

# **2017 Predictive Analytics Symposium**

## **Session 22, TensorFlow (workshop)**

### **Moderator:**

Stuart Klugman, FSA, CERA, Ph.D.

### **Presenter:**

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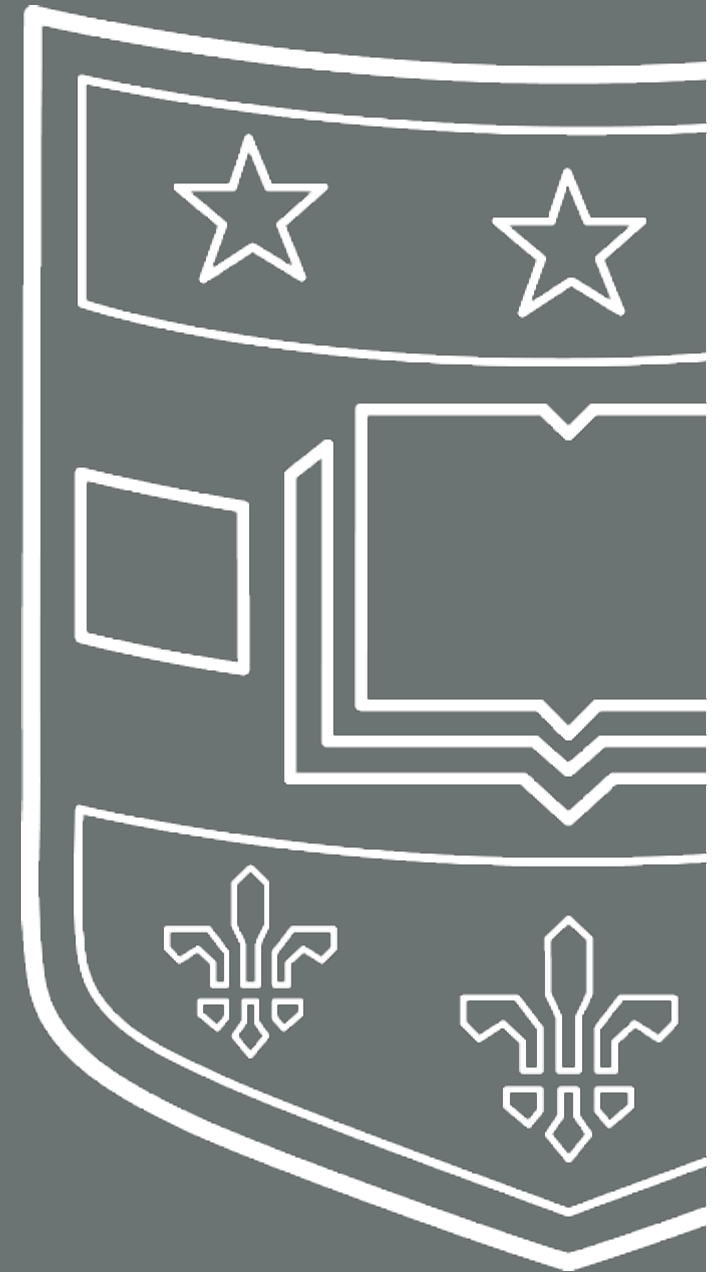
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# Session 22: TensorFlow (workshop)

Presented by Jeff Heaton, Ph.D.

September 14, 2017 – SOA Predictive Analytics Symposium.





# Jeff Heaton, Ph.D.

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- Adjunct Instructor at Washington University
- Fellow of the Life Management Institute (FLMI)
- Senior Member of IEEE
- Kagglер (Expert level)
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# T81-558: Applications of Deep Learning



- **Course Website:** <https://sites.wustl.edu/jeffheaton/t81-558/>
- **Instructor Website:** <https://sites.wustl.edu/jeffheaton/>
- **Course Videos:** <https://www.youtube.com/user/HeatonResearch>

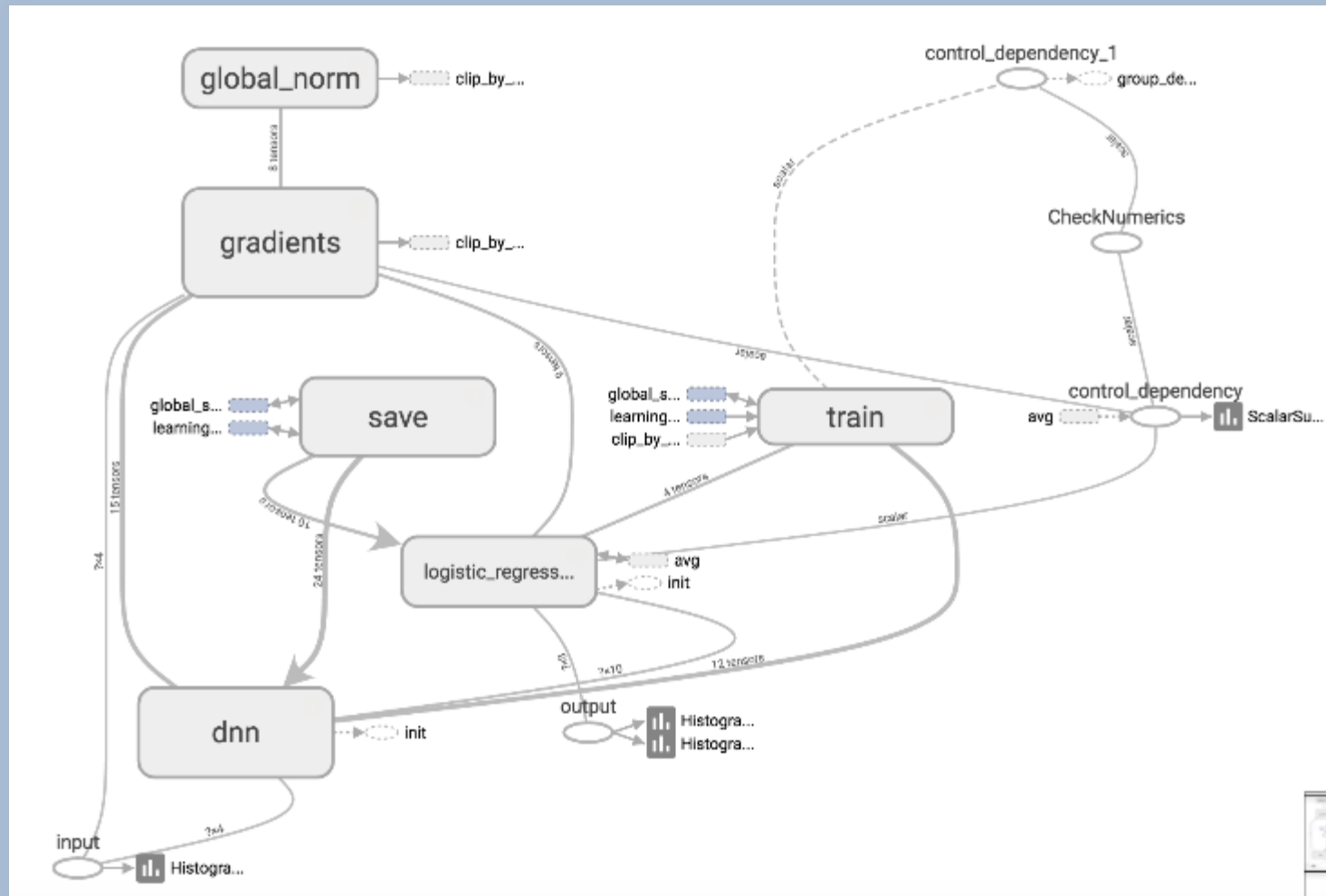




# Presentation Outline

- TensorFlow as a Compute Graph/Engine
- Keras and TensorFlow
- Keras: Classification
- Keras: Regression
- Keras: Computer Vision and CNN
- Keras: Time Series and RNN
- GPU

