Load Forecasting with Artificial Intelligence on Big Data

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Biography

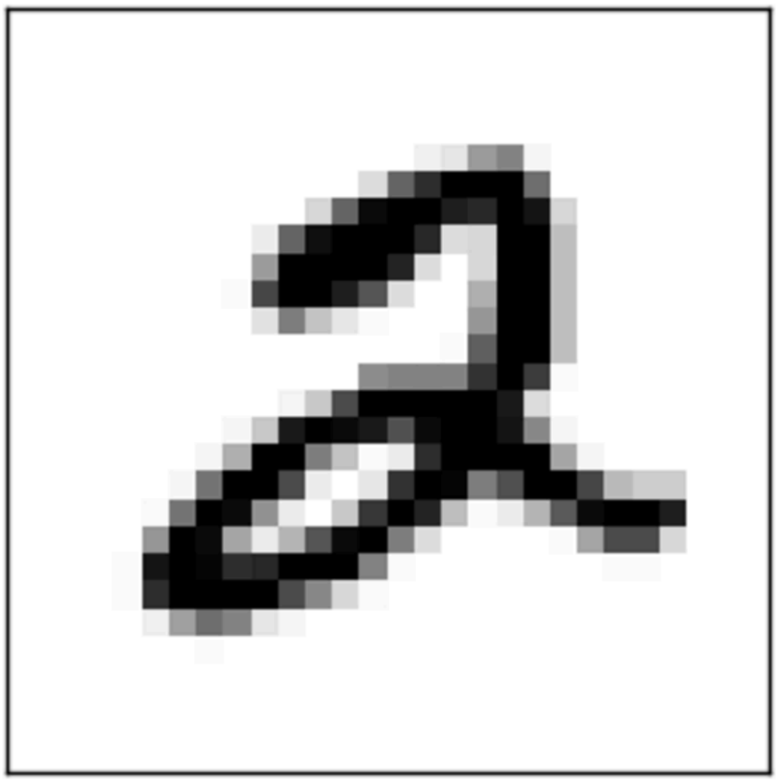
- PhD student at the University of Luxembourg
- Collaboration with Choice Technologies Holding on detection of non-technical losses (NTL)
- MSc in Machine Learning from Imperial College London
- Previously worked at CERN and SAP

Motivation

- **Artificial Intelligence**: "AI is the science of knowing what to do when you don't know what to do." (Peter Norvig, www.youtube.com/watch?v=rtmQ3xlt-4A4m45)
- **Machine Learning** is the field of study that gives computers the ability to learn without being explicitly programmed.

Motivation

Data:

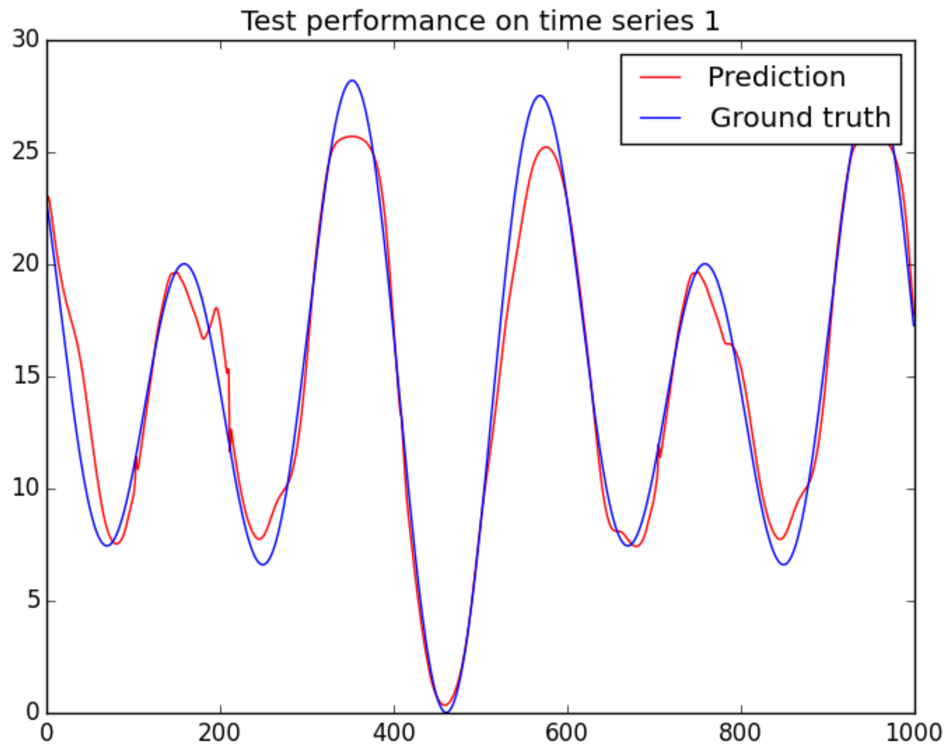


Label/target:

2

Motivation

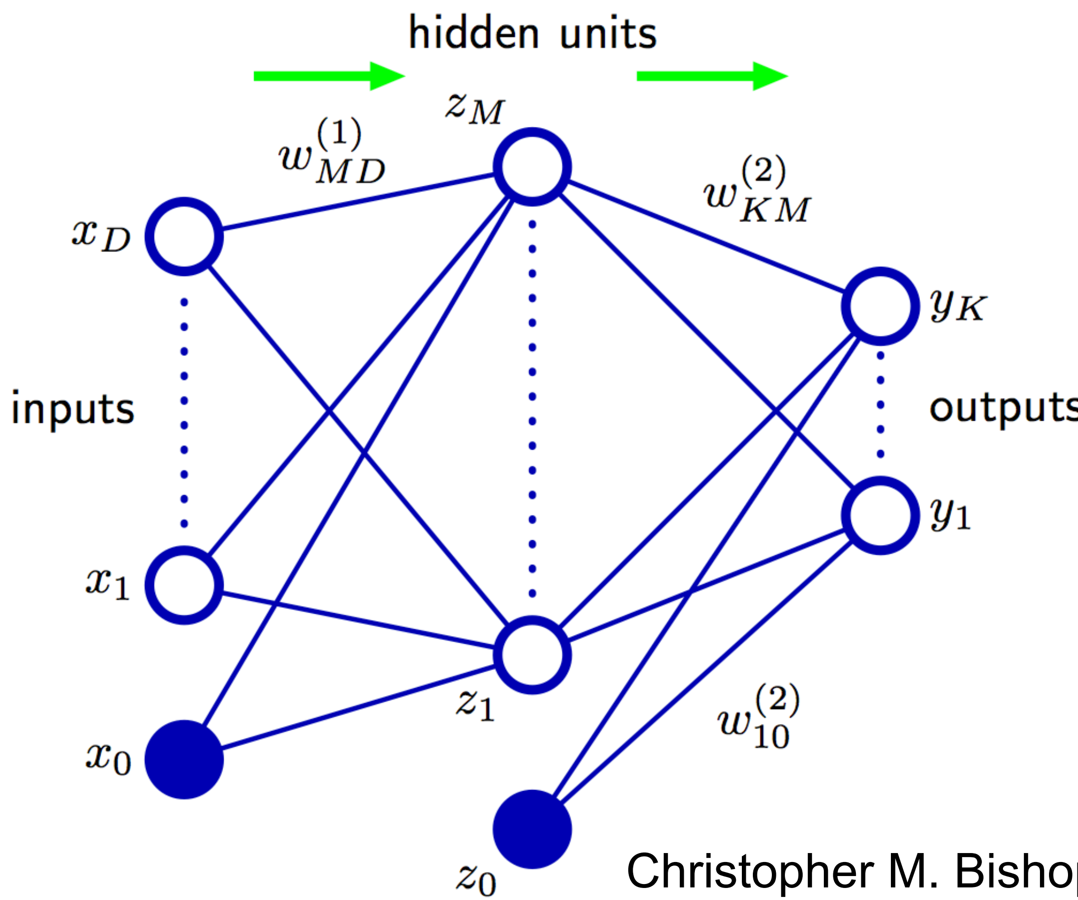
- Goal: Predict time series of load



Agenda

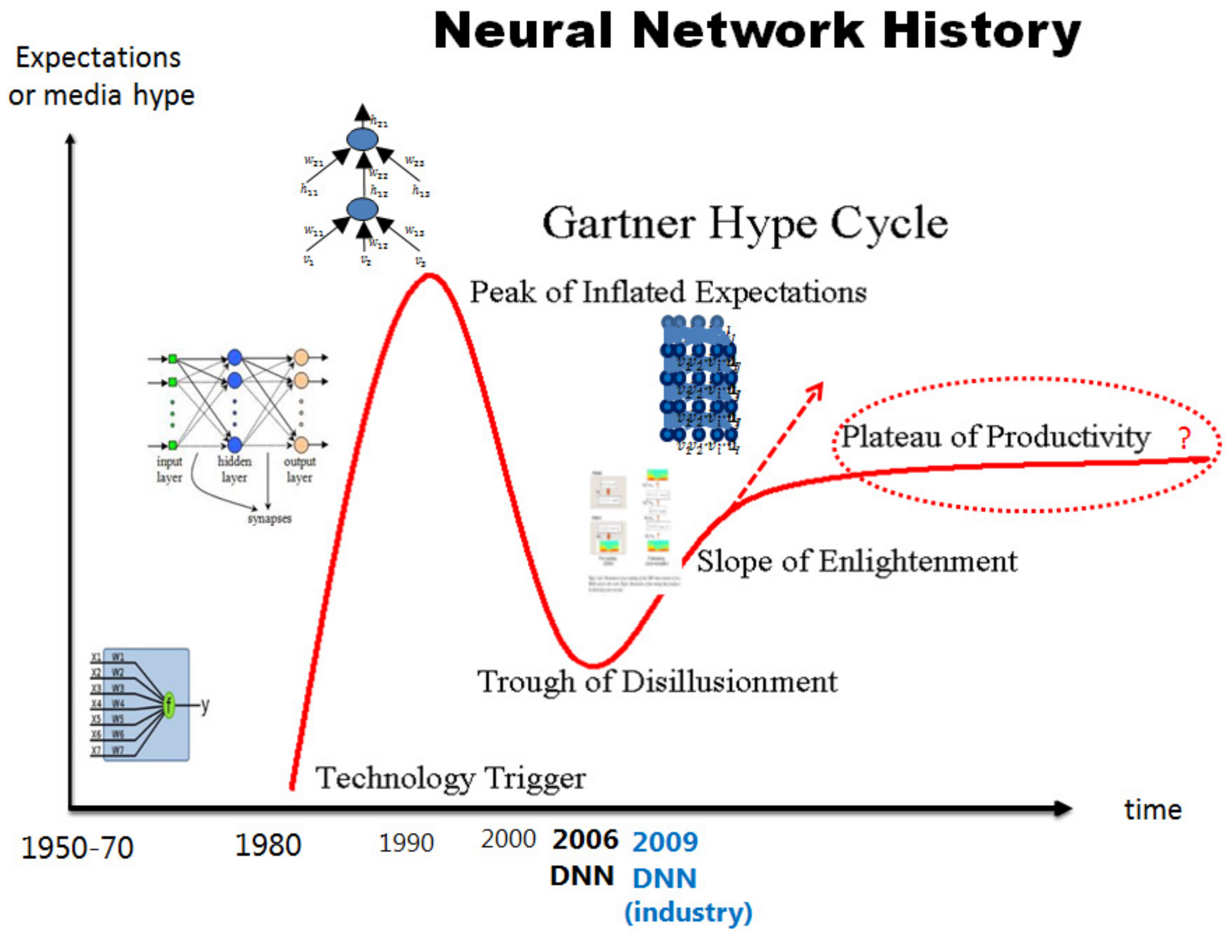
1. Neural networks
2. Deep Learning
3. TensorFlow
4. Load forecasting
5. Conclusions and outreach

Neural networks



Christopher M. Bishop, ``Pattern Recognition and Machine Learning", Springer, 2007.

Neural networks



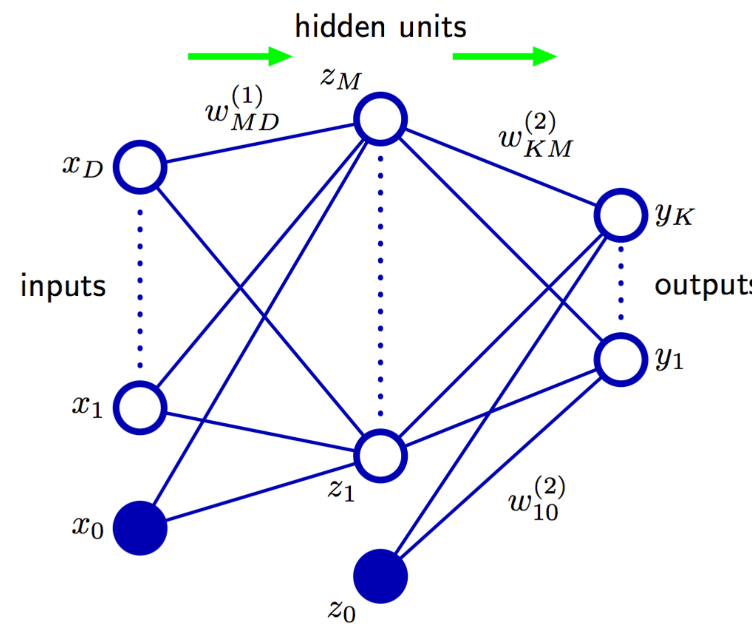
Li Deng and Dong Yu, ``Deep Learning Methods and Applications", Foundations and Trends in Signal Processing, vol. 7, issues 3-4, pp. 197-387, 2014.

