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# AML

**John Min - Victor Ferrand**

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Predict Heat Consumption with Deep  
Learning

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# Goals

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- Implement our own deep learning library (get our hands dirty)
  - Beat “classical” methods on this learning problem (miserable results: 300% error)
  - Hope to actually get better results
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# Deep Learning Implementation

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- Neural Network
  - Restricted Boltzmann Machine
  - Deep Belief Network
-

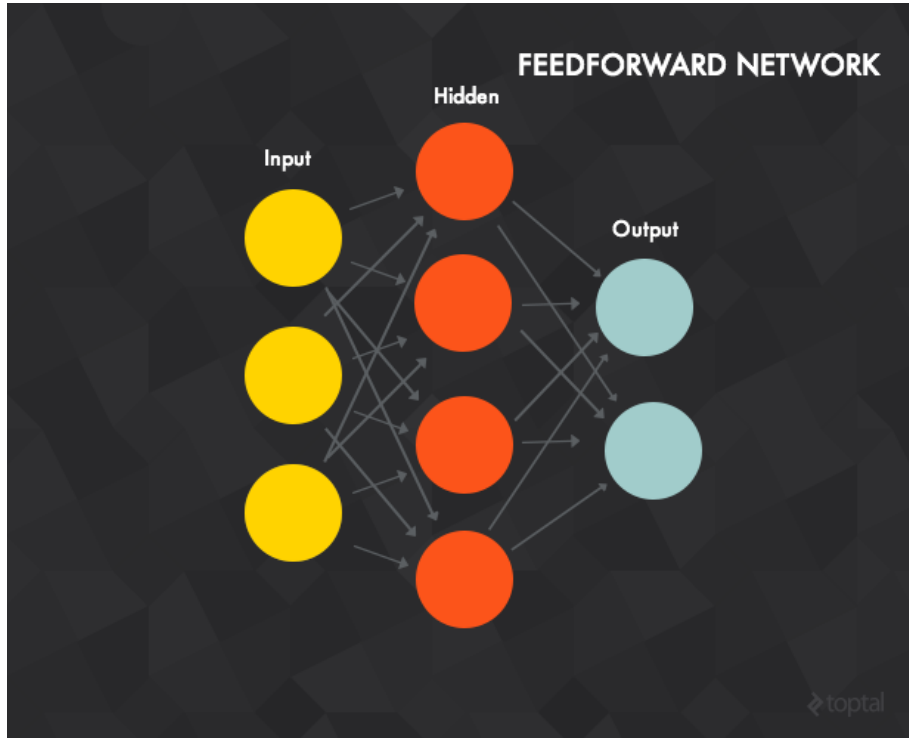
# Neural Network

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- Classic implementation:
    - Feed forward / Back propagation
    - L2 cost function
    - Activation/Output functions (sigm / tanh / linear)
  - Weights Initialization inspired from /\*some paper\*/
    - Uniform distribution over  $\left[-\frac{\sqrt{6}}{in+out}, \frac{\sqrt{6}}{in+out}\right]$
-