# TensorFlow as a Compute Graph/Engine





# What are Tensors? Why are they flowing?

- Tensor of Rank 0 (or scalar) – simple variable
- Tensor of Rank 1 (or vector) – array/list
- Tensor of Rank 2 (or matrix) – 2D array
- Tensor of Rank 3 (or cube) – 3D array
- Tensor of Rank 4 (tesseract/hypercube) – 4D array
- Higher ranks (hypercube) – nD array



# What is a Computation Graph?

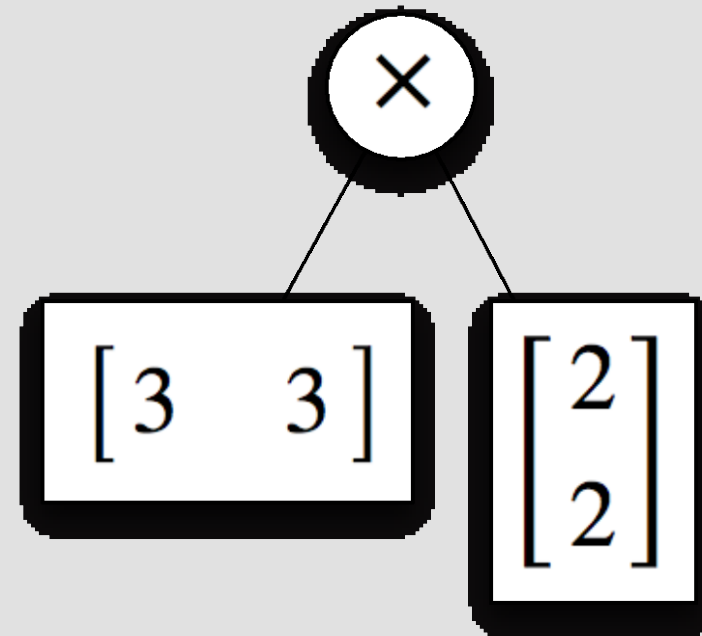
```
import tensorflow as tf

matrix1 = tf.constant([[3., 3.]])
matrix2 = tf.constant([[2.],[2.]])
product = tf.matmul(matrix1, matrix2)

with tf.Session() as sess:
    result = sess.run([product])

print(result)
```

$$\begin{bmatrix} 3 & 3 \end{bmatrix} \times \begin{bmatrix} 2 \\ 2 \end{bmatrix} = [3 \times 2 + 3 \times 2] = [12]$$







# Computation Graph with Variables

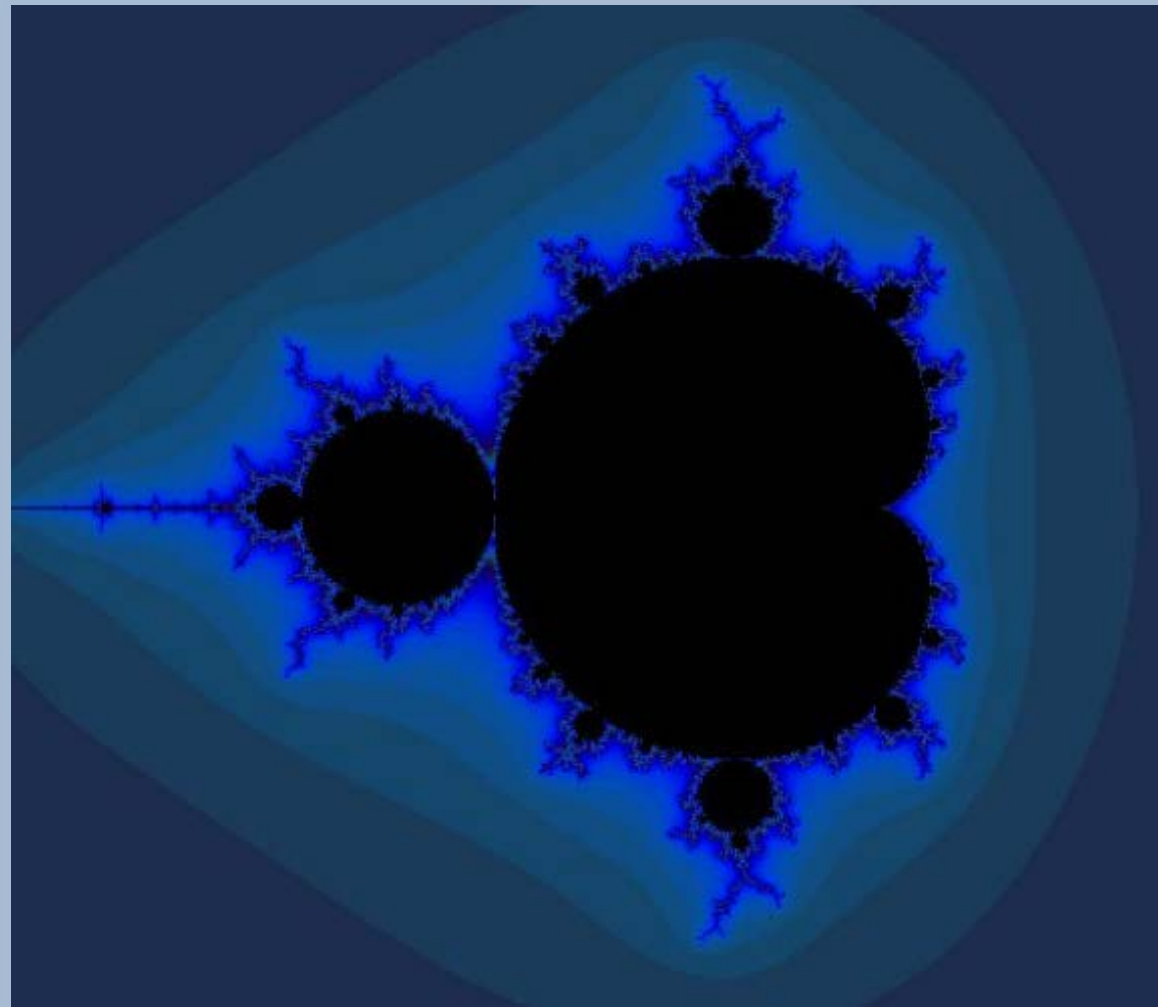
```
import tensorflow as tf
sess = tf.InteractiveSession()
```

```
x = tf.Variable([1.0, 2.0])
a = tf.constant([3.0, 3.0])
x.initializer.run()
```

```
sub = tf.subtract(x, a)
print(sub.eval())
# ==> [-2. -1.]
```

```
sess.run(x.assign([4.0, 6.0]))
print(sub.eval())
# ==> [1. 3.]
```

# Computation Graph for Mandelbrot Set





# Mandelbrot Set Review

- Some point  $c$  is a complex number with  $x$  as the real part,  $y$  as the imaginary part.
- $z_0 = 0$
- $z_1 = c$
- $z_2 = z_1^2 + c$
- ...
- $z_{n+1} = z_n^2 + c$



# Mandelbrot Rendering in TensorFlow

```
xs = tf.constant(Z.astype(np.complex64))
zs = tf.Variable(xs)
ns = tf.Variable(tf.zeros_like(xs, tf.float32))
tf.global_variables_initializer().run()
# Compute the new values of z: z^2 + x
zs_ = zs*zs + xs
# Have we diverged with this new value?
not_diverged = tf.abs(zs_) < 4
step = tf.group(
    zs.assign(zs_),
    ns.assign_add(tf.cast(not_diverged, tf.float32))
)
for i in range(200): step.run()
```

