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Beijing Institute of Technology(BIT)

October 27, 2019





Outline

- 1 Overview
- 2 Feedforward Network
 - Perceptron
 - Deep Network
 - Self-Organizing Feature Map
- 3 Feedback Network
 - Hopfield Network
 - Long Short-Term Memory
- 4 Review



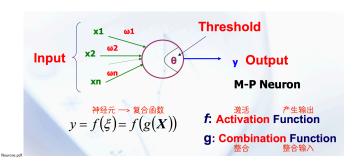


Outline

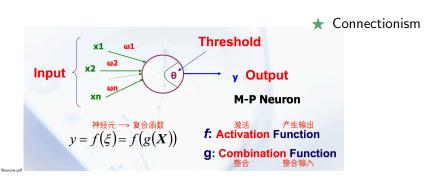
- 1 Overview
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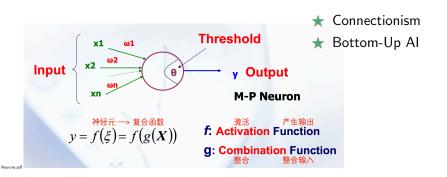














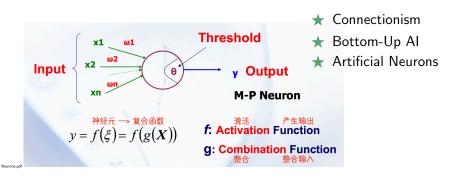


Figure: Artificial Neuron



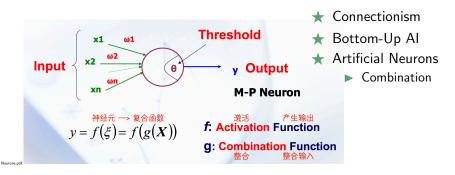
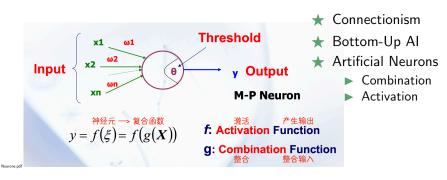


Figure: Artificial Neuron







Main problems

Architecture





- Architecture
 - feedforward (static)





Main problems

Architecture

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- feedforward (static)
- feedback (dynamic)





- Architecture
 - feedforward (static)
 - feedback (dynamic)
- Learning Approach





- Architecture
 - feedforward (static)
 - feedback (dynamic)
- Learning Approach
 - Incremental vs. Batch





- Architecture
 - feedforward (static)
 - feedback (dynamic)
- Learning Approach
 - Incremental vs. Batch
 - Supervised vs. Unsupervised

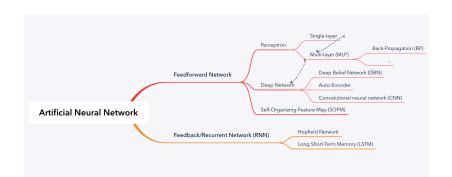




- Architecture
 - feedforward (static)
 - feedback (dynamic)
- Learning Approach
 - Incremental vs. Batch
 - Supervised vs. Unsupervised
 - Error Correction vs. Hebbrian Learning vs. Competitive Learning











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Single-layer vs. Multi-layer

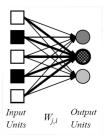


Figure: Single-layer Perceptron

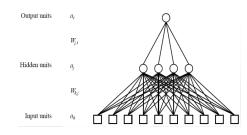


Figure: Multi-layer Perceptron



Single-layer vs. Multi-layer

■ Single-layer : only linear functions



Single-layer vs. Multi-layer

- Single-layer : only linear functions
- Multi-layer : non-linear operations hidden layer added
 - ▶ BP : Use sigmoid activation function



Multi-layer ► BP Network

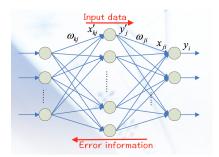


Figure: BP Structure



Multi-layer ► BP Network

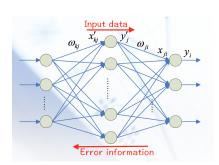


Figure: BP Structure

- objectiveness (measuring criterion)
 - ► MSE :

$$e(\omega) = \frac{1}{2} \sum_{i=1}^{n} [d_i - y_i]^2$$





Multi-layer ► BP Network

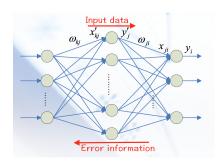


Figure: BP Structure

- objectiveness (measuring criterion)
 - ► MSE :

$$e(\omega) = \frac{1}{2} \sum_{i=1}^{n} [d_i - y_i]^2$$

- optimization
 - ► Gradient Descent :

$$\omega = \omega - \eta rac{\partial e}{\partial \omega}$$
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Multi-layer ► BP Network