Neural networks

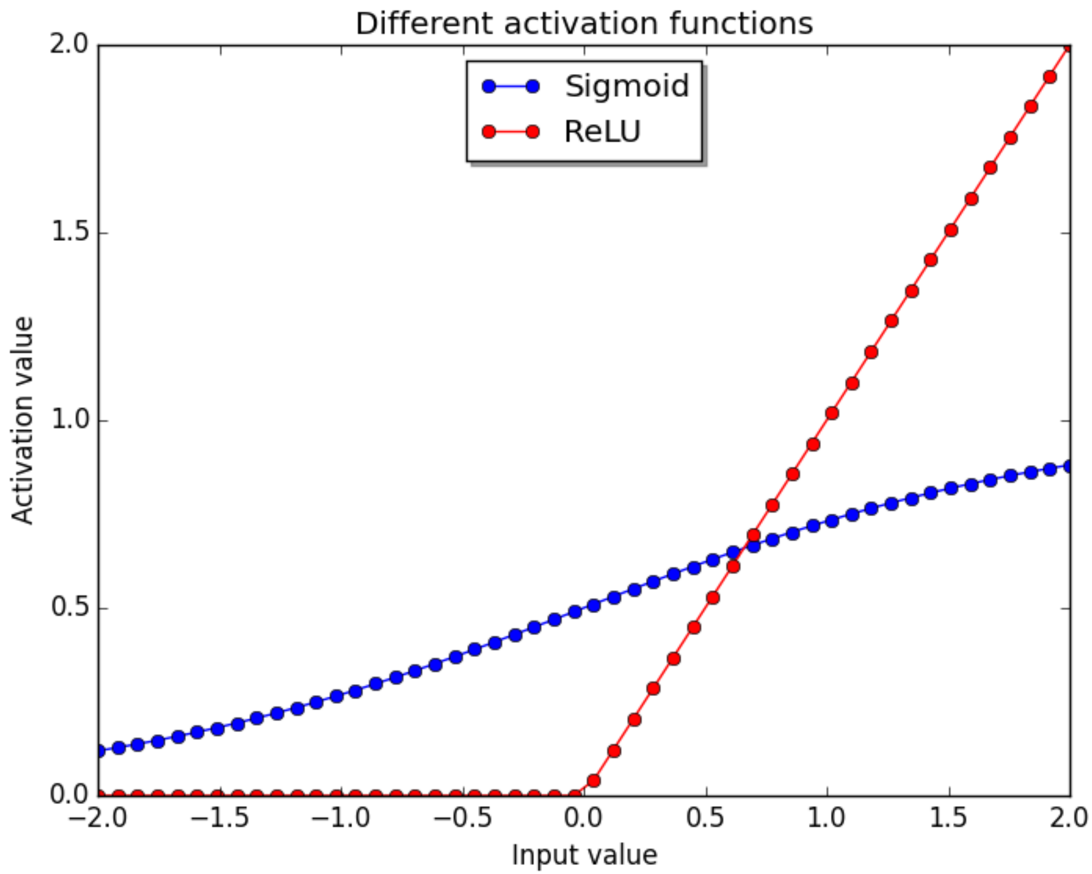
The activation of unit *i* of layer *j+1* can be calculated:

$$z_i^{(j+1)} = \sum_{k=0}^{s_j} \Theta_{ik}^{(j)} x_k$$

$$a_i^{(j+1)} = g\left(z_i^{(j+1)}\right)$$



Neural networks



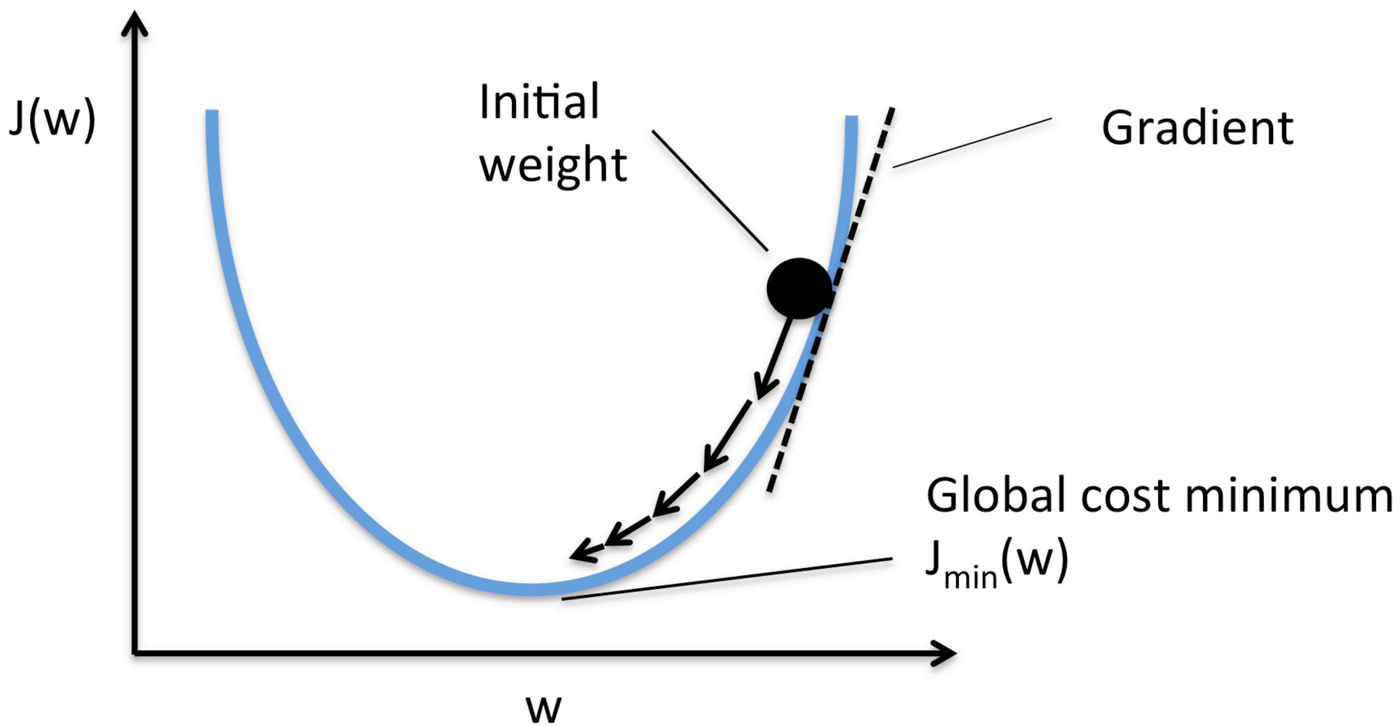
Neural networks

Cost function for *m* examples, hypothesis h_θ and target values $y^{(i)}$:

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$$

Neural networks

How to optimize the weights?



http://sebastianraschka.com/faq/docs/closed-form-vs-gd.html

Neural networks

Algorithm 2.1 Batch gradient descent: training size m, learning rate α

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repeat

$\theta_j \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$ (simultaneously for all j)

until convergence

Neural networks

Algorithm 2.2 Stochastic gradient descent: training size m, learning rate α

Randomly shuffle data set
repeat
  for $i = 1$ to m **do**
    $\theta_j \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta, (x^{(i)}, y^{(i)}))$ (simultaneously for all j)
  end for
until convergence

Neural networks

How to compute the partial derivatives?

Neural networks

Algorithm 3 Backpropagation: training size m

$\Theta_{ij}^{(l)} \leftarrow rand(-\varepsilon, \varepsilon)$ (for all l, i, j)

$\Delta_{ij}^{(l)} \leftarrow 0$ (for all l, i, j)

for $i = 1$ to m **do**

$a^{(1)} \leftarrow x^{(i)}$

Perform forward propagation to compute $a^{(l)}$ for $l = 2, 3, ..., L$

Using $y^{(i)}$, compute $\delta^{(L)} = a^{(L)} - y^{(i)}$ ▷ "error"