# Keras and TensorFlow





# Tools Used in this Presentation

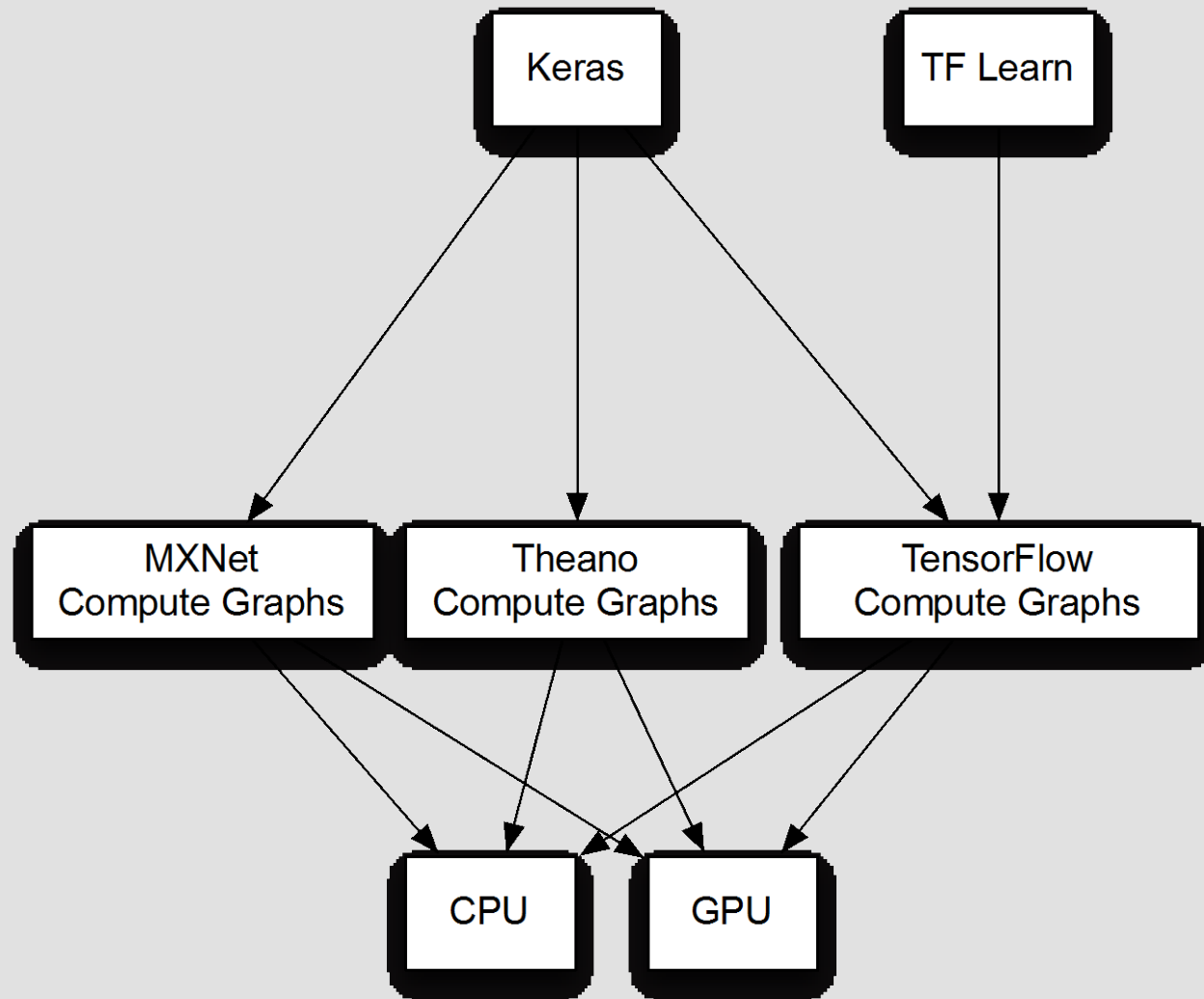
- Anaconda Python 3.6
- Google TensorFlow 1.2
- Keras 2.0.6
- Scikit-Learn
- Jupyter Notebooks



# Installing These Tools

- Install Anaconda Python 3.6
- Then run the following:
  - `conda install scipy`
  - `pip install sklearn`
  - `pip install pandas`
  - `pip install pandas-datareader`
  - `pip install matplotlib`
  - `pip install pillow`
  - `pip install requests`
  - `pip install h5py`
  - `pip install tensorflow==1.2.1`
  - `pip install keras==2.0.6`

# Keras and TensorFlow



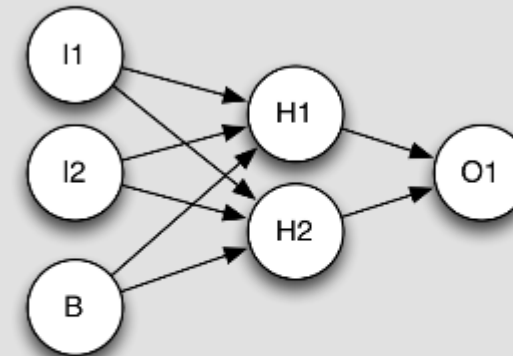




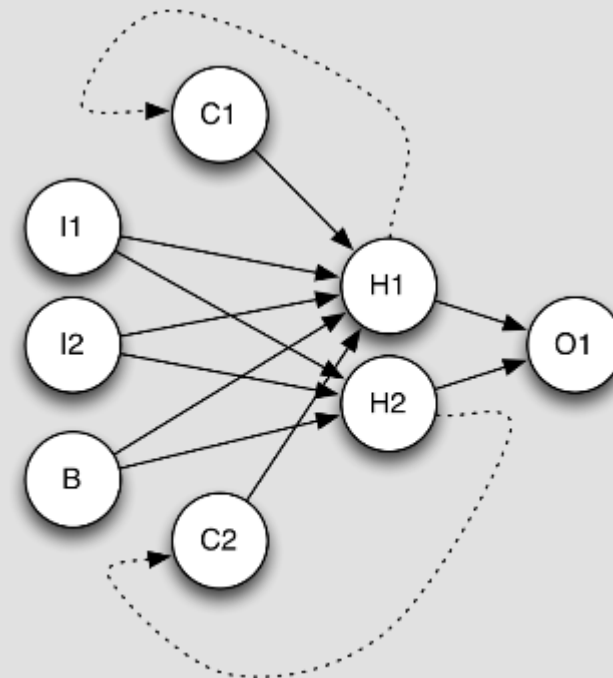
# Anatomy of a Neural Network

- **Input Layer** – Maps inputs to the neural network.
- **Hidden Layer(s)** – Helps form prediction.
- **Output Layer** – Provides prediction based on inputs.
- **Context Layer** – Holds state between calls to the neural network for predictions.

