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Use the Q&A box to queue questions, reserving the chat box for comments, and questions will be answered during the last 5-10 minutes of the session.

If you are connected via the dial-in information only, please email questions or comments to Ms. Mimi Marcus at mmarcus@stevens.edu.

Any issues? Use the chat feature for any technical difficulties or other comments, or email Ms. Mimi Marcus at mmarcus@stevens.edu.
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Can Graphical Models Provide a Sufficient Basis for General Intelligence?

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4.5.2017

The work depicted here was sponsored by the U.S. Army, the Office of Naval Research, and the Air Force Office of Scientific Research. Statements and opinions expressed do not necessarily reflect the position or the policy of the United States Government, and no official endorsement should be inferred.
Preliminary Definitions

- **Intelligence**
  - “… a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience.” *(Editorial in Intelligence with 52 signatories)*

- **General intelligence**
  - What is common across cognitive tasks

- **Artificial Intelligence**
  - “… the scientific understanding of the mechanisms underlying thought and intelligent behavior and their embodiment in machines.” *(AAAI)*

- **Artificial general intelligence**
  - The ability of a machine to perform any (human) cognitive task
Cognitive Architecture

- Model of the fixed structure of a/the mind
  - Memory, reasoning, learning, interaction, ...
  - Integration across these capabilities
- Supports knowledge and skills above the architecture

Examples are from Soar, an effort I co-led for 15 years
Overall Desiderata for the Sigma (Σ) Architecture

- A new breed of cognitive architecture that is
  - *Grand unified*
    - Cognitive + key non-cognitive (perceptuomotor, affective, attentive, …)
  - *Generically cognitive*
    - Spanning both natural and artificial cognition
  - *Functionally elegant*
    - Broadly capable yet simple and theoretically elegant
      - “cognitive Newton’s laws”
  - *Sufficiently efficient*
    - Fast enough for anticipated applications

- For virtual humans & intelligent agents/robots that can
  - Think – Broadly, deeply and robustly *cognitive*
  - Behave – *Interactive* with their physical and social worlds
  - Learn – *Adaptive* given their interactions and experience
Modular versus Functionally Elegant

Goal: Advancing *elegance*, *depth* and *breadth* of both science and systems
Approach: Graphical Architecture Hypothesis

Key to success is blending what has been learned from over three decades of independent work in cognitive architectures and graphical models.

Cognitive Architectures

Graphical Models

\[ f(u,w,x,y,z) = f_1(u,w,x)f_2(x,y,z)f_3(z) \]
Graphical Models

- Efficient computation over multivariate functions by leveraging forms of independence to decompose them into products of simpler subfunctions
  - Bayesian/Markov networks, Markov/conditional random fields, factor graphs
  \[ p(u,w,x,y,z) = p(u)p(w)p(x|u,w)p(y|x)p(z|x) \]
  \[ f(u,w,x,y,z) = f_1(u,w,x)f_2(x,y,z)f_3(z) \]

- Solve typically via some form of message passing or sampling

- State of the art performance across symbols, probabilities and signals from uniform representation and reasoning algorithm
  - (Loopy) belief propagation, forward-backward algorithm, Kalman filters, Viterbi algorithm, FFT, turbo decoding, arc-consistency, production match, …

- Can support mixed and hybrid processing
- Several neural network models map directly onto them
Bayesian Network vs. Factor Graph

- **Bayesian network**
  - Directed graph
  - Only variable nodes
  - A distribution at each node $n$
    - $p(n | \text{parents}_n)$
  - Decompose probabilities

- **Factor graph**
  - Undirected graph
  - Variable and factor nodes
  - A function at each factor node $n$
    - $f_n(vs_n)$
  - Decompose arbitrary functions

$p(u,w,x,y,z) = p(u)p(w)p(x|u,w)p(y|x)p(z|x)$

$f(u,w,x,y,z) = f_1(u,w,x)f_2(x,y,z)f_3(z)$
Summary Product Algorithm

- Compute variable marginals \((\text{sum/integral-product})\) or mode of entire graph \((\text{max-product})\)
- Pass messages on links and process at nodes
  - Messages are distributions over link variables (starting w/ evidence)
  - At variable nodes messages are combined via \textit{pointwise product}
  - At factor nodes do products, and summarize out unneeded variables:

\[
m(y) = m(x) f_1(x,y)
\]

\[
f(x,y,z) = y^2 + yz + 2yx + 2xz = (2x+y)(y+z) = f_1(x,y)f_2(y,z)
\]
The Structure of Sigma
Conjoining the Two Halves of the Hypothesis

Σ

Cognitive Architecture:
- Predicates
- Conditionals
- Nested tri-level control

Graphical Architecture:
- Graphical models
- Piecewise linear functions
- Gradient-descent learning

Computer System

- Programs & Services
- Computer Architecture
- Microcode Architecture
- Hardware

Σ Cognitive System

- Knowledge & Skills
- Cognitive Architecture
- Graphical Architecture
- Lisp
Sigma’s Cognitive Architecture