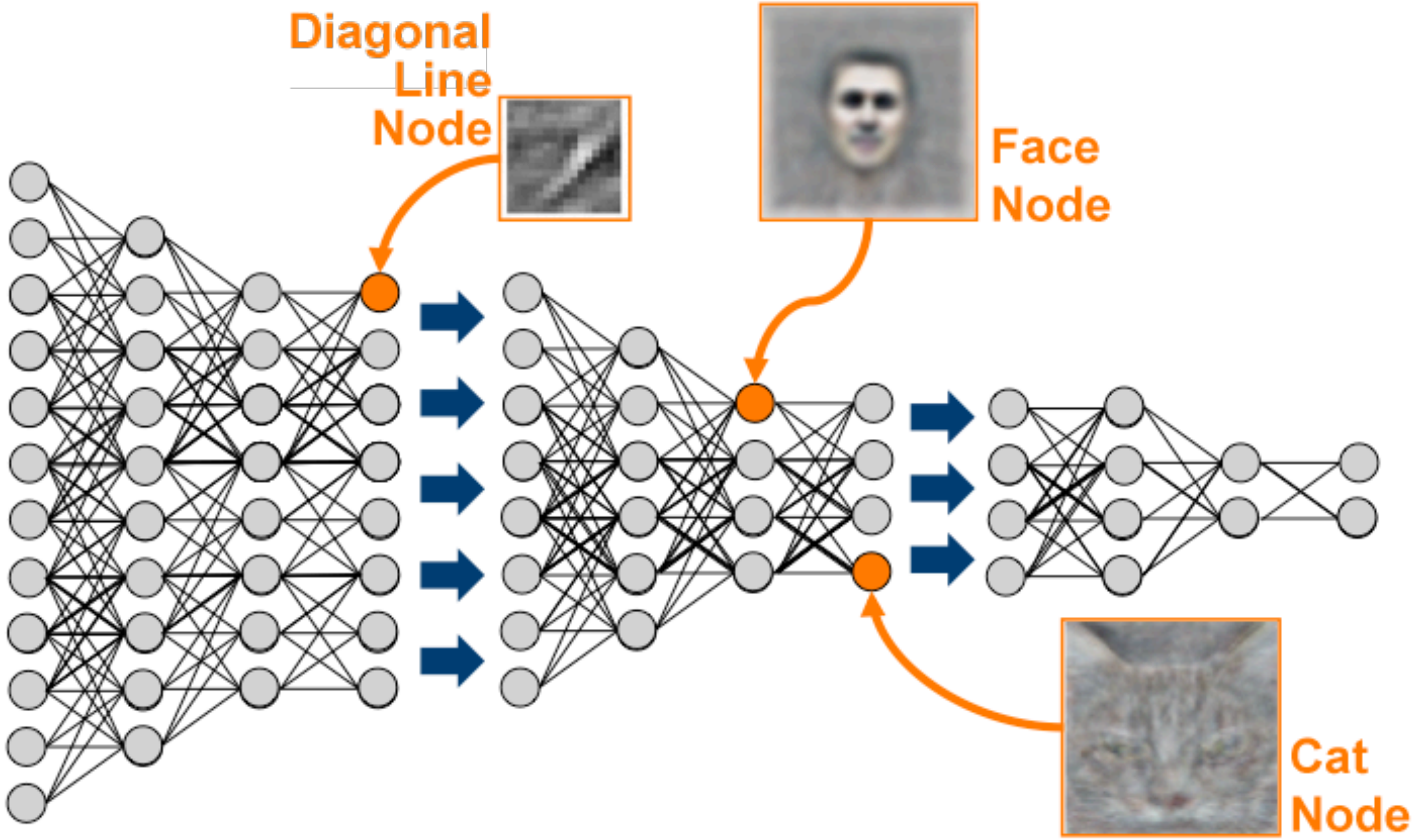
Compute $\delta^{(L-1)}, \delta^{(L-2)}, ..., \delta^{(2)}$: $\delta^{(l)} = (\Theta^{(l)})^T \delta^{(l+1)} \circ g'(z^{(l)})$

$\Delta^{(l)} \leftarrow \Delta^{(l)} + \delta^{(l+1)}(a^{(l)})^T$ ▷ Matrix of errors for units of a layer

end for

$\frac{\partial}{\partial \Theta_{ij}^{(l)}} J(\Theta) \leftarrow \frac{1}{m} \Delta_{ij}^{(l)}$

Deep Learning



The Analytics Store, ``Deep Learning”, http://theanalyticsstore.com/deep-learning/, retrieved: March 1, 2015.

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Deep Learning: DeepMind

- Founded in 2010 in London
- Created a neural network that learns how to play video games in a similar fashion to humans
- Acquired by Google in 2014, estimates range from USD 400 million to over GBP 500 million
- Now being used in Google's search engine
- AlphaGo played the game of Go at super-human performance

TensorFlow

TensorFlow (J. Dean, R. Monga et al., `` TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems", 2015.) is used by Google for most of its Deep Learning products:

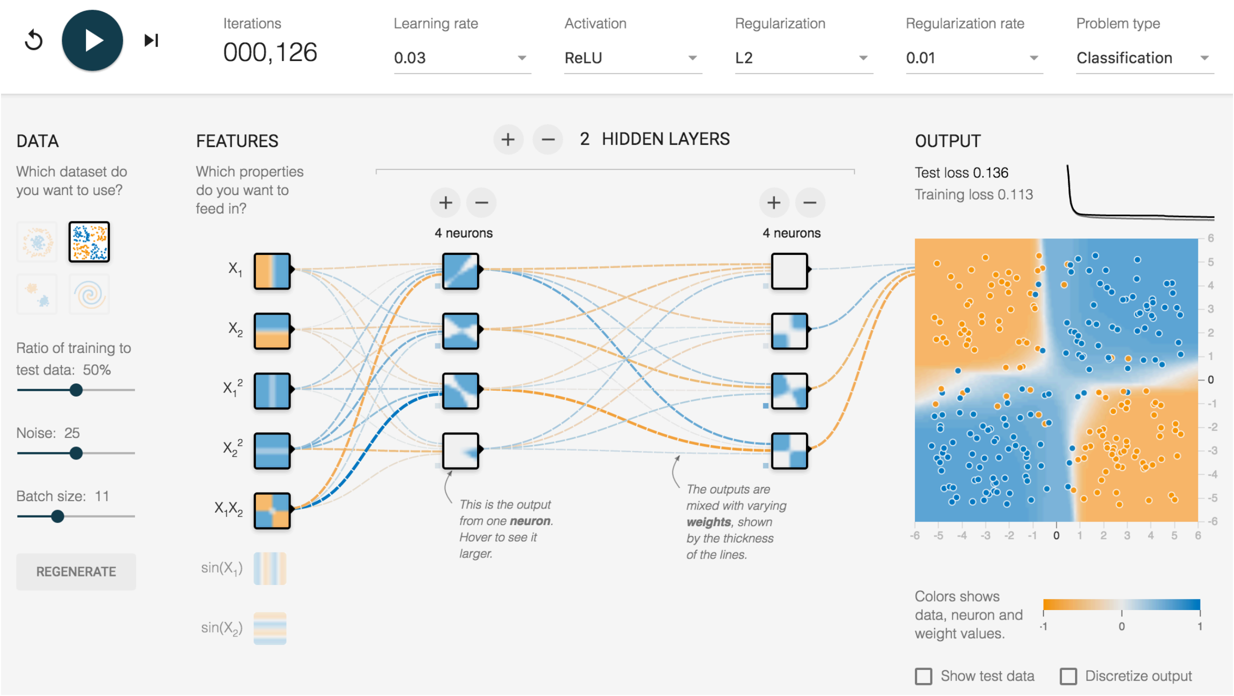
- Offers neural networks (NN), convolutional neural networks (CNN), recurrent neural networks (RNN) and long-short term memories (LSTM)
- Computations are expressed as a data flow graph
- Can be used for research and production
- Python and C++ interfaces

TensorFlow

- Code snippets available from Udacity class: https://www.udacity.com/course/deep-learning--ud730
- iPython notebooks: https://github.com/tensorflow/tensorflow/tree/master/tensorflow/examples/udacity