Feedforward Neural Network



Recurrent Neural Network





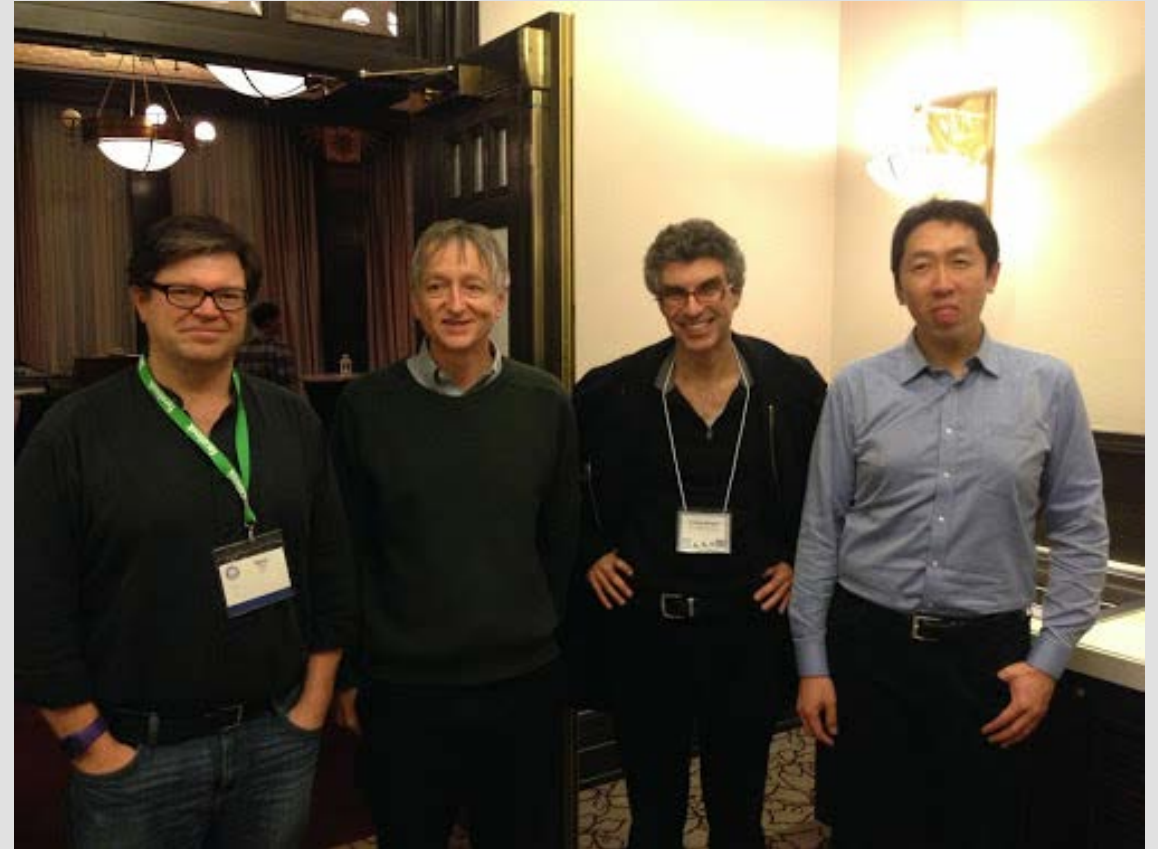
# What is Deep Learning

- Deep learning is almost always applied to neural networks.
- A deep neural network has more than 2 hidden layers.
- Deep neural networks have existed as long as traditional neural networks.
  - We just did not have a way to train deep neural networks.
  - Hinton (et al.) introduced a means to train deep belief neural networks in 2006.
- Neural networks have risen three times and fallen twice in their history. Currently, they are on the rise.

# The True Believers – Luminaries of Deep Learning



- From left to right:
- Yann LeCun
- Geoffrey Hinton
- Yoshua Bengio
- Andrew Ng





# Why Use Deep Learning

- Deep neural networks often accomplish the same task as other models, such as:
  - Support Vector Machines
  - Random Forests
  - Gradient Boosted Machines
- For many problems deep learning will give a less accurate answer than the other models.
- However, for certain problems, deep neural networks perform considerably better than other models.

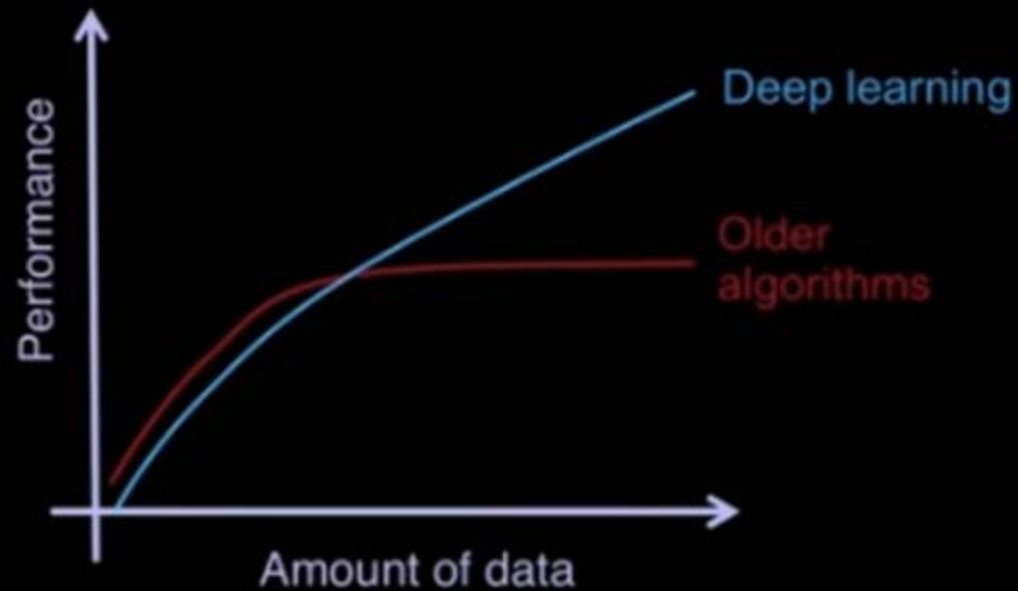
# Why Deep Learning (high y-axis is good)



Andrew Ng on Deep Learning

where AI will learn from untagged data

Learning from tagged data



Baidu 百度



# Supervised or Unsupervised?



## Supervised Machine Learning

- Usually classification or regression.
- For an input, the correct output is provided.
- Examples of supervised learning:
  - Propensity to buy
  - Credit scoring

## Unsupervised Machine Learning

- Usually clustering.
- Inputs analyzed without any specification of a correct output.
- Examples of unsupervised learning:
  - Clustering
  - Dimension reduction



# Types of Machine Learning Algorithm

- **Clustering:** Group records together that have similar field values. For example, customers with common attributes in a propensity to buy model.
- **Regression:** Learn to predict a numeric outcome field, based on all of the other fields present in each record. For example, predict the amount of coverage a potential customer might buy.
- **Classification:** Learn to predict a non-numeric outcome field. For example, learn the type of policy an existing customer has a potential of buying next.

# Application of Machine Learning Algorithm



	<b>Predictive Modeling</b>	<b>Computer Vision</b>	<b>Time Series</b>
<b>Classification</b>	<ul style="list-style-type: none"><li>• Intrusion Detection</li></ul>	<ul style="list-style-type: none"><li>• Face Recognition</li></ul>	<ul style="list-style-type: none"><li>• Buy, Sell, or Hold?</li><li>• Intrusion Detection</li></ul>
<b>Regression</b>	<ul style="list-style-type: none"><li>• Normal Operating Levels</li></ul>	<ul style="list-style-type: none"><li>• Age Determination</li></ul>	<ul style="list-style-type: none"><li>• Tomorrow's opening stock price</li></ul>
<b>Clustering</b>	<ul style="list-style-type: none"><li>• Product Recommendation</li></ul>	<ul style="list-style-type: none"><li>• Design Recommendation</li></ul>	<ul style="list-style-type: none"><li>• Anomaly Detection</li></ul>