- **Predicates** define relations among typed elements
  - Both symbolic and numeric (discrete and continuous)

- **Conditionals** yield patterns over predicates
  - Deep blend of rule and probabilistic-graph behavior

(Soar-like) **Nested Tri-Level Control**

- A (parallel) reactive layer
  - Single graph/cognitive cycle
- A (serial/iterative) deliberative layer
  - Repeated operator/action selection & application

- A (recursive) reflective layer
  - Impasse-driven meta-level processing

Maps onto bi/tri-level models in psychology and robotics
- But unique (with Soar) in functional elegance of nesting
Sigma’s Graphical Architecture

- **Graphical models:** Factor graphs & summary product algorithm
  \[ f(u,w,x,y,z) = f_1(u,w,x)f_2(x,y,z)f_3(z) \]

- **Piecewise linear** functions and messages
  - Continuous, discrete & symbolic

- **Gradient-descent learning** of functions locally at factor nodes
Example: Semantic Memory (SM) Graph

Given cues, retrieve/predict object category and missing attributes
E.g., Given Alive=T & Legs=4 Retrieve Category=Dog, Color=Brown, Mobile=T, Weight=50

A subset of factor nodes (and no variable nodes)

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Piecewise Linear Functions

(a) Continuous (approximation)

(b) Discrete

(d) Symbolic
Learning by Local Incremental Gradient Descent

- Concept (S)
- Weight (C)
- Color (S)
- Mobile (B)
- Alive (B)
- Legs (D)

Gradient defined by feedback to function node:
- Normalize (and subtract out average)
- Multiply by learning rate
- Add to function, smooth and normalize

Similar to backpropagation in NNs, but don’t need a separate backprop phase

Local, incremental search for optimal weights

http://www.mathworks.com/matlabcentral/fx_files/27631/1/fff.png
Overall Progress on Sigma [JAGI 16]

- Memory
  - Procedural (rule) [ICCM 10]
  - Declarative (semantic/episodic) [ICCM 10, CogSci 14]
  - Constraint [ICCM 10]
  - Distributed vectors [AGI 14a]
  - Perceptual [BICA 14a, AGI 15]
  - Neural network [AGI 16]

- Problem solving
  - Preference based decisions [AGI 11]
  - Impasse-driven reflection [AGI 13]
  - Decision-theoretic (POMDP) [BICA 11b]
  - Theory of Mind [AGI 13, AGI 14b]

- Learning [ICCM 13]
  - Concept (supervised/unsupervised)
  - Episodic [CogSci 14]
  - Reinforcement [AGI 12a, AGI 14b]
  - Action/transition models [AGI 12a]
  - Models of other agents [AGI 14b]
  - Perceptual (including maps in SLAM)
  - Neural network

- Efficiency [ICCM 12, BICA 14b]

- Mental imagery [BICA 11a, AGI 12b]
  - 1-3D continuous imagery buffer
  - Object transformation
  - Feature & relationship detection

- Perception
  - Object recognition (CRFs) [BICA 11b]
  - Speech recognition (HMMs) [BICA 14a, BICA 16]
  - Localization [BICA 11b]

- Natural language
  - Word sense disambiguation [ICCM 13]
  - Part of speech tagging [ICCM 13]
  - Sentence identification [WS 15]
  - Dialogue [WS 15]

- Affect [AGI 15]
  - Appraisal
  - Attention

- Integration
  - CRF+Localization+POMDP [BICA 11b]
  - Rules+SLAM+RL+ToM+VH [IVA 15, WS 15]
  - SLAM+Appraisal+Attention+VH
  - SentenceID+Dialogue [WS 15, ICAVCD 16]

Example: Supervised Naïve Bayes Probabilistic Classifier Learning

Learn prior distribution on Concept: \( P(C) \)

Learn conditional distributions on features given Concept: \( P(f | C) \)

\[
P(C,A,L,Col,M,W) = P(C)P(A|C)P(L|C) \ldots
\]
Example: Learning Maps in SLAM

- Map: \( P(\text{Objects} \mid \text{Locations}) \)

**CONDITIONAL Object-Location-Map**

**Conditions:** \( \text{Object}(\text{value}: o) \)

**Contact:** \( \text{Location}(x:x) \)

**Function** \( x, o \):

\[ .25 \]

### 138 Moves

![138 Moves Graph]

### 1000 Moves

![1000 Moves Graph]
Learn values of actions for states by backwards propagation of rewards received during exploration:

\[ Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_t + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)] \]
Example: Reinforcement Learning

Learn values of actions for states by backwards propagation of rewards received during exploration:

\[ Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_t + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)] \]
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Deconstructing RL in Sigma

Knowledge:
- Initial uniform predictors for:
  - Current reward ($R$)
  - Projected future reward ($P$)
  - Action preferences ($Q$)
- Regression (backup) knowledge
- Action models (predict next states)

Supervised learning of:
- Current reward ($R$)
- Projected future reward ($P$)
- Action preferences ($Q$)