TensorFlow: Playground

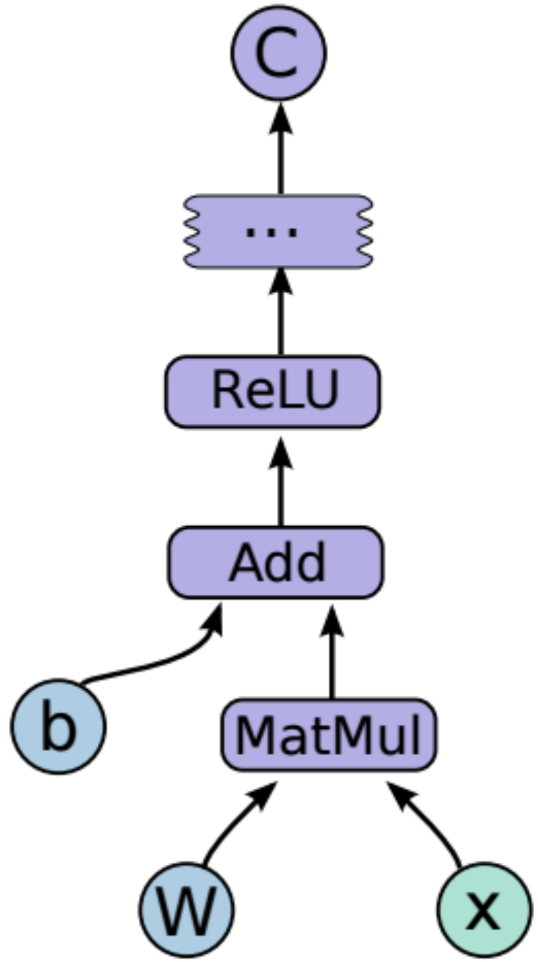
- Let us use the playground together: http://playground.tensorflow.org



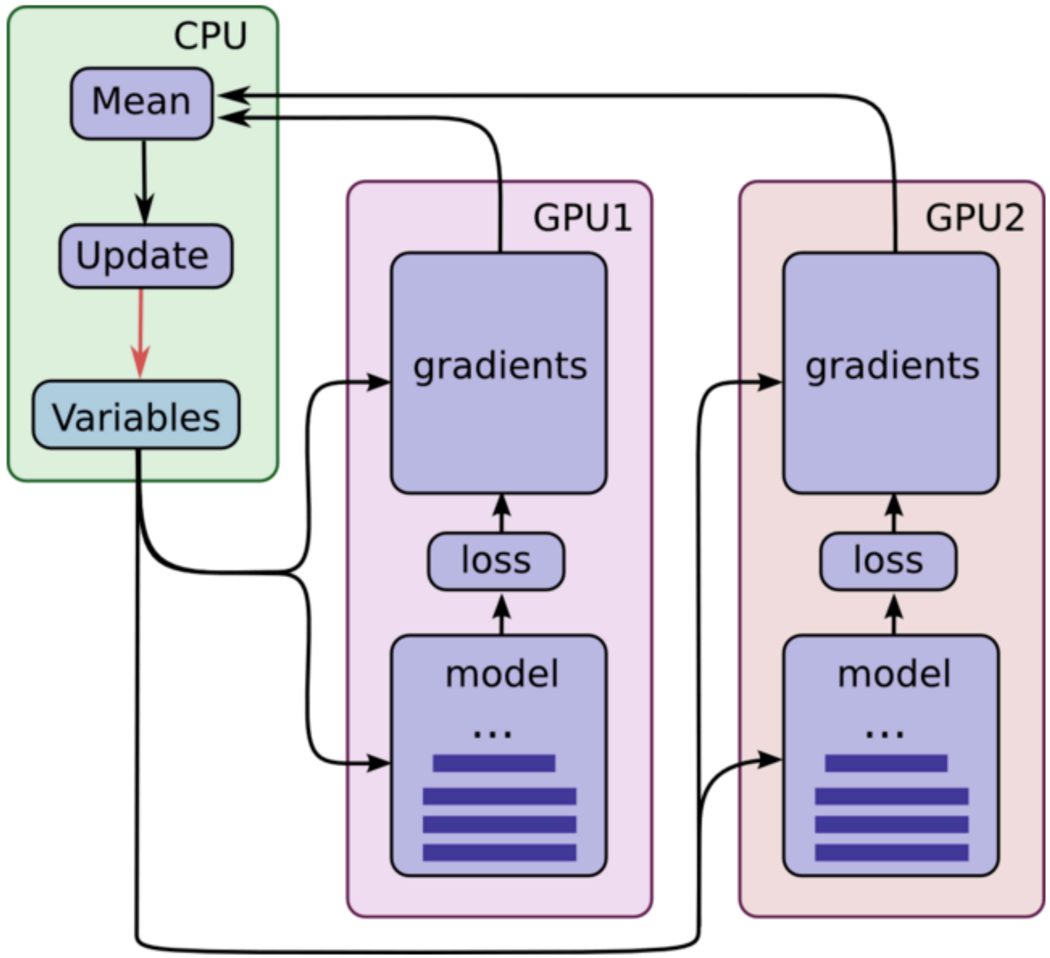
TensorFlow

- A Tensor is a typed multi-dimensional array
- Nodes in the graph are called ops
- An op takes zero or more Tensors, performs some computation, and produces zero or more Tensors
- Two phases:
  - Construction phase, that assembles a graph
  - Execution phase that uses a session to execute ops in the graph
- Auto-differentation of the graph to compute partial derivatives used in stochastic gradient descent (SGD)