# Problems that Deep Learning is Well Suited to



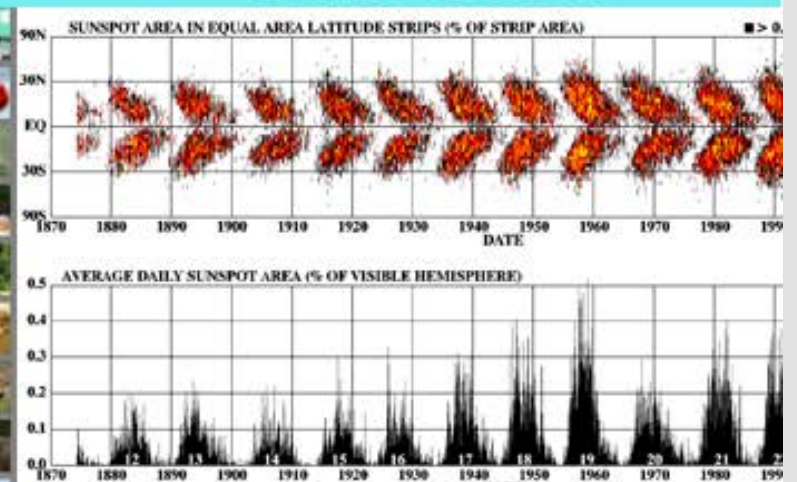
## Predictive Modeling

Sepal length ◊	Sepal width ◊	Petal length ◊	Petal width ◊	Species ◊
5.1	3.5	1.4	0.2	<i>I. setosa</i>
4.9	3.0	1.4	0.2	<i>I. setosa</i>
4.7	3.2	1.3	0.2	<i>I. setosa</i>
4.6	3.1	1.5	0.2	<i>I. setosa</i>
5.0	3.6	1.4	0.2	<i>I. setosa</i>
5.4	3.9	1.7	0.4	<i>I. setosa</i>
4.6	3.4	1.4	0.3	<i>I. setosa</i>
5.0	3.4	1.5	0.2	<i>I. setosa</i>
4.4	2.9	1.4	0.2	<i>I. setosa</i>
4.9	3.1	1.5	0.1	<i>I. setosa</i>
5.4	3.7	1.5	0.2	<i>I. setosa</i>

## Computer Vision



## Time Series



# Keras: Classification





# The Classic Iris Dataset

- Classic classification problem.
- 150 rows with 4 predictor columns.
- All 150 rows are labeled as a species of iris.
- Three different iris species.
- Created by Sir Ronald Fisher in 1936.
- Predictors:
  - Petal length
  - Petal width
  - Sepal length
  - Sepal width

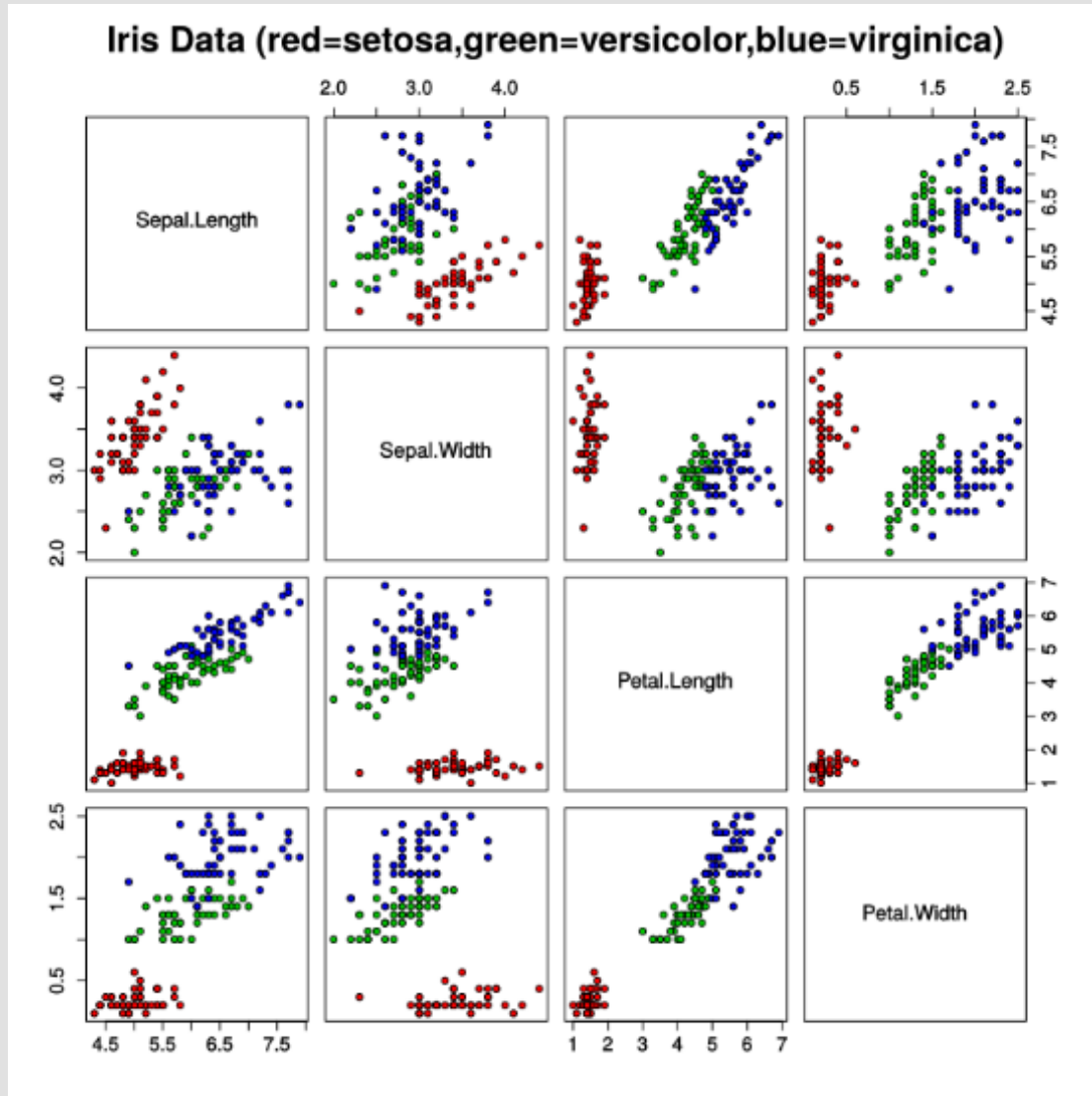


# The Classic Iris Dataset



sepal_length	sepal_width	petal_length	petal_width	class
5.1	3.5	1.4	0.2	Iris-setosa
7.0	3.2	4.7	1.4	Iris-versico
6.3	3.3	6.0	2.5	Iris-virginica
6.4	3.2	4.5	1.5	Iris-versicolor
5.8	2.7	5.1	1.9	Iris-virginica
4.9	3.0	1.4	0.2	Iris-setosa
...	...	...	...	...

# Are the Iris Data Predictive?





# Keras Classification: Load and Train/Test Split

```
path = "./data/"

filename = os.path.join(path, "iris.csv")
df = pd.read_csv(filename, na_values=['NA', '?'])

species = encode_text_index(df, "species")
x, y = to_xy(df, "species")

# Split into train/test
x_train, x_test, y_train, y_test = train_test_split(
    x, y, test_size=0.25, random_state=42)
```



# Keras Classification: Build NN and Fit

```
model = Sequential()  
model.add(Dense(10, input_dim=x.shape[1],  
kernel_initializer='normal', activation='relu'))  
model.add(Dense(1, kernel_initializer='normal'))  
model.add(Dense(y.shape[1], activation='softmax'))  
model.compile(loss='categorical_crossentropy', optimizer='adam')  
monitor = EarlyStopping(monitor='val_loss', min_delta=1e-3,  
patience=5, verbose=1, mode='auto')  
  
model.fit(x,y,validation_data=(x_test,y_test),callbacks=[monitor],ve  
rbose=2,epochs=1000)
```



# Keras Classification: Build NN and Fit

```
# Evaluate success using accuracy
# raw probabilities to chosen class (highest probability)
pred = model.predict(x_test)

pred = np.argmax(pred,axis=1)

y_compare = np.argmax(y_test,axis=1)
score = metrics.accuracy_score(y_compare, pred)
print("Accuracy score: {}".format(score))
```



# Keras: Regression



# Predict a Car's Miles Per Gallon (MPG)



- Classic regression problem.
- Target: mpg
- Predictors:
  - cylinders
  - displacement
  - horsepower
  - weight
  - acceleration
  - year
  - origin
  - name