Add *diachronic cycles* to also learn action models

Graphs are of expected values, but learning is actually of full distributions
Example: Neural Network Learning in Sigma

- Implementing NNs in Sigma is quite simple w/o learning
  - Each link simply becomes a rule with the weight as its function
  - Extended GA's existing non-linear processing for sigmoid
- Can compress units at each layer (yielding speedups)
  - Yields one rule per layer, with weight matrix as function
- Implement *backpropagation* via “backward” rules
  - Use *correctness* to measure the error
Aside: Emotions in Sigma

- Motivated by combination of:
  - Theoretical desiderata of *grand unification* and *generic cognition*
  - Practical goal of building useful *virtual humans*
  - Hypothesis that emotion is *critical for surviving and thriving in complex physical and social environments*
    - Part of the *wisdom of evolution*
  - Largely non-voluntary and immutable
    - Likely a significant architectural component
  - But also affected by knowledge and skills
Appraisal-Driven Emotional Processing

- Expectedness
- Desirability
- Familiarity
- Correctness

Expectedness → Attention
Desirability → Curiosity
Familiarity → Learning (BP)
Correctness → Emotional State

Emotional State → Knowledge & Skills

Knowledge & Skills → Architecture

Architecture → Modulation
Modulation → Appraisal
Appraisal → Expectedness

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Example: Neural Network Learning in Sigma

- Implementing NNs in Sigma is quite simple w/o learning
  - Each link simply becomes a *rule* with the weight as its function
  - Extended GA’s existing non-linear processing for sigmoid
- Can compress units at each layer, yielding speedups as in SM
  - Yields one rule per layer, with weight matrix as function
- Implement *backpropagation* via “backward” rules
  - Use *correctness* to measure the error
  - *Tie* corresponding functions/messages together
  - Reuse forward messages as needed going backward
- Can replace standard GML in RL to yield *neural RL*
- Provides an architectural embedding for neural networks
  - Enables unification within a single graph of neural networks, probabilistic graphical models, symbolic rules, etc.
  - May provide guidance for how to combine deep learning with other necessary components, such as memories, search and attention
INTEGRATION
Example: Interactive, Adaptive Virtual Humans

- Control behavior of SmartBody VH(s) in a retail store scenario
  - A civilian instance of a *physical security system*
  - Rule-based, probabilistic and social reasoning (ToM)
  - Simultaneous localization and mapping (SLAM)
  - Multiagent reinforcement learning (RL)
Before Map Learned

After Map Learned

Before Model Learned

After Model Learned
Example: Appraisal Based Exploration

Searching for an item only leveraging architectural *appraisal variables*

- Appraisal is the first stage of the full emotional arc
- Attention (surprise & desirability) and Curiosity (surprise & familiarity)
Example: Conversational Virtual Human Mind

- Immersive Naval Officer Training System (INOTS)
  - Targets leadership and basic counseling for junior Navy leaders
  - Trained over 12,000 sailors since 2012

- INOTS “mind” based on two tools
  - Statistical query-answering tool (NPCEditor)
  - Transition diagram for dialogue management

- Both aspects reimplemented and integrated together in Sigma
  - Query answering via (naïve Bayes) semantic memory (reactive)
  - Dialogue management by sequences of operators (deliberative)

- Being extended to include speech via graphical models in Sigma
Fundamental Questions about Sigma

- Can general intelligence be provided in this manner?
- Can it all be sufficiently efficient for real time behavior?
- What are the functional gains?
- Can the human mind (and brain) be modeled?
Sigma embodies a new approach to cognitive architecture
  - Based on a broadly uniform, (largely) mathematically sound, and (potentially) efficient graphical architecture
  - For next generation virtual humans and intelligent agents/robots

But does require some extensions to graphical models

... and still has a ways to go for full general intelligence

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The National Artificial Intelligence Research and Development Strategic Plan (Basic R&D segment of Fig. 4)
3. The Deep Learning Revolution

5. Areas of Rapid Progress other than Deep Learning
   5.1. Reinforcement Learning
   5.2. Graphical Models
   5.3. Generative Models and Probabilistic Programming Languages
   5.4. Hybrid Architectures

Selected Recommendations from report:

DoD should both track (via a knowledgeable cadre) and invest in (via a 6.1 research portfolio) the most dynamic and rapidly advancing areas of AI, including, but by no means limited to DL. DoD’s portfolio in AGI should be modest and recognize that it is not currently a rapidly advancing area of AI. …

But can AGI based on these five concepts advance more rapidly?
UPCOMING TOPICS:

**What Are Cyber-Social Learning Systems And How Will We Form Them?**
Dr. Kevin Sullivan, University of Virginia

*June 7, 2017 | 1:00 pm ET*

**Cybersecurity**

Dr. Barry Horowitz, University of Virginia
Munster Professor of Systems and Information Engineering and Chair

*August 2, 2017 | 1:00 pm ET*

Thank you for joining us!
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