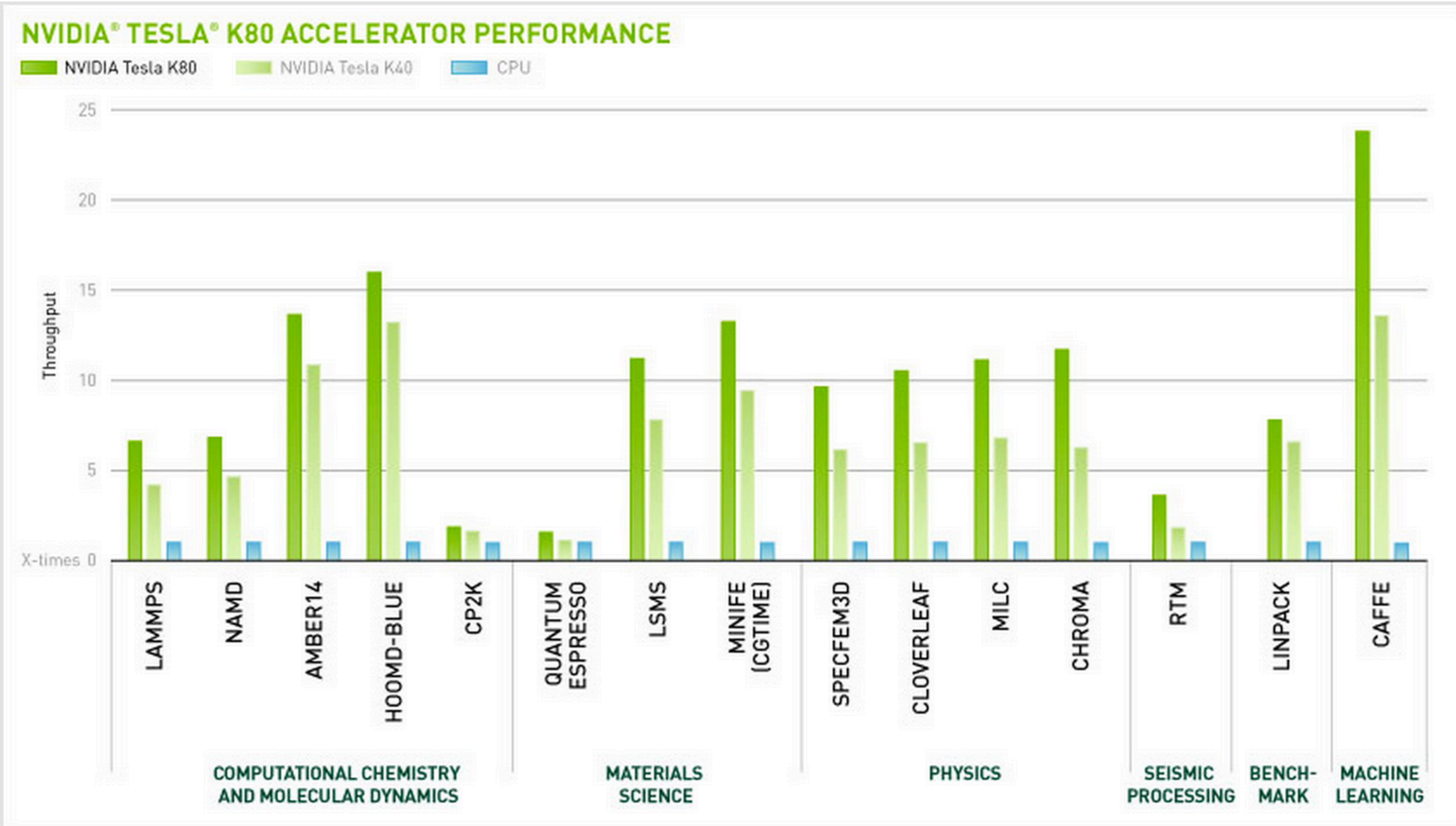
TensorFlow



TensorFlow: GPU acceleration



TensorFlow: GPU acceleration



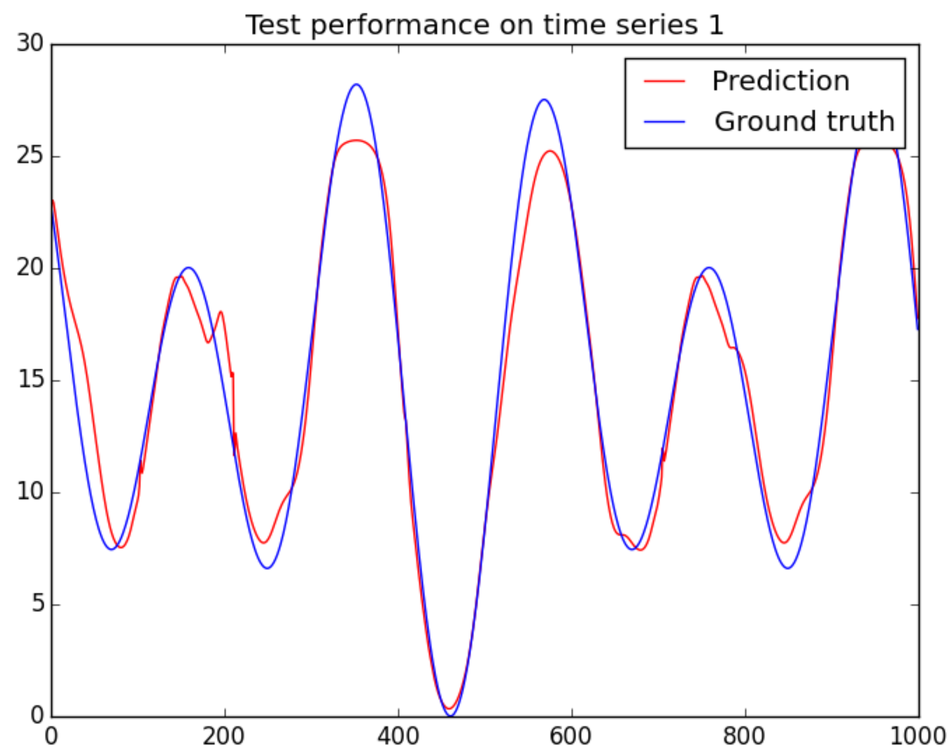
http://www.nvidia.com/object/tesla-servers.html

TensorFlow

- Great documentation: https://www.tensorflow.org/versions/0.6.0/get_started
- Installation: https://www.tensorflow.org/versions/0.6.0/get_started/os_setup.html

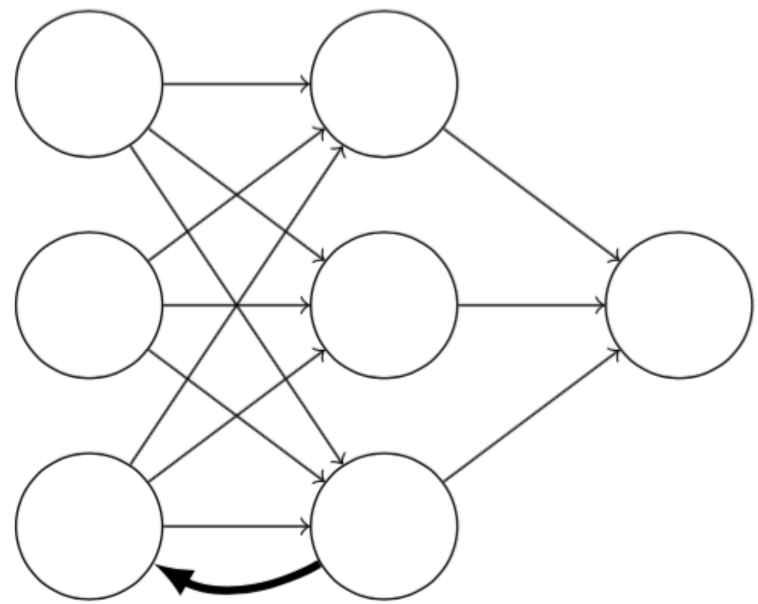
Load forecasting

- Goal: Predict time series of load



Load forecasting

- Feed-forward networks lack the ability to handle temporal data
- Recurrent neural networks (RNN) have cycles in the graph structure, allowing them to keep temporal information



Load forecasting

- A long short-term memory (LSTM) (S. Hochreiter and J. Schmidhuber, ``Long short-term memory", Neural Computation, vol. 9, issue 8, pp. 1735-1780, 1997.) is a modular recurrent neural network composed of LSTM cells
- LSTM cells can be put together in a modular structure to build complex recurrent neural networks
- LSTMs have been reported to outperform regular RNNs and Hidden Markov Models in classification and time series prediction tasks (N. Srivastava, E. Mansimov and R. Salakhutdinov, ``Unsupervised Learning of Video Representations using LSTMs", University of Toronto, 2015.)