# Predict a Car's Miles Per Gallon (MPG)



mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	name
18	8	307	130	3504	12	70	1	chevrolet chevelle malibu
15	8	350	165	3693	11.5	70	1	buick skylark 320
18	8	318	150	3436	11	70	1	plymouth satellite
16	8	304	150	3433	12	70	1	amc rebel sst
17	8	302	140	3449	10.5	70	1	ford torino
15	8	429	198	4341	10	70	1	ford galaxie 500
14	8	454	220	4354	9	70	1	chevrolet impala



# Regression Models - MPG

- Models such as GBM or Neural Network can predict the MPG to around +/-2.7 accuracy.
- Result of regression can be given in equation form (though not as accurate as a model):

$$mpg = 0.002 \left( acc + \frac{1}{3}(-dsp - 1) - wgt \right) + 29.6$$



# Keras Regression: Load and Train/Test Split

```
path = "./data/"

filename_read = os.path.join(path, "auto-mpg.csv")
df = pd.read_csv(filename_read, na_values=['NA', '?'])

cars = df['name']
df.drop('name', 1, inplace=True)
missing_median(df, 'horsepower')
x, y = to_xy(df, "mpg")
```



# Keras Regression: Build and Fit

```
model = Sequential()  
model.add(Dense(10, input_dim=x.shape[1],  
kernel_initializer='normal', activation='relu'))  
model.add(Dense(1, kernel_initializer='normal'))  
model.compile(loss='mean_squared_error', optimizer='adam')  
monitor = EarlyStopping(monitor='val_loss', min_delta=1e-3,  
patience=5, verbose=1, mode='auto')  
model.fit(x,y,validation_data=(x_test,y_test),callbacks=[monitor],ve  
rbose=2,epochs=1000)
```

# Keras Regression: Predict and Evaluate



```
# Predict
pred = model.predict(x_test)

# Measure RMSE error. RMSE is common for regression.
score = np.sqrt(metrics.mean_squared_error(pred, y_test))
print("Final score (RMSE): {}".format(score))
```



# Preparing Data for Predictive Modeling is Hard

- The iris and MPG datasets are nicely formatted.
- Real world data is a complex mix of XML, JSON, textual formats, binary formats, and web service accessed content (the variety  $V$  in “Big Data”).
- More complex security data will be presented later in this talk.



# Keras: Computer Vision and CNN

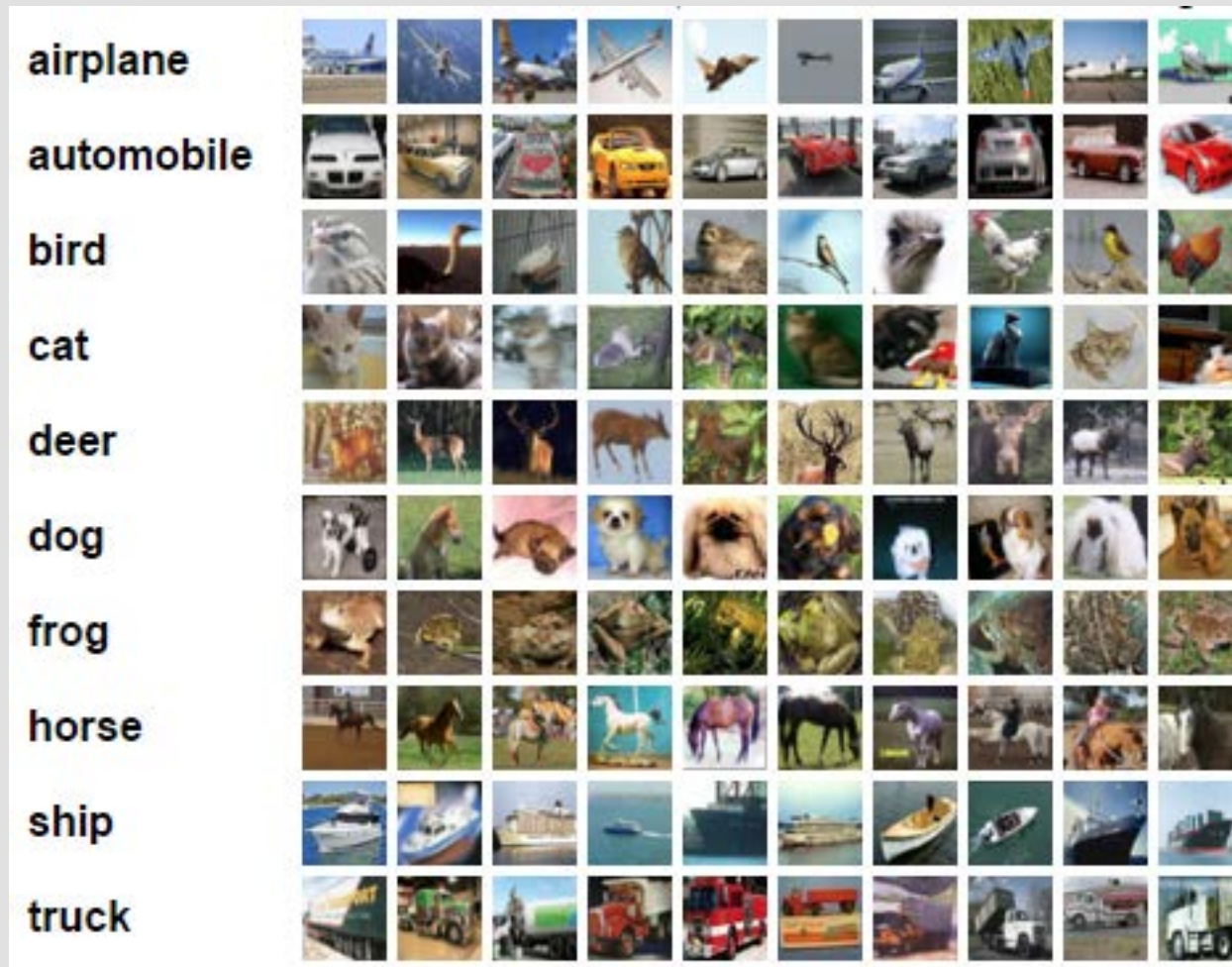




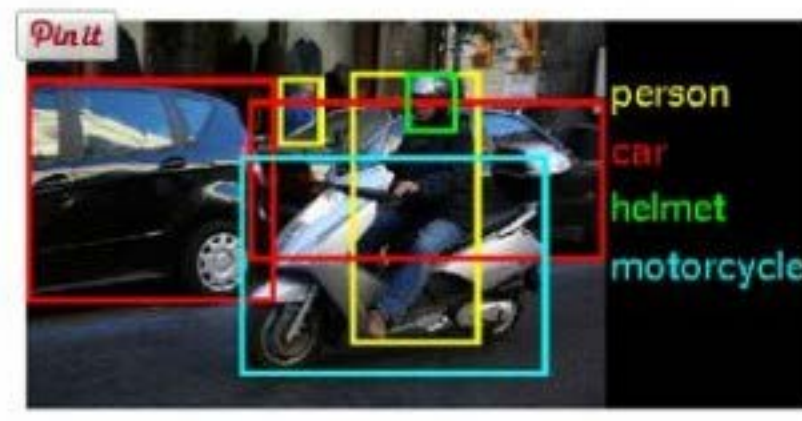
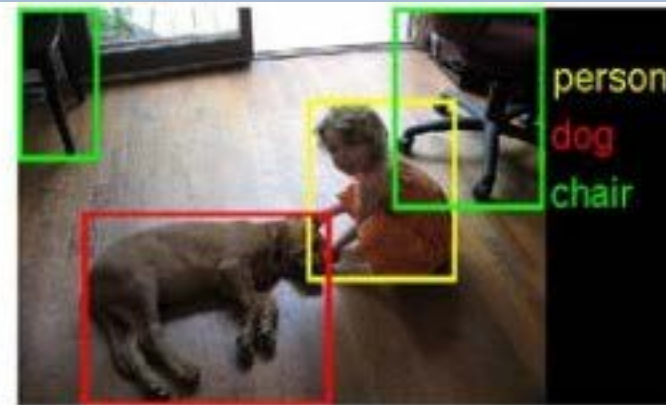
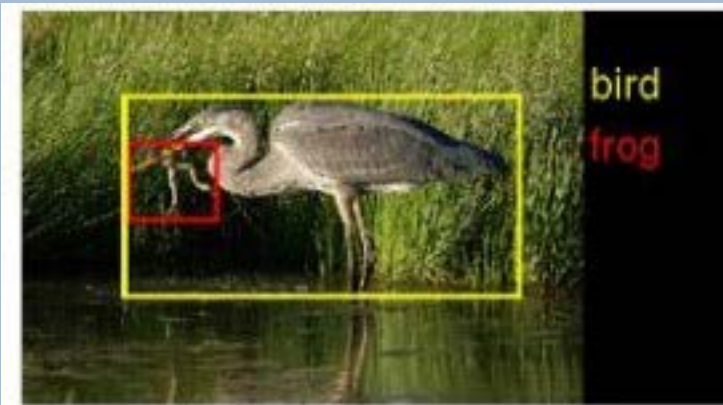
# Predicting Images: What is Different?

