4190.408 Artificial Intelligence 2015-Spring

Brain, Mind and AI

Byoung-Tak Zhang
School of Computer Science and Engineering
Seoul National University
Von Neumann’s The Computer and the Brain (1958)

John von Neumann (1903-1957)
The Brain and the Computer

- $10^{11}$ neurons with $10^{14}$ synapses
- Speed: $10^{-3}$ sec
- Distributed processing
- Nonlinear processing
- Parallel processing

- A single processor with complex circuits
- Speed: $10^{-9}$ sec
- Central processing
- Arithmetic operation (linearity)
- Sequential processing
From Biological Neurons to Artificial Neurons
Properties of Artificial Neural Networks

- A network of artificial neurons
- Characteristics
  - Nonlinear I/O mapping
  - Adaptivity
  - Generalization ability
  - Fault-tolerance (graceful degradation)
  - Biological analogy

<Multilayer Perceptron Network>
From Mind to Molecules and Back

How does the brain learn so rapidly, flexibly and robustly in an ever-changing environment over lifetime?
Neural Representations and Processing

- “Chemical” and “molecular” basis of synapses
- Distributed representation
- Multiple overlapping representations
- Hierarchical representation
- Associative recall
- Population coding
- Assembly coding
- Sparse coding
- Temporal coding
- Synfire chain
- Dynamic coordination
- Correlation coding
Brain Principle: Sparse Coding in Neural Populations

[O’Connor et al., Neuron, 2010]
Sparse Population Coding: Maradona Cells

[Quiroga, Nat Rev Neurosci. 2012]
Sparse Population Coding: Basic Principles

[Quiroga, Nat Rev Neurosci. 2012]
Population Coding and Assembly

Sparse population codes (assembly codes)

Encoding

Decoding
Hypernetwork as a Probabilistic Model of Distributed Parallel Associative Memory

The hypernetwork is defined as

\[ H = (X, S, W) \]

\[ X = (x_1, x_2, ..., x_N) \]

\[ S = \sum_i S_i, \quad S_i \subseteq X, \quad k = |S_i| \]

\[ W = (W^{(2)}, W^{(3)}, ..., W^{(K)}) \]

Training set:

\[ D = \{x^{(n)}\}_{i=1}^N \]

The energy of the hypernetwork

\[ E(x^{(n)}, W) = -\frac{1}{2} \sum_{i,j} w^{(2)}_{ij} x^{(n)}_i x^{(n)}_j - \frac{1}{6} \sum_{i,j,k} w^{(3)}_{ijk} x^{(n)}_i x^{(n)}_j x^{(n)}_k - ... \]

The probability distribution

\[ P(x^{(n)} | W) = \frac{1}{Z(W)} \exp[-\beta E(x^{(n)}, W)] \]

\[ = \frac{1}{Z(W)} \exp \left[ \frac{1}{2} \sum_{i,j} w^{(2)}_{ij} x^{(n)}_i x^{(n)}_j + \frac{1}{6} \sum_{i,j,k} w^{(3)}_{ijk} x^{(n)}_i x^{(n)}_j x^{(n)}_k + ... \right] \]

\[ = \frac{1}{Z(W)} \exp \left[ \sum_{k=2}^K \frac{1}{c(k)} \sum_{i_1, i_2, ..., i_k} w^{(k)}_{i_1, i_2, ..., i_k} x^{(n)}_{i_1} x^{(n)}_{i_2} ... x^{(n)}_{i_k} \right] \]

where the partition function is

\[ Z(W) = \sum_{x^{(n)}} \exp \left[ \sum_{k=2}^K \frac{1}{c(k)} \sum_{i_1, i_2, ..., i_k} w^{(k)}_{i_1, i_2, ..., i_k} x^{(m)}_{i_1} x^{(m)}_{i_2} ... x^{(m)}_{i_k} \right] \]

[Zhang, DNA-2006]
[Zhang, IEEE CIM, 2008]
Hypernetwork: Self-Organized Assembly Structure Learning from Data

4 Data Items

Round 3
Machine Learning

• Improving performance by knowledge acquisition through experience from interaction with an environment

• Machine vs. human
  – Semantic vs. skill
  – Symbolic vs. statistical
Machine Learning: Three tasks

