm_cell(input, state)

input = tf.zeros([10, 10]); state = [tf.zeros([10, 10])] * 2
lstm_cell(input, state); fn(input, state) # warm up
# benchmark
timeit.timeit(lambda: lstm_cell(input, state), number=10) # 0.03
```

AutoGraph makes this possible

Say, for a sample function

```
@tf.function
def f(x):
  while tf.reduce_sum(x) > 1:
    x = tf.tanh(x)
  return x
# you never need to run this (unless curious)
print(tf.autograph.to_code(f))
```

Generated code

We need not undesrtand this, but still . . .

```
def tf__f(x):
  def loop_test(x_1):
    with ag__.function_scope('loop_test'):
      return ag__.gt(tf.reduce_sum(x_1), 1)
  def loop_body(x_1):
    with ag__.function_scope('loop_body'):
      with ag__.utils.control_dependency_on_returns(tf.print(x_1)):
        tf_1, x = ag__.utils.alias_tensors(tf, x_1)
        x = tf_1.tanh(x)
        return x,
  x = ag__.while_stmt(loop_test, loop_body, (x,), (tf,))
  return x
```

tf .distribute.Strategy

For the sample code below . . .

```
model = tf.keras.models.Sequential([
     tf.keras.layers.Dense(64, input_shape=[10]),
     tf.keras.layers.Dense(64, activation='relu'),
     tf.keras.layers.Dense(10, activation='softmax')])
 model.compile(optimizer='adam',
               loss='categorical_crossentropy',
               metrics=['accuracy'])
```

Multi-GPU

One of the computations distribution strategy could be . . .

```
strategy = tf.distribute.MirroredStrategy()
with strategy.scope():
  model = tf.keras.models.Sequential([
      tf.keras.layers.Dense(64, input_shape=[10]),
      tf.keras.layers.Dense(64, activation='relu'),
      tf.keras.layers.Dense(10, activation='softmax')])
  model.compile(optimizer='adam',
                loss='categorical_crossentropy',
                metrics=['accuracy'])
```

TensorFlow Datasets

- audio
  - "nsynth"
- image
  - "cifar10"
  - "diabetic_retinopathy_detection"
  - "imagenet2012"
  - "mnist"
- structured
  - "titanic"
- text
  - "imdb_reviews"
  - "lm1b"
  - "squad"
- translate
  - "wmt_translate_ende"
  - "wmt_translate_enfr"
- video
  - "bair_robot_pushing_small"
  - "moving_mnist"
  - "starcraft_video"

More at tensorflow.org/datasets

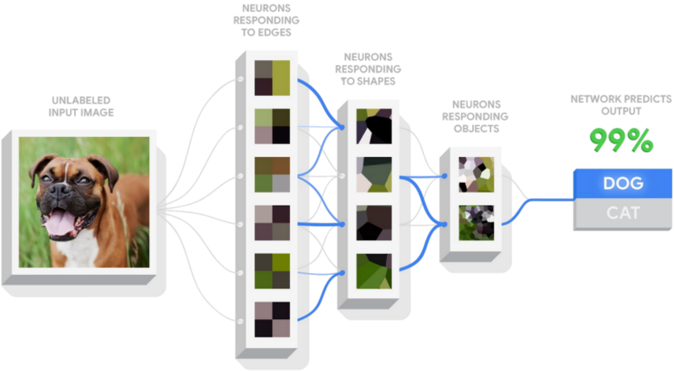
(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Terminologies

In the neural network terminology:

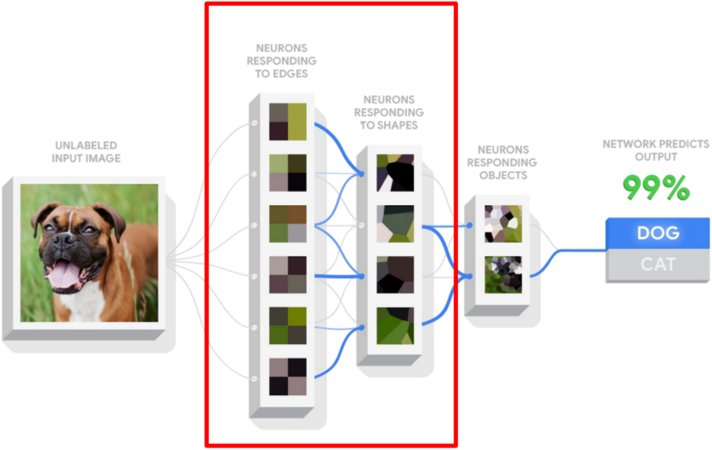
- one epoch = one forward pass and one backward pass of all the training examples
- batch size = the number of training examples in one forward/backward pass. The higher the batch size, the more memory space you'll need.
- number of iterations = number of passes, each pass using [batch size] number of examples. To be clear, one pass = one forward pass + one backward pass (we do not count the forward pass and backward pass as two different passes).
- Example: if you have 1000 training examples, and your batch size is 500, then it will take 2 iterations to complete 1 epoch.

Transfer Learning



(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Transfer Learning



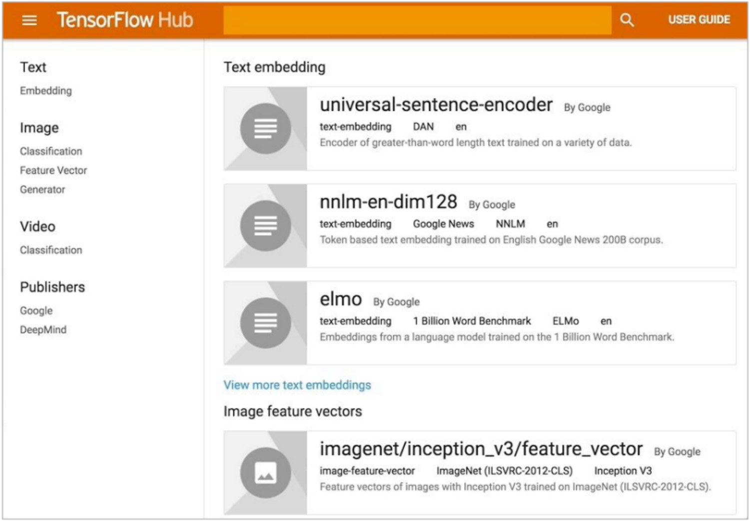
(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Transfer Learning

```
import tensorflow as tf
base_model = tf.keras.applications.SequentialMobileNetV2(
                 input_shape=(160, 160, 3),
                 include_top=False,
                 weights='imagenet')
base_model.trainable = False
model = tf.keras.models.Sequential([
  base_model,
  tf.keras.layers.GlobalAveragePooling2D(),
  tf.keras.layers.Dense(1)
])
# Compile and fit
```

(Ref: Introduction to TensorFlow 2.0 - Brad Miro)

Transfer Learning



References

Many publicly available resources have been refereed for making this presentation. Some of the notable ones are:

- TensorFlow 2 Tutorial: Get Started in Deep Learning With tf.keras - Jason Brownlee
- Deep Learning using Keras- Alyosamah
- Introduction to Keras - Francois Chollet
- Michael Nielsen's Neural Networks and Deep Learning: http://neuralnetworksanddeeplearning.com/

Thanks ... yogeshkulkarni@yahoo.com