- We will usually use classification, though regression is still an option.
- The input to the neural network is now 3D (height, width, color).
- Data are not transformed, no zscores or dummy variables.
- Processing time is usually much longer.
- We now have different layer types: dense layers (just like before), convolution layers and max pooling layers.
- Data will no longer arrive as CSV files. TensorFlow provides some utilities for going directly from image to the input of a neural network.

# Sources of Image Data: CIFAR10 and CIFAR100



# Sources of Image Data: ImageNet





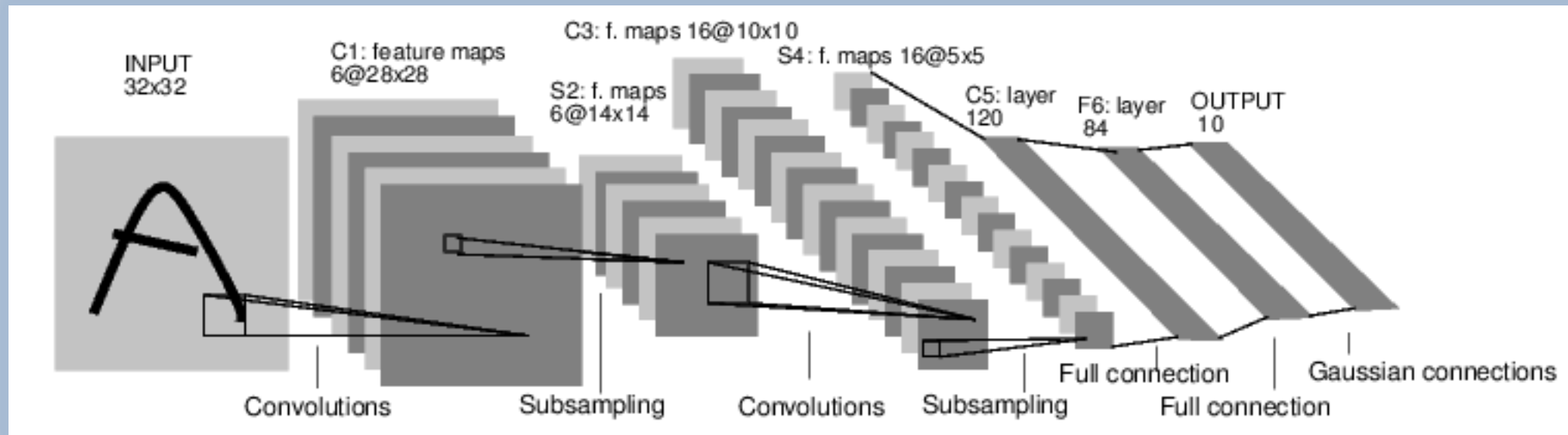
# Recognizing Digits





# Convolutional Neural Networks (CNN)

## A LeNET-5/CNN Network (LeCun, 1998)



**Dense Layers** - Fully connected layers.

**Convolution Layers** - Used to scan across images.

**Max Pooling Layers** - Used to downsample images.

**Dropout Layer** - Used to add regularization.



# Loading the Digits

```
(x_train, y_train), (x_test, y_test) = mnist.load_data()  
print("Shape of x_train: {}".format(x_train.shape))  
print("Shape of y_train: {}".format(y_train.shape))  
print()  
print("Shape of x_test: {}".format(x_test.shape))  
print("Shape of y_test: {}".format(y_test.shape))
```

→Shape of x\_train: (60000, 28, 28)

→Shape of y\_train: (60000,)

→Shape of x\_test: (10000, 28, 28)

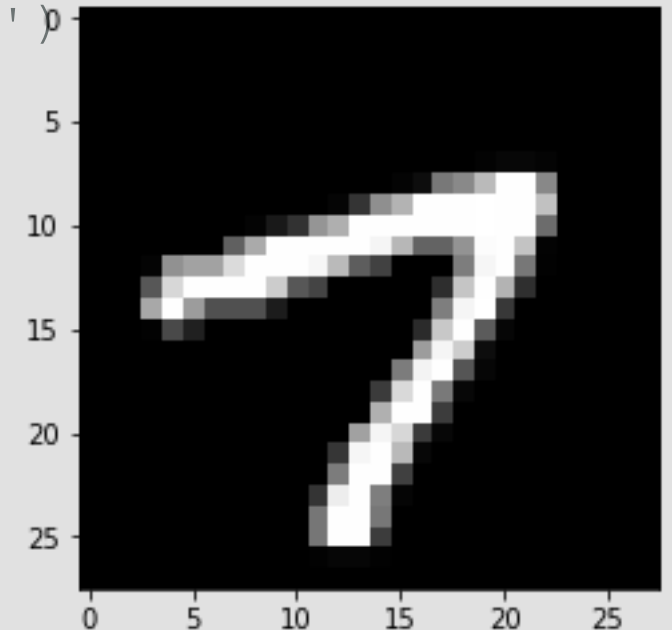
→Shape of y\_test: (10000,)





# Display a Digit

```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
digit = 101 # Change to choose new digit
a = x_train[digit]
plt.imshow(a, cmap='gray', interpolation='nearest')
print("Image ({}) : Which is digit '{}'".
      format(digit, y_train[digit]))
```





# Build the CNN Network

```
model = Sequential()  
model.add(Conv2D(32, kernel_size=(3, 3),  
                activation='relu',  
                input_shape=input_shape))  
model.add(Conv2D(64, (3, 3), activation='relu'))  
model.add(MaxPooling2D(pool_size=(2, 2)))  
model.add(Dropout(0.25))  
model.add(Flatten())  
model.add(Dense(128, activation='relu'))  
model.add(Dropout(0.5))  
model.add(Dense(num_classes, activation='softmax'))  
model.compile(loss=keras.losses.categorical_crossentropy,  
              optimizer=keras.optimizers.Adadelta(),  
              metrics=['accuracy'])
```