# Neural Network

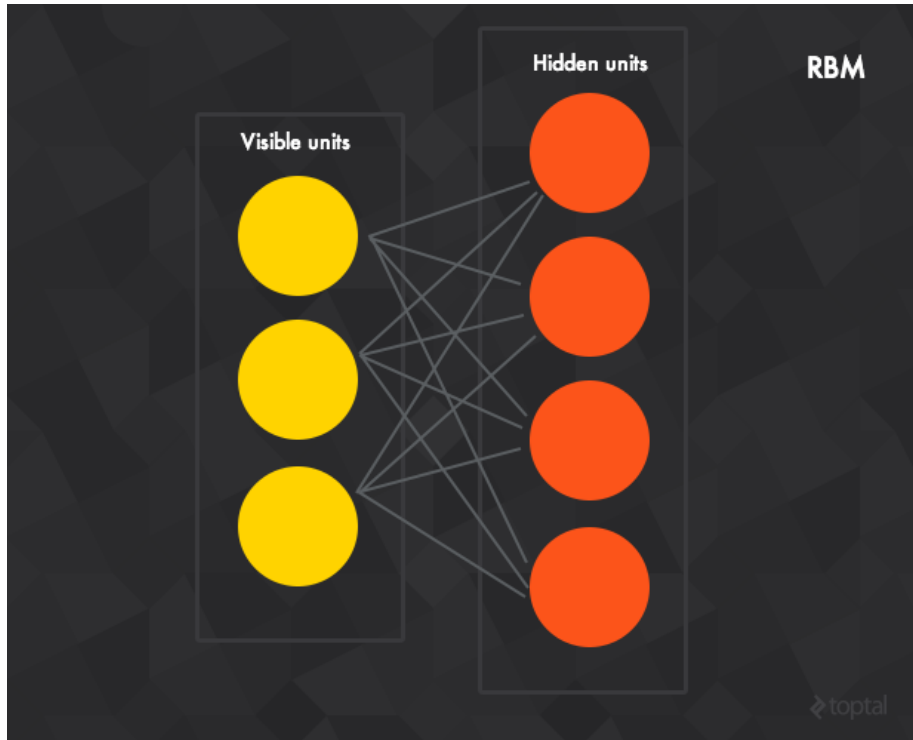
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- Directed network
- Training algorithm
  - feed forward
  - error L2
  - backpropagation

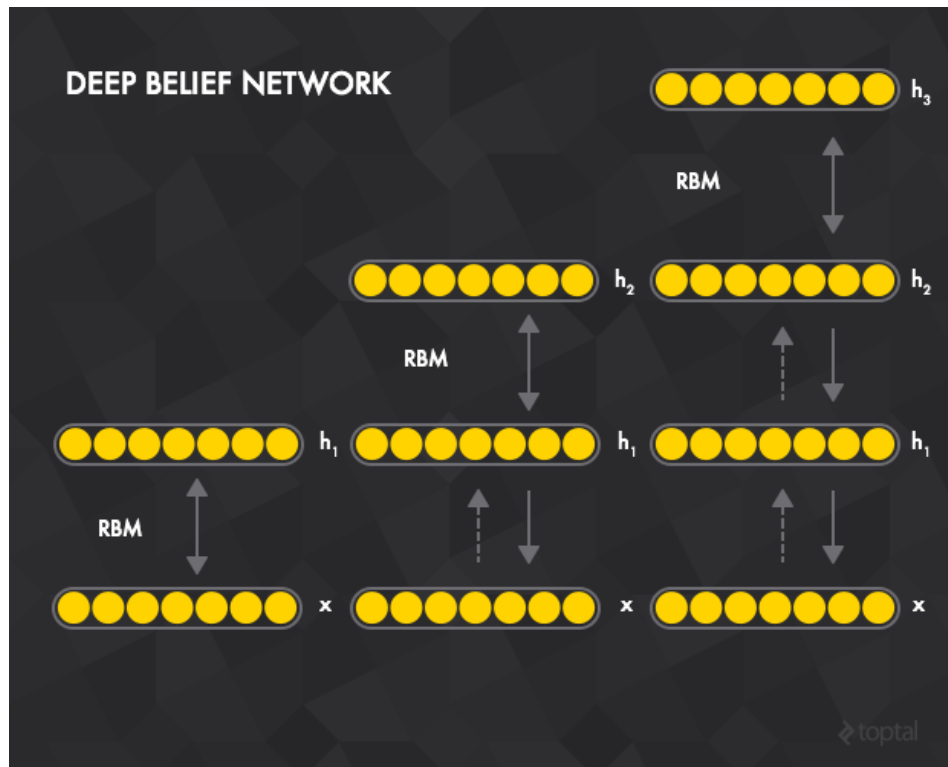
$$\Delta w_i = \alpha(t - y)\varphi'x_i$$

# RBM



- Undirected network
- Fully connected network
- Contrastive divergence training algorithm (2 phases)
  - positive:  $ff^+(x) = h$
  - negative:  $ff^+(ff^-(h)) = h'$
  - update with  $\text{error}(h' - h)$