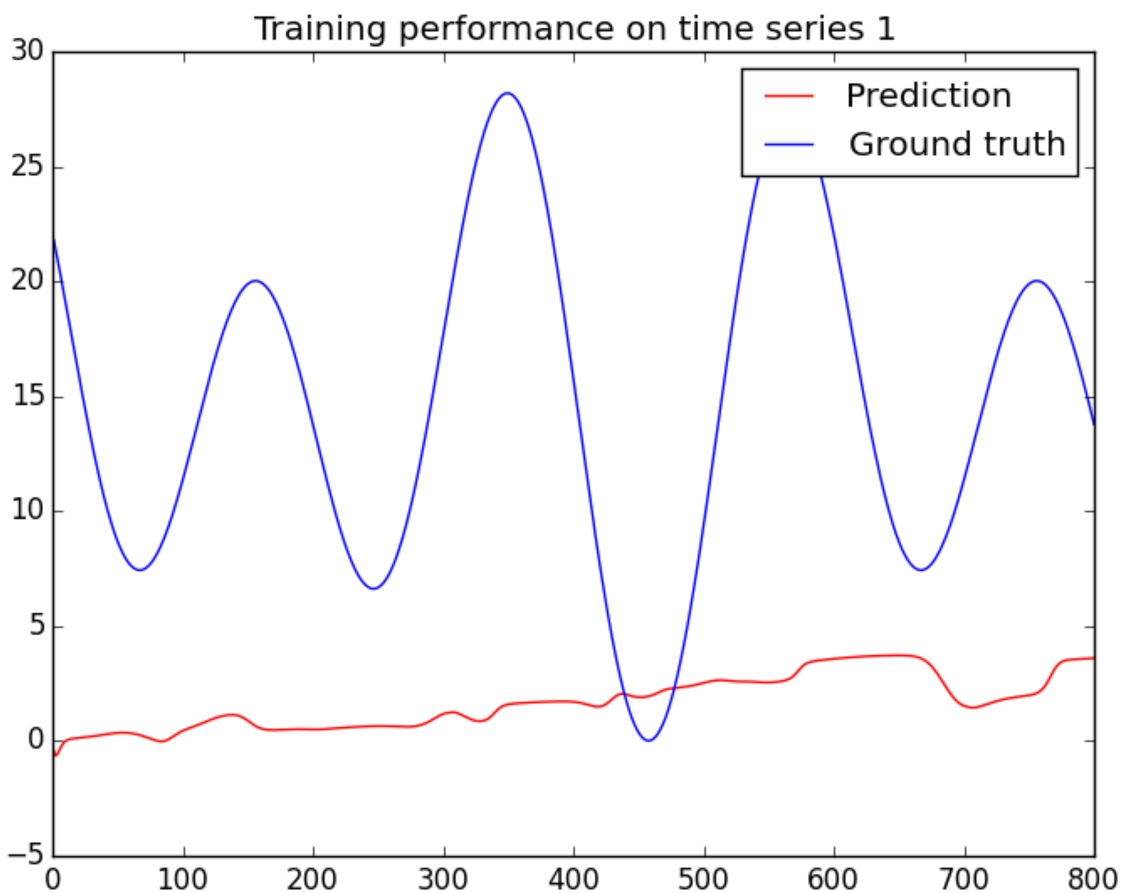
Load forecasting

- Source code: https://github.com/pglauner/ISGT_Europe_2016_Tutorial
- Simplified example, as time series is synthetic and harmonic
- More complex task will follow later

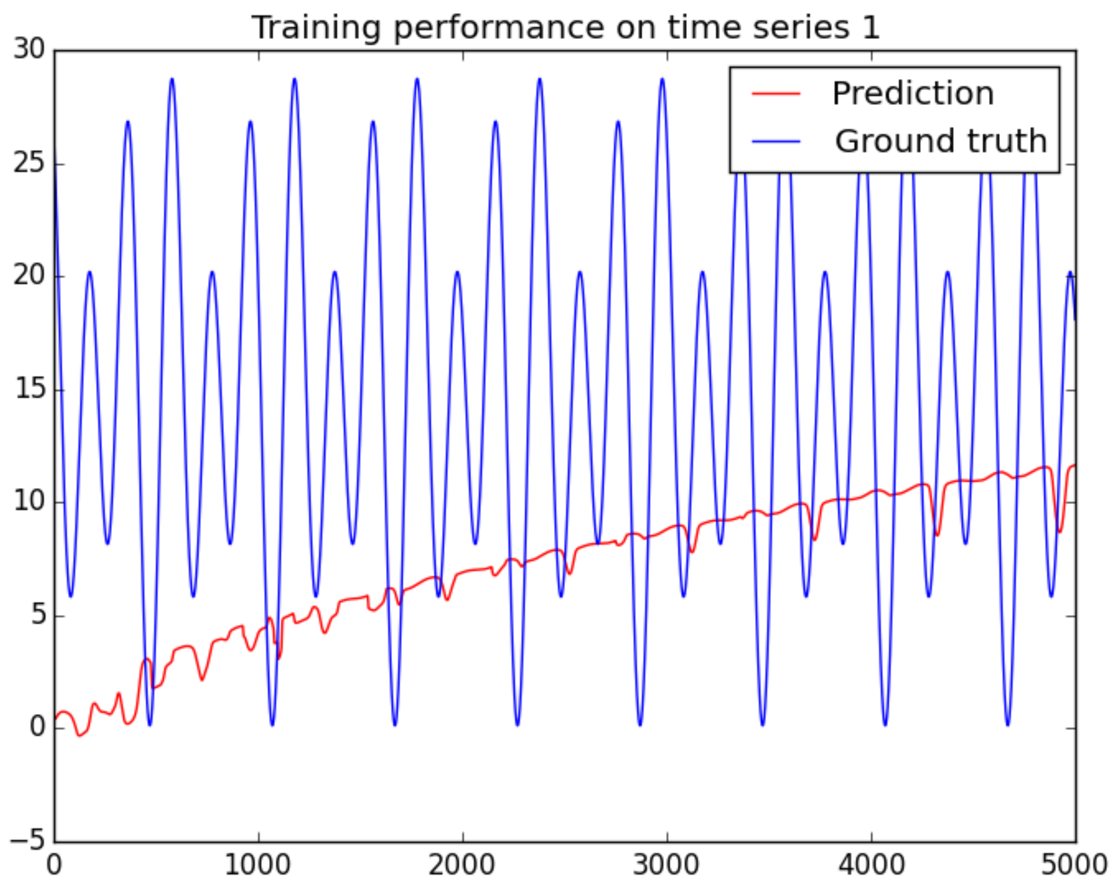
Load forecasting

- Training on two time series at the same time
- Input values of each time series: value, derivative, second-order derivative
- Training data must be sufficiently long