Problems: (especially for deeper layers)

lacktriangle Diffusion of Gradient o early layers not trained well





Multi-layer ► BP Network

Problems: (especially for deeper layers)

- Diffusion of Gradient \rightarrow early layers not trained well
- lacksquare Supervised learning o not enough labeled data

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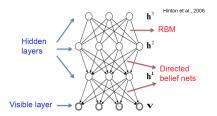
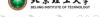
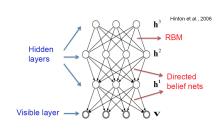


Figure: DBN Structure

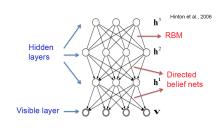




Key points :

Figure: DBN Structure





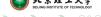
Key points :

Feedforward Network

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Unsupervised pre-learning

Figure: DBN Structure



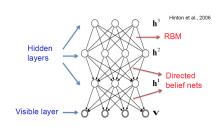


Figure: DBN Structure

Key points :

Feedforward Network

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- Unsupervised pre-learning
- Greedy layer-wise training





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Deep Network

Deep Belifef Network (DBN)

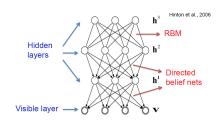


Figure: DBN Structure

Key points :

- Unsupervised pre-learning
- Greedy layer-wise training
- Use softmax for output layer





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Deep Belifef Network (DBN)

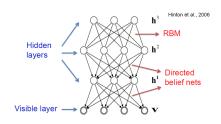


Figure: DBN Structure

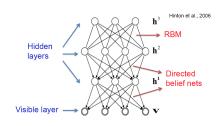
- Key points :
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 - Use softmax for output layer
- objectiveness: MLE





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Deep Belifef Network (DBN)



- Key points :
 - Unsupervised pre-learning
 - Greedy layer-wise training
 - Use softmax for output layer
- objectiveness: MLE
- optimization: Gradient Ascent





Deep Network

DBN ▶ Bases

Statistical distribution

random variable for each neuron

$$P(v, h^1, h^2, \dots, h^l) = P(v|h^1)P(h^1|h^2)\dots P(h^{l-2}|h^{l-1})P(h^{l-1}, h^l)$$

$$P(h^{i}|h^{i+1}) = \prod_{j=1}^{n^{i}} P(h_{j}^{i}|h^{i+1})$$





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DBN ► Bases

Statistical distribution

random variable for each neuron

$$P(v, h^1, h^2, \dots, h^l) = P(v|h^1)P(h^1|h^2)\dots P(h^{l-2}|h^{l-1})P(h^{l-1}, h^l)$$

$$P(h^{i}|h^{i+1}) = \prod_{j=1}^{n^{i}} P(h_{j}^{i}|h^{i+1})$$

RBM for distribution between layers





DBN ► Training

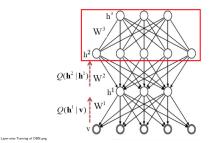
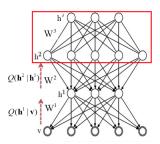


Figure: Greedy Layer-wise Training



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DBN ► Training



Greedy Layer-wise Training

Figure: Greedy Layer-wise Training





Feedforward Network

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DBN ► Training

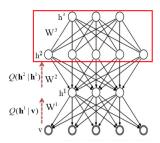


Figure: Greedy Layer-wise Training

Greedy Layer-wise Training i construct a RBM with v and h^1



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DBN ► Training

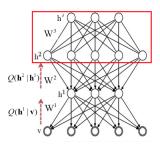


Figure: Greedy Layer-wise Training

- Greedy Layer-wise Training
 - construct a RBM with v and h^1
 - ii form a new RBM with h^1 and h^2





Feedforward Network

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DBN ► Training

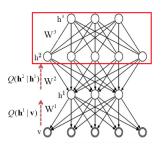


Figure: Greedy Layer-wise Training

Greedy Layer-wise Training

- construct a RBM with v and h^1
- ii form a new RBM with h^1 and h^2
- iii continued...





