Features↓ vs. Architectures→ (download this table) Contributors to this table: → Curator: Alexei Samsonovich Last update: 2010-09-20	4D/RCS James Albus	ACT-R Andrea Stocco and Christian Lebiere	ART Stephen Grossberg	BECCA Brandon Rohrer, updated 8/3/2011	biSoarCERA-CRANIUMB. Chandrasekaran and U. KurupRaul Arrabales	Chrest Fernand Gobet and Peter Lane	Clarion C Ron Sun E	CogPrime CoJACK Ben Goertzel Frank Ritter & Rick Evertsz	Disciple George Tecuci agent development Cognitive Assistant Cogni	Epic Shane Mueller, Andrea Stocco	FORR Susan L. Esptein	GLAIR Stuart C. Shapiro	GMU-BICA Alexei Samsonovich	HTM Jeff Hawkins	Leabra David C. Noelle	LIDANARSStan FranklinPei Wang	Nexting Akshay Vashist, Shoshana Loeb	Pogamut Cyril Brom	Polyscheme Nick Cassimatis	Recommendation Architecture REM L. Andrew Coward Ashok K. Goel, J. William Murdock, and Spencer Rugaber	Soar Ymir Andrea Stocco / John Laird Kristinn R. Thórisson	other architectures to consider including:
Iconic link to diagrams		Coal Insugnal Vessal Messal Vessal	Nemspecific shibitory gain control	BECCA agent feature creator upper data and a set of the set of t					Choiciple Agent Shell Weil and	EPIC Architecture Diagram	Ground level Sensors Actuators action Control learning Tier 2 Advisors Tier 3 Advisors Control learning Procedure output Strategy Control learning Strategy Control learning	CECE States	Procedural memory Procedural memory Driving engine Reward & punish.	& Numenta			recontine Action Action Nexting Reasoning Reasoning Reasoning Reasoning Reasoning Reasoning Reasoning Memory Nexting			Association Cortex Amygdata Hypothalamus Basa/ Ganglia	Image: Second	lcarus SAL Tosca
Knowledge and experiences are represented using	images, maps, objects, events, state, attributes, relationships, situations, episodes, frames		Visual 3D boundary and surface representations; auditory streams; spatial, object, and verbal working memories; list chunks; drive representations for reinforcement learning; orienting system; expectation filter; spectral timing networks	transitions between experiences.	 The representational framework of Soar plus diagrams – the diagrammatic part can also be combined with any symbolic general architecture, such as ACT-R Single percepts, comp percepts, and mission percepts. Single and complex behaviors. 	ex chunks and productions	r Iv t	CogPrime is a multi-representational system. The core representation consists of a hypergraphs with uncertain ogical relationships and associative relations operating cogether. Procedures are stored as functional programs; episodes are stored in part as "movies" in a simulation engine; and there are other specialized methods too.	1 5	memory entries	<i>Descriptives</i> are shared knowledge resources computed on demand and refreshed only when necessary <i>Advisors</i> are domain-dependent decision rationales for actions. Measurements are synopses of problem solving experiences.	assertional frame-based, and propositiona	al	Memory and representations are distributed across a hierarchy of nodes. Within each node representations are large sparse binary vectors.	patterns of neural firing rates and patterns of synaptic strengths. Sensory event drive patterns of neural activation, and such activation-based representations m drive further processing and the production of actions. Knowledge that is retai for long periods is encoded in patterns of synaptic connections, with synaptic strengths determining the activation patterns that arise when knowledge or previous experiences are to be employed.	ined types attached to nodes;	Facts, Rules, frames (learned/ declared), symbolic representation of raw sensory inputs, expectation generation and matching	n	constraint graphs, first-order literals, taxonomies, weight	A large set of heuristically defined similarity circumstances, each of which is a group of information conditions that are similar and have tended to occur at the same time in past experience. One similarity circumstance does not correlate unambiguously with any one cognitive category, but each similarity circumstance is associated with a range of recommendation weights in favour of different behaviours (such	Procedural knowledge: Rules. Semantic knowledge: relational graph structure, Episodic memory: episodes of relational graph structures	4CAPS AIS Apex Atlantis CogNet Copycat DUAL Emotion Machine
Main components	Behavior Generation, World Modeling, Value Judgment, Sensory Processing, Knowledge Database. These are organized in hierarchical real-time control system (RCS) architecture	memory; buffers; procedural knowledge encoded as	Many model brain regions, notably laminar cortical and thalamic circuits	r BECCA is a solution to the general reinforcement learning problem It consists of two parts, an unsupervised feature creator and a model-based incremental learner. Both are incremental and on-lin designed for a physically embodied agent operating in an unstructured environment.	representation; perceptual workspace, Mission-		knowledge (each in both in plicit and explicit forms rules and NNs) in	The primary knowledge store is the AtomSpace, a neural- symbolic "weighted labeled hypergraph" with multiple cognitive processes acting on it (in a manner carefully designed to manifest cross-process "cognitive synergy"), and other specialized knowledge stores ndexed by it. The cognitive processes are numerous but nclude: an uncertain inference engine (PLN, Probabilistic Logic Networks), a probabilistic evolutionary program learning engine (MOSES, developed initially by Moshe Looks), an attention allocation algorithm (ECAN, Economic Attention Networks, which is somewhat neural net like), concept formation and blending heuristics, etc. Work is under way to incorporate a variant of Itamar Arel's DeSTIN system as a perception and action layer. Motivation and emotion are handled via a variant of Joscha Bach's MicroPsi framework called CogPsi.	solutions of the simpler problems are successively combined into the solutions of the corresponding complex problems. To exhibit this type of behavior, the knowledge base of the agent contains a hierarchy of ontologies, as well as problem reduction rules and solution synthesis rules which	 production rule interpreter and working memory), long term memory, production memory, detailed perceptual-motor interfaces (auditory processor, visual processor, ocular motor processor, vocal motor processor, manual motor 	 consulted in a pre-specified order. Tier-2 Advisors trigger in the presence of a recognized situation, recommend (possible partially ordered) sets of actions, and are consulted in a pre-specified order. Tier-3 Advisors are heuristics, recommend individual actions, and are consulted together. Tier-3 Advisors' opinions express preference strengths that are combines with weights during <i>voting</i> to select an action. A FORR-based system learns those weights from traces of its problem-solving 	Memory, Episodic Memory, Quantified & conditional beliefs, Plans for non-primitive acts, Plans to achieve goals, Beliefs about preconditions & effects of acts, Policies (