# Fit and Evaluate

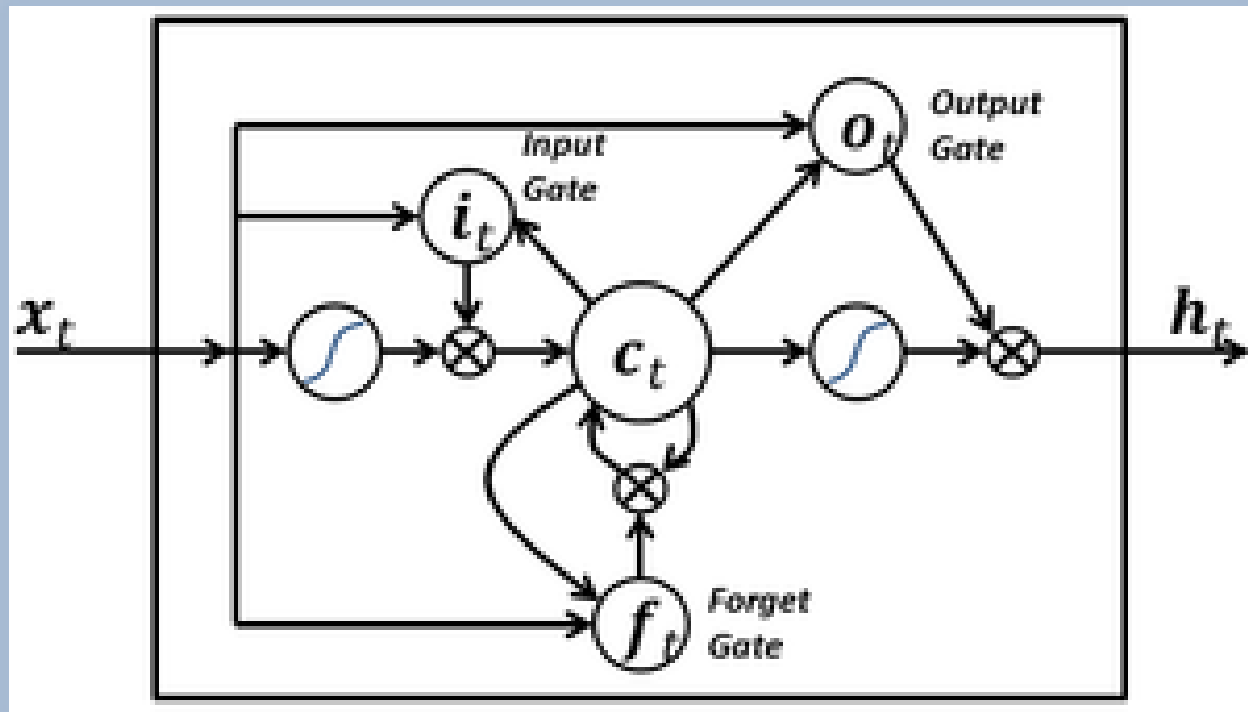
```
model.fit(x_train, y_train,  
          batch_size=batch_size,  
          epochs=epochs,  
          verbose=2,  
          validation_data=(x_test, y_test))  
score = model.evaluate(x_test, y_test, verbose=0)  
print('Test loss: {}'.format(score[0]))  
print('Test accuracy: {}'.format(score[1]))
```

→ Test loss: 0.03047790436172363

→ Test accuracy: 0.9902

→ Elapsed time: 1:30:40.79 (for CPU, approx 30 min GPU)

# Keras: Time Series and RNN





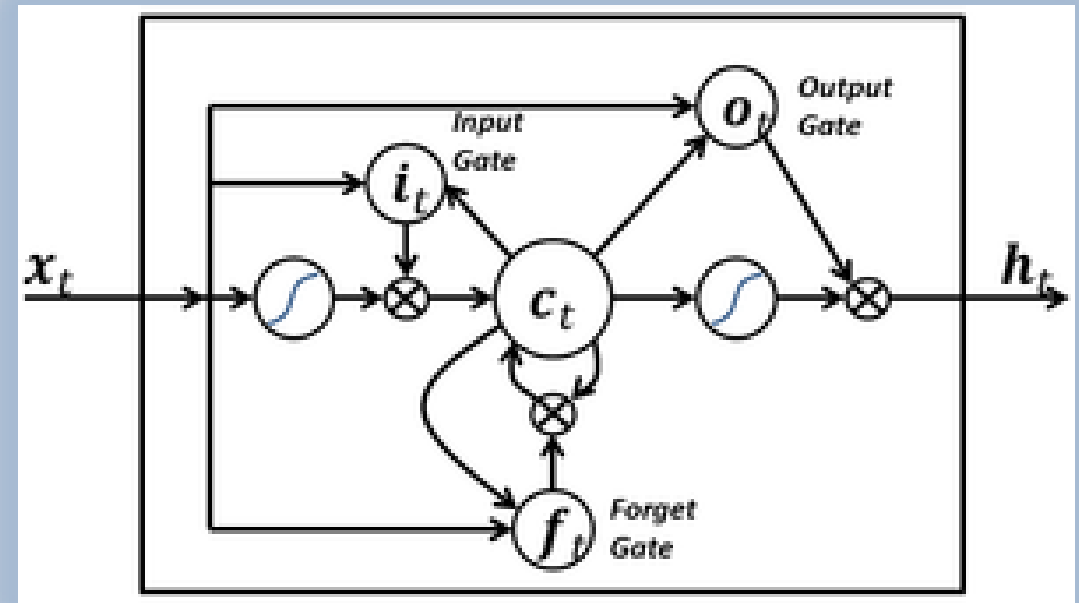
# How is a RNN Different?

- RNN = Recurrent Neural Network.
- LSTM = Long Short Term Memory.
- Most models will always produce the same output for the same input.
- Previous input does not matter to a non-recurrent neural network.
- To convert today's temperature from Fahrenheit to Celsius, the value of yesterdays temperature does not matter.
- To predict tomorrow's closing price for a stock you need more than just today's price.
- To determine if a packet is part of an attack, previous packets must be considered.



# How do LSTM's Work?

- The LSTM units in a deep neural network are short-term memory.
- This short term memory is governed by 3 gates:
  - Input Gate: When do we remember?
  - Output Gate: When do we act?
  - Forget Gate: When do we forget?





# Sample Recurrent Data: Stock Price & Volume

```
x = [  
  [[32,1383],[41,2928],[39,8823],[20,1252],[15,1532]],  
  [[35,8272],[32,1383],[41,2928],[39,8823],[20,1252]],  
  [[37,2738],[35,8272],[32,1383],[41,2928],[39,8823]],  
  [[34,2845],[37,2738],[35,8272],[32,1383],[41,2928]],  
  [[32,2345],[34,2845],[37,2738],[35,8272],[32,1383]],  
]  
y = [  
  1,  
  -1,  
  0,  
  -1,  
  1  
]
```



# LSTM Example

```
max_features = 4 # 0,1,2,3 (total of 4)
x = [
    [[0],[1],[1],[0],[0],[0]],
    [[0],[0],[0],[2],[2],[0]],
    [[0],[0],[0],[0],[3],[3]],
    [[0],[2],[2],[0],[0],[0]],
    [[0],[0],[3],[3],[0],[0]],
    [[0],[0],[0],[0],[1],[1]]
]
x = np.array(x,dtype=np.float32)
y = np.array([1,2,3,2,3,1],dtype=np.int32)
```



# Build a LSTM



```
model = Sequential()  
model.add(LSTM(128, dropout=0.2, recurrent_dropout=0.2,  
input_dim=1))  
model.add(Dense(4, activation='sigmoid'))  
  
model.compile(loss='binary_crossentropy',  
              optimizer='adam',  
              metrics=['accuracy'])
```



# Test the LSTM

```
def runit(model, inp):  
    inp = np.array(inp, dtype=np.float32)  
    pred = model.predict(inp)  
    return np.argmax(pred[0])
```

```
print( runit( model, [[[0],[0],[0],[0],[3],[3]]] ))
```

→3

```
print( runit( model, [[[4],[4],[0],[0],[0],[0]]] ))
```

→4

# GPU's and Deep Learning





# Low Level GPU Frameworks

- CUDA

CUDA is NVidia's low-level GPGPU framework.



- OpenCL

An open framework supporting CPU's, GPU's and other devices. Managed by the Khronos Group.



# Thank you!

- Jeff Heaton
- <http://www.jeffheaton.com>