Feedforward Network

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Deep Network

DBN ► Training

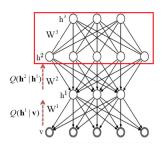


Figure: Greedy Layer-wise Training

- Greedy Layer-wise Training
 - i construct a RBM with v and h^1
 - ii form a new RBM with h^1 and h^2
 - iii continued...
- Fine-tuning





DBN ► Training

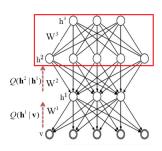


Figure: Greedy Layer-wise Training

- Greedy Layer-wise Training
 - construct a RBM with v and h^1
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- Fine-tuning

Feedforward Network

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Generative (unsupervised): Up-down algorithm





DBN ► Training

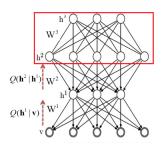


Figure: Greedy Layer-wise Training

- Greedy Layer-wise Training
 - construct a RBM with ν and h^1
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Feedforward Network

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- Generative (unsupervised): Up-down algorithm
- Discriminative (supervised): Back propagation



Auto-encoder



Auto-encoder

- Bases
 - Encoder



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Auto-encoder

- Bases
 - Encoder
 - Decoder



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Auto-encoder

- Bases
 - Encoder
 - Decoder
- AutoEncoder vs. RBM





Auto-encoder

- Bases
 - Encoder
 - Decoder
- AutoEncoder vs. RBM
 - AutoEncoder: reconstruct each training data

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Auto-encoder

- Bases
 - Encoder
 - Decoder
- AutoEncoder vs. RBM
 - AutoEncoder: reconstruct each training data

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RBM: reconstruct distribution of data





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SOFM

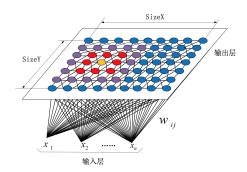
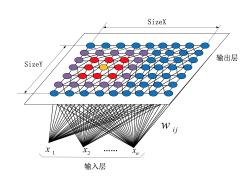


Figure: SOFM structure



SOFM

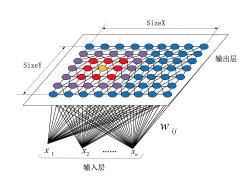


Fundamental idea Dimensionality reduction



Self-Organizing Feature Map

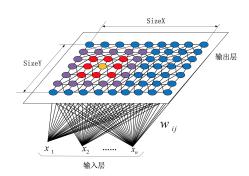
SOFM



- Fundamental ideaDimensionality reduction
- Principles



SOFM



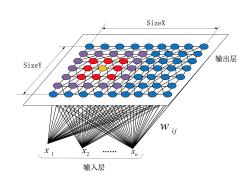
- Fundamental idea Dimensionality reduction
- Principles
 - Self-reinforcing





Feedforward Network

SOFM



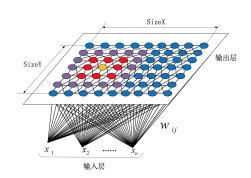
- Fundamental idea Dimensionality reduction
- Principles
 - Self-reinforcing
 - Competition





Feedforward Network

SOFM



- Fundamental idea Dimensionality reduction
- Principles
 - Self-reinforcing
 - Competition
 - Cooperation





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Feedback (Recurrent) Network (RNN)

(1) Stable feedback network



- (1) Stable feedback network
 - Hopfield Network





Feedback (Recurrent) Network (RNN)

- (1) Stable feedback network
 - Hopfield Network
- (2) Sequential feedback network \to Deep Network





Feedback (Recurrent) Network (RNN)

- (1) Stable feedback network
 - Hopfield Network
- (2) Sequential feedback network \to Deep Network
 - LSTM





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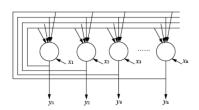
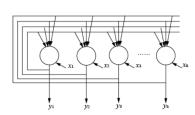


Figure: Hopfield Network Structure



Network.png



Network.png Figure: Hopfield Network Structure ■ Full link network



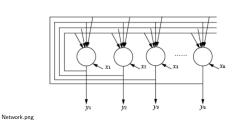


Figure: Hopfield Network Structure

- Full link network
- Training method : change network state





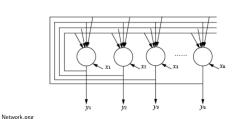


Figure: Hopfield Network Structure

- Full link network
- Training method : change network state
 - asynchronous





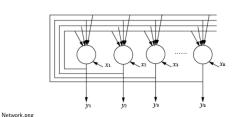


Figure: Hopfield Network Structure

- Full link network
- Training method : change network state
 - asynchronous
 - synchronous





Energy Function

$$E = -\frac{1}{2} \sum_{i=0}^{n} \sum_{j=0}^{n} \omega_{ij} s_{i} s_{j} \quad \left(-\sum_{i=1}^{n} I_{i} s_{i}\right)$$