# Stacked RBMs = DBN



- Deep Belief Networks are a concatenation of RBMs
- Train with contrastive divergence algorithm 2 layers by 2 layers
  - train RBM1
  - train RBM2 with input (ff (inputs) in first layer)

# DBN

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- Modularity of the Network
    - one global training
    - train any added layer as an independant RBM with the previous output layer
  - Big picture : Neural Network with different training
-



# Data

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- Weather data over 2 years (2012-2013)
    - temperature / humidity / pressure / wind speed / precipitation / global conditions
    - collected hourly
  - Steam data from a NY building
    - evaluate heat consumption of the building (Mlbs/hr)
    - collected every 15 min
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# Data

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## Tidy up data:

- Linear interpolation on steam data
  - Filter (where some data aren't accurate)
  - Separate in 3 datasets:
    - Seasons
    - Week days
    - Weekends
-

# Results SVM / Random Tree

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	Season data: Winter / Summer Spring / Fall	Week days	Weekends
SVM			
Random Tree			

# Results Neural Net / DBN

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	Season data: Winter / Summer Spring / Fall	Week days	Weekends
Neural Net			
DBN			

# Result Graphics

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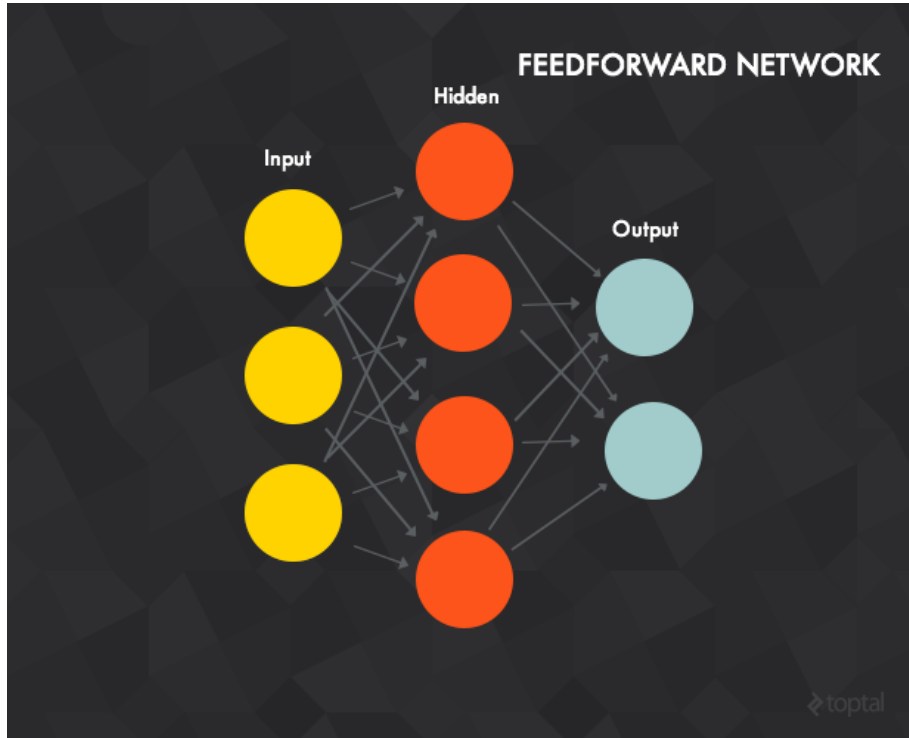
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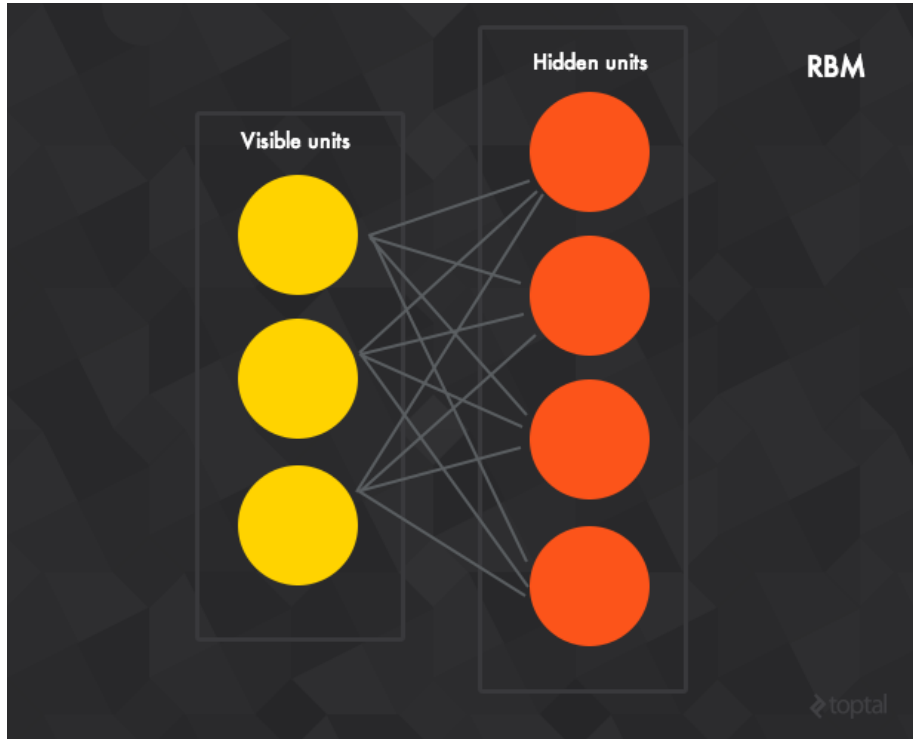
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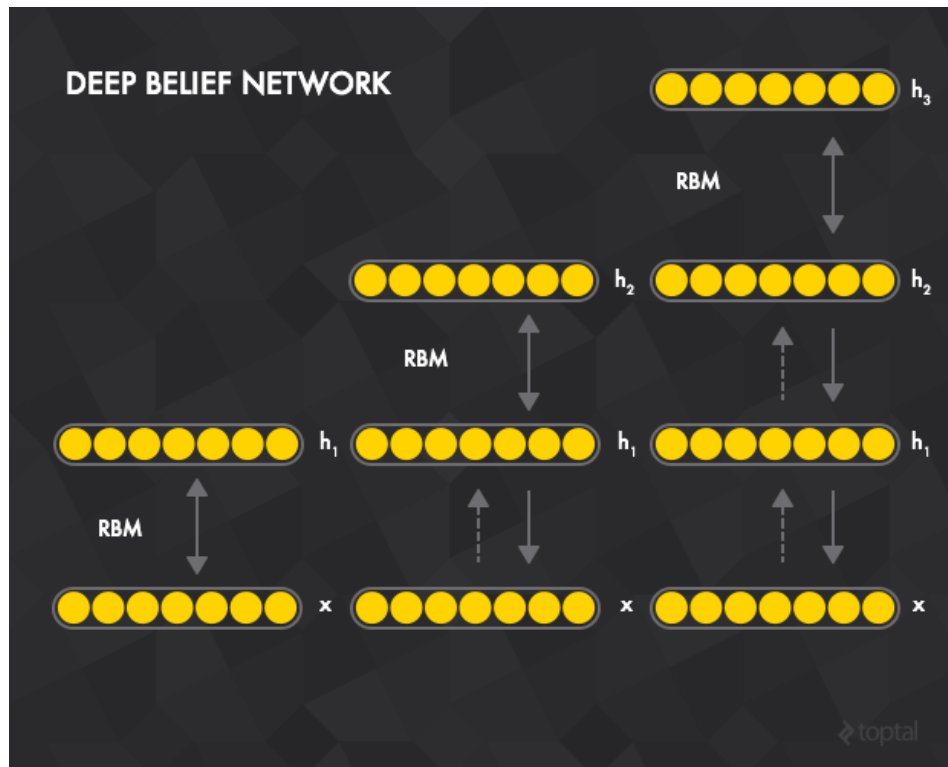
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# Result Graphics

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# References

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