• **Supervised Learning**
  – Estimate an unknown mapping from known input and target output pairs
  – Learn $f_w$ from training set $D = \{(x,y)\}$ s.t.
  – Classification: $y$ is discrete
  – Regression: $y$ is continuous

\[ f_w(x) = y = f(x) \]

• **Unsupervised Learning**
  – Only input values are provided
  – Learn $f_w$ from $D = \{(x)\}$ s.t.
  – Compression
  – Clustering

\[ f_w(x) = x \]

• **Reinforcement Learning**
  – Not target, but rewards (critiques) are provided “sequentially”
  – Learn a heuristic function $f_w$ from $D_t = \{(s_t, a_t, r_t) \mid t = 1, 2, \ldots\}$ s.t.
  – Sequential decision-making
  – Action selection
  – Policy learning

\[ f_w(s_t, a_t, r_t) \]

Machine Learning: Architectures and Algorithms

• Symbolic Learning
  – Version Space Learning
  – Case-Based Learning

• Neural (Connectionist) Learning
  – Multilayer Perceptrons
  – Self-Organizing Maps
  – Support Vector Machines
  – Kernel Machines

• Evolutionary Learning
  – Evolution Strategies
  – Evolutionary Programming
  – Genetic Algorithms
  – Genetic Programming
  – Molecular Programming

• Probabilistic Learning
  – Bayesian Networks
  – Hidden Markov Models
  – Helmholtz Machines
  – Markov Random Fields
  – Conditional Random Fields
  – Latent Variable Models
  – Generative Topographic Mapping
  – Topic Models

• Other Methods
  – Decision Trees
  – Reinforcement Learning
  – Boosting Algorithms
  – Mixture of Experts
  – Independent Component Analysis
# Machine Learning: Applications

<table>
<thead>
<tr>
<th>응용 분야</th>
<th>적용 사례</th>
</tr>
</thead>
<tbody>
<tr>
<td>인터넷 정보검색</td>
<td>텍스트 마이닝, 웹로그 분석, 스팸필터, 문서 분류, 여과, 추출, 요약, 추천</td>
</tr>
<tr>
<td>컴퓨터 시각</td>
<td>문자 인식, 패턴 인식, 물체 인식, 얼굴 인식, 정면전환 검출, 화상 복구</td>
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<tr>
<td>음성인식/언어처리</td>
<td>음성 인식, 단어 모호성 제거, 번역 단어 선택, 문법 학습, 대화 패턴 분석</td>
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<td>모바일 HCI</td>
<td>동작 인식, 제스처 인식, 휴대기기의 각종 센서 정보 인식, 떨림 방지</td>
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<td>생물정보</td>
<td>유전자 인식, 단백질 분류, 유전자 조절망 분석, DNA 칩 분석, 질병 진단</td>
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<td>바이오메트릭스</td>
<td>홍채 인식, 심장 박동수 측정, 혈압 측정, 당뇨치 측정, 지문 인식</td>
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<td>컴퓨터 그래픽</td>
<td>데이터기반 애니메이션, 캐릭터 동작 제어, 역운동학, 행동전화, 가상현실</td>
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<tr>
<td>로보틱스</td>
<td>장애물 인식, 물체분류, 지도 작성, 무인자동차 운전, 경로 계획, 모터 제어</td>
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<tr>
<td>서비스업</td>
<td>고객 분석, 시장 클러스터 분석, 고객 관리(CRM), 마켓팅, 상품 추천</td>
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</table>
**Human-Like ML: Next Generation of ML**

### Generations of Machine Learning Technology

<table>
<thead>
<tr>
<th>Generation</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
<th>4th</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time</strong></td>
<td>~ 1985</td>
<td>~ 2000</td>
<td>~ Today</td>
<td>In 10 years</td>
</tr>
<tr>
<td><strong>Status</strong></td>
<td><img src="image1.png" alt="Artificial Neural Networks" /></td>
<td><img src="image2.png" alt="Support Vector Machines" /></td>
<td><img src="image3.png" alt="Deep Networks" /></td>
<td><img src="image4.png" alt="Human-Like Machine Learning" /></td>
</tr>
<tr>
<td><strong>Models</strong></td>
<td>Perceptrons, Self-Organizing Maps</td>
<td>Kernel Machines, Ind. Component Analysis</td>
<td>Markov Random Fields, Bayesian Networks</td>
<td>E.g.: Hierarchical hypernetworks that learn rapidly, flexibly, and robustly in a changing environment</td>
</tr>
<tr>
<td><strong>Property</strong></td>
<td>• Discriminative&lt;br&gt;• Symbolic Concept&lt;br&gt;• Static &amp; Batch-style</td>
<td>• Discriminative&lt;br&gt;• Error Minimization&lt;br&gt;• Static &amp; Batch-style</td>
<td>• Generative&lt;br&gt;• Feature Learning&lt;br&gt;• Static &amp; Batch-style</td>
<td>• Lifelong &amp; Self-developing&lt;br&gt;• Perception-Action Cycle&lt;br&gt;• Dynamic &amp; Online</td>
</tr>
</tbody>
</table>