Hopfield Network

Energy Function

$$E = -\frac{1}{2} \sum_{i=0}^{n} \sum_{j=0}^{n} \omega_{ij} s_{i} s_{j} \quad (-\sum_{i=1}^{n} I_{i} s_{i})$$

Stability condition

$$\omega_{ij} = \begin{cases} \omega_{ji} & i \neq j \\ 0 & i = j \end{cases}$$



Application

- Associative memory (CRM)
 - ▶ each local minimum represents one memorized data





Hopfield Network

Application

- Associative memory (CRM)
 - ▶ each local minimum represents one memorized data
- Combinatorial Optimization
 - ► TSP



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Long Short-Term Memory

Back-Propagation Through Time (BPTT)

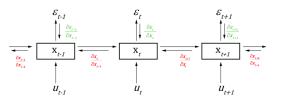
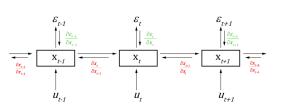


Figure: BPTT Structure





Back-Propagation Through Time (BPTT)

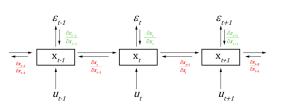


Problems

Figure: BPTT Structure



Back-Propagation Through Time (BPTT)



- **Problems**
 - **Gradient Vanishing**

Figure: BPTT Structure



Back-Propagation Through Time (BPTT)

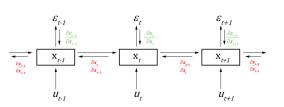


Figure: BPTT Structure

Problems

- **Gradient Vanishing**
- **Gradient Exploding**



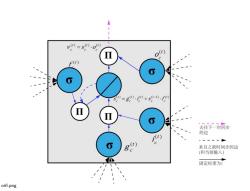
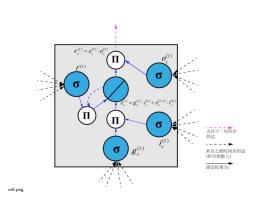


Figure: LSTM Memory Cell





Internal state (constant error carousel): kernel, linear activation function, self-cycling edge(weight fixed to 1)

Figure: LSTM Memory Cell



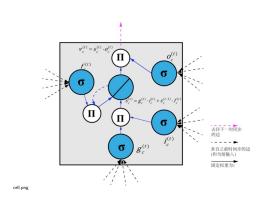


Figure: LSTM Memory Cell

- Internal state (constant error carousel): kernel, linear activation function, self-cycling edge(weight fixed to 1)
- Input node : receive earlier signals





Long Short-Term Memory

LSTM Memory Cell

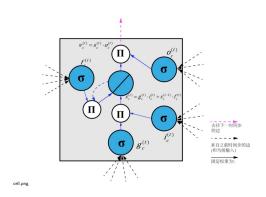


Figure: LSTM Memory Cell

- Internal state (constant error carousel): kernel, linear activation function, self-cycling edge(weight fixed to 1)
- Input node : receive earlier signals
- Input gate : same as Input node, control result of input





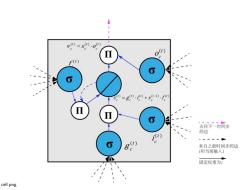
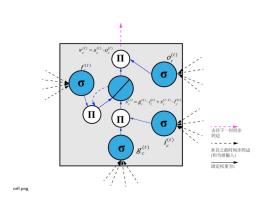


Figure: LSTM Memory Cell







Forget gate: eliminate previous internal state value

Figure: LSTM Memory Cell



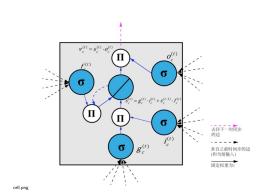


Figure: LSTM Memory Cell

Forget gate: eliminate previous internal state value

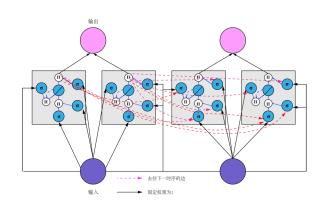
Feedback Network

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Output gate : control result of output



LSTM Structure



structure.png

Figure: LSTM structure



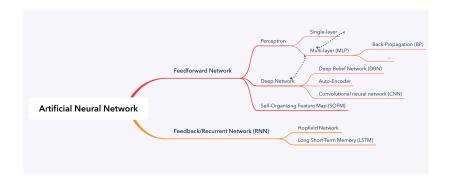
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Review







Thank you

Thank you for listening!