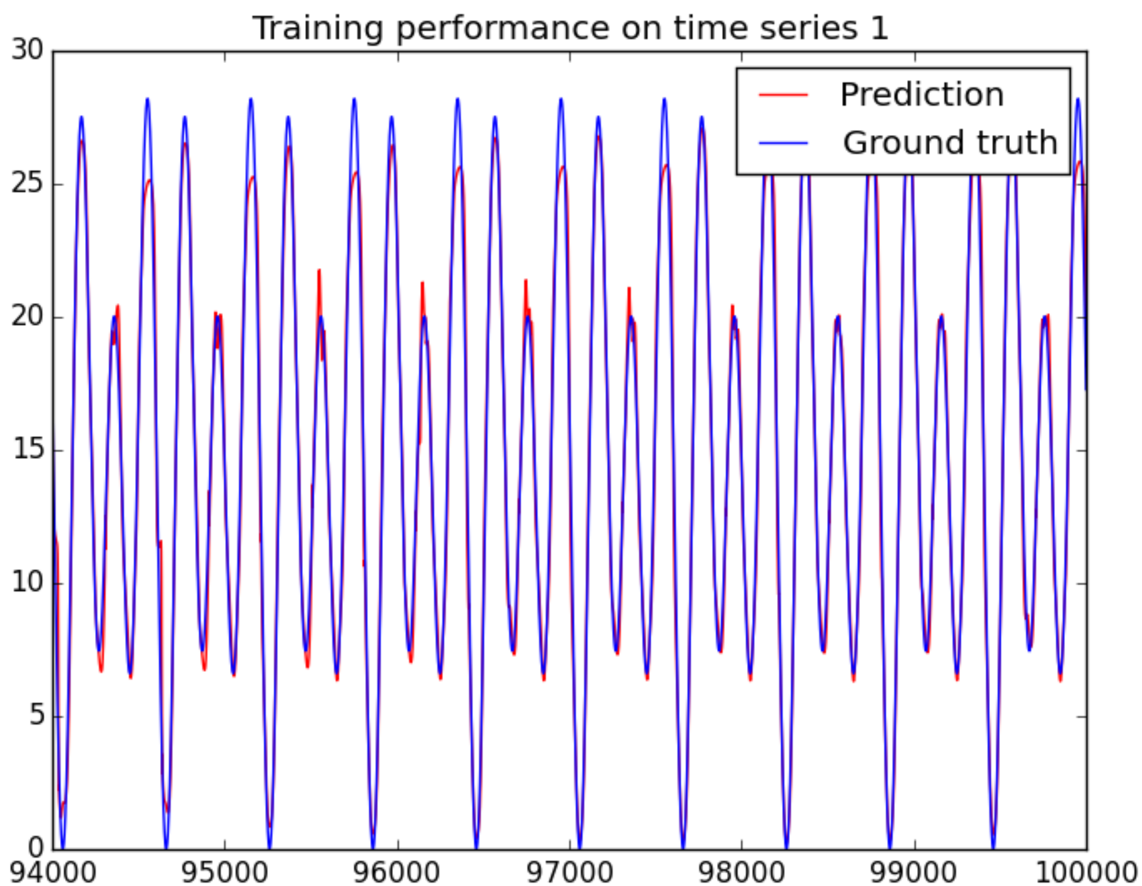
Load forecasting



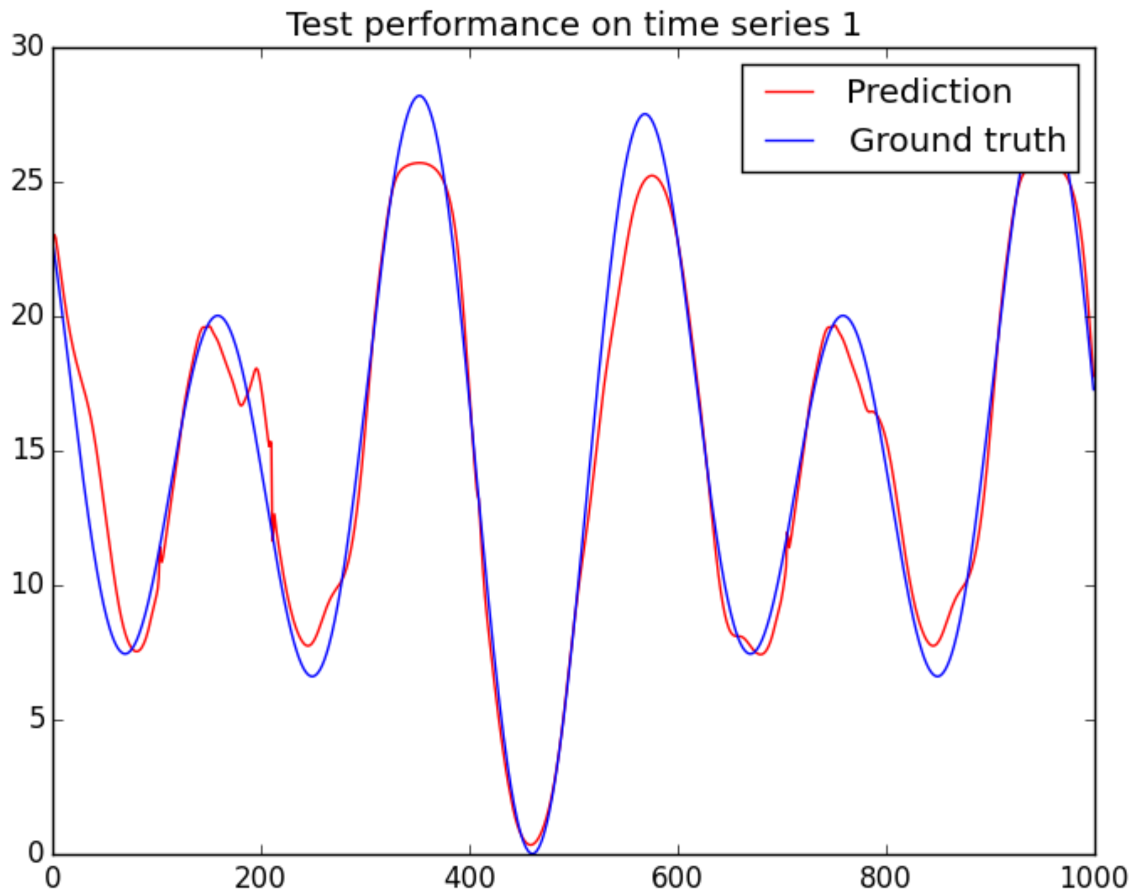
Load forecasting



Load forecasting



Load forecasting



Load forecasting

```
# Input layer for 6 inputs, batch size 1
input_layer = tf.placeholder(tf.float32, [1, INPUT_DIM * 3])

# Initialization of LSTM layer
lstm_layer = rnn_cell.BasicLSTMCell(INPUT_DIM * 3)
# LSTM state, initialized to 0
lstm_state = tf.Variable(tf.zeros([1, lstm_layer.state_size]))
# Connect input layer to LSTM
lstm_output, lstm_state_output1 = lstm_layer(input_layer, lstm_state)
# Update of LSTM state
lstm_update = lstm_state.assign(lstm_state_output1)
```

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Load forecasting

```
# Regression output layer
# Weights and biases
output_W = tf.Variable(tf.truncated_normal([INPUT_DIM * 3, INPUT_DIM]))
output_b = tf.Variable(tf.zeros([INPUT_DIM]))
output_layer = tf.matmul(lstm_output, output_W) + output_b

# Input for correct output (for training)
output_ground_truth = tf.placeholder(tf.float32, [1, INPUT_DIM])

# Sum of squared error terms
error = tf.pow(tf.sub(output_layer, output_ground_truth), 2)

# Adam optimizer
optimizer = tf.train.AdamOptimizer(0.0006).minimize(error)
```

Load forecasting

```
# Flush LSTM state for testing (learned weights do not change)
sess.run(lstm_state.assign(tf.zeros([1, lstm_layer.state_size])))

ground_truth1 = []
ground_truth2 = []
prediction1 = []
prediction2 = []
x_axis = []

for i in range(TEST_SIZE):
    input_v, output_v = get_total_input_output()
    _, network_output = sess.run([lstm_update,
                                  output_layer],
                                 feed_dict={
                                     input_layer: input_v,
                                     output_ground_truth: output_v})

    ground_truth1.append(output_v[0][0])
    ground_truth2.append(output_v[0][1])
    prediction1.append(network_output[0][0])
    prediction2.append(network_output[0][1])
    x_axis.append(i)
```

Load forecasting: Outreach

- Add some noise for more realistic synthetic data
- Real-world load forecasting problem: www.kaggle.com/c/global-energy-forecasting-competition-2012-load-forecasting
- Models can be applied to other regression problems or time series classification (e.g. for detection of non-technical losses)
- Usually more features need to be added
- Model selection in order to tweak hyper parameters (architecture, learning rate, etc.)

Conclusions and outreach

- Deep neural networks can learn complex feature hierarchies
- Significant speedup of training due to GPU acceleration
- TensorFlow is a easy-to-use Deep Learning framework
- Interfaces for Python and C++
- Offers rich functionality and advanced features, such as LSTMs
- Udacity class and lots of documentation and examples available