Neural Networks: Brain-Like AI

Input: $x_1, x_2, x_3$

Weights

Output: $o = f(x)$

Error Backpropagation

$w_i \leftarrow w_i + \Delta w_i$, $\Delta w_i = -\eta \frac{\partial E}{\partial w_i}$

Output Comparison

$E_d(\tilde{w}) \equiv \frac{1}{2} \sum_{k \in \text{outputs}} (t_k - o_k)^2$

Input Layer
Scaling Function

Hidden Layer
Activation Function

Output Layer
Activation Function

Activation Function

Scaling Function

Neural Networks: Brain-Like AI

(c) 2005-2012 SNU Biointelligence Laboratory, http://bi.snu.ac.kr/
Application Example: Autonomous Land Vehicle (ALV)

- NN learns to steer an autonomous vehicle.
- 960 input units, 4 hidden units, 30 output units
- Driving at speeds up to 70 miles per hour

Image of a forward-mounted camera

ALVINN System
CMU

Weight values for one of the hidden units

(c) 2005-2012 SNU Biointelligence Laboratory, http://bi.snu.ac.kr/
Deep Neural Networks (2006)

- Key idea:
  - Greedy Layer-wise training
  - Pre-training + Fine tuning
  - Contrastive Divergence

**Restricted Boltzmann Machine**

\[
p(v, h) = \frac{e^{-E(v,h)}}{\sum_{u,g} e^{-E(u,g)}}
\]

\[
\frac{\partial \log p(v)}{\partial w_{ij}} = <v_i h_j>^0 - <v_i h_j>^\infty
\]

## History of Deep Learning

### Historical Events on Deep Learning

<table>
<thead>
<tr>
<th>Generation</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
<th>4th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Status</td>
<td><img src="image" alt="Artificial Neural Networks" /></td>
<td><img src="image" alt="Convolutional Neural Networks" /></td>
<td><img src="image" alt="Deep Neural Networks" /></td>
<td><img src="image" alt="Application in Company" /></td>
</tr>
<tr>
<td>Monument</td>
<td>Multi-Layer Perceptron</td>
<td>Neocognitron</td>
<td>Deep Belief Networks</td>
<td>Parallel Processing</td>
</tr>
<tr>
<td></td>
<td>Restricted Boltzmann Machine</td>
<td>LeNet</td>
<td>Deep Boltzmann Machines</td>
<td>Dropout</td>
</tr>
<tr>
<td>Property</td>
<td>• Fail to learn deep architecture</td>
<td>• Only for few modality (e.g., image)</td>
<td>• Pre-training technique for learning deep architecture</td>
<td>• Deep learning helps Google, Facebook, and Microsoft</td>
</tr>
</tbody>
</table>
Application of Deep Learning

Deep Learning as state of the art tools in business fields

- Image competition
- Speech recognition
- Web search engine

Deep Learning as future IT technology

- Gartner thinks Deep Learning makes future disruption
- Google undertakes Deep Learning Start-ups
- Facebook makes human-level face detector (DeepFace)

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Text Corpus: TV Drama Series

Friends, 24, House, Grey Anatomy, Gilmore Girls, Sex and the City

I don't know what happened.
Take a look at this.

? have ? visit the ? room.

289,468 Sentences (Training Data)

700 Sentences with Blanks (Test Data)
Why are you going down here? I appreciate it if you call her by the way.

Would you like to meet you in Tuesday and?

I'm gonna go upstairs and take a shower.

I have to visit the ladies' room.

I still can't believe you did this.

to make a decision

I appreciate it if you call her by the way.

Would you like to meet you in Tuesday and?

Why are you going down here?
### Concept Maps for *Friends* and *Prison Break*

<table>
<thead>
<tr>
<th><strong>Corpus: Friends</strong></th>
<th><strong>Corpus: Prison Break</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Keyword: “mother”</strong></td>
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</tr>
</tbody>
</table>

- *Friends*
  - you're mother killed herself
  - it's my mother was shot by a woman at eight
  - we're just gonna go to your mother that i love it
  - feeling that something's wrong with my mother and father
  - she's the single mother
  - i put this on my friend's mother
  - apparently phoebe's mother killed herself
  - thanks for pleasing my mother killed herself
  - i'm your mother told you this
  - is an incredible mother
  - that's not his mother or his hunger strike
  - holy mother of god woman
  - i like your mother and father on their honeymoon suite
  - with her and never called your mother really did like us
  - is my mother was shot by a drug dealer

- *Prison Break*
  - tells his mother and his family
  - she's the mother of my eyes
  - speak to your mother used to be
  - tells his mother made it pretty clear on the floor has
  - speak to your mother never had life insurance
  - she's the mother of lincoln's child
  - she's the mother of my own crap to deal with you
  - just lost his mother is fine
  - just lost his mother and his god
  - tells his mother and his stepfather
  - she's the mother of my time
  - his mother made is clear you couldn't deliver fibonacci
  - she's the mother of my brother is facing the electric chair
  - same guy who was it your mother before you do it
  - they gunned my mother down

---

[J.-H. Lee et al., 2009]
Scores generated by Evolutionary Hypernetworks that learned American (A), Scottish (B), Korean Singer Kim (C), and Korean Singer Shin (D) with the cue (left side of the bar in the middle) from “Swanee River”, the famous American folk song
Multimodal Word Learning from Video

- **Utterance-scene representation**

  Original sentence-scene pairs

  ![Scene 1](image1.png) Oh, the rabbit's followed you home, Maisy.

  ![Scene 2](image2.png) Oh, and don't forget panda.

  ![Scene 3](image3.png) Good night, bird. See you in the morning.

  **Visual words**

  ![Visual Words](image4.png) rabbit, followed, home, maisy

  ![Visual Words](image5.png) forget, panda

  ![Visual Words](image6.png) good, night, bird, see, morning

  **Textual words**
Sparse Population Code Models

- Concept representation

Concept map for MOUSE

Concept map for RABBIT
Experimental Results

- Concept generalization and specialization

Episode 1

Episodes 1-2
Experimental Results

- Concept generalization and specialization (cont’d)

Episodes 1-4

- rabbit
- excited
- onion
- favorite
- doing
- farm
- bird
- little
- today

Episodes 1-6

- morning
- night
- idea
- helping
- look
- hole
- Penguin
- tree
- good
- want
- digging
- ride
- need
- Maisy
- rabbit
- water
- new
- helping
- look
- hole
KidsVideo: Concept Construction Modeling of Kids

- **Research goal:** Modeling of concept construction from cartoon videos
- **Method:** Cognitive modeling using a Bayesian concept learning
- **Contributions**
  - Online, incremental, multimodal concept learning
  - A basis for lifelong learning from various sensor data
  - Automatic knowledge acquisition and representation from multimodal data for human-level artificial intelligence

Schematic View of CogLearn Studio
CogTV: Multimodal Interactive Recommender Platform

Data
- Multimodal Stream Data
  - Image/Audio/Text
- User Data
  - User Log
  - User Environments
  - User Descriptor

Learning/Inference
- Content-based Recommendation
- Cognitive Associative Retrieval
- User Learning & Modeling
- Cognitive Inference

Recommendation Service

User Interface

User A

Interaction

Recommendation

User B

User recognition

User C
Brain-in-a-Test-Tube: From Neural Populations to Molecular Populations

- Neural assemblies encoded as molecular assemblies
- **Brain**: $10^{11}$ neurons and $10^{14}$ synapses
- **DNA Tube**: $10^{17}$ molecules in uM ($6.02 \times 10^{23} \times 10^{-6}$)
Molecular Properties for Learning

- Massively-parallel association (3D reaction in liquid state)
- Molecular recognition (A-T, G-C specific binding)
- Molecular self-assembly (hybridization)

Molecular Computing of Hypernetworks

Molecular Recognition

Molecular Self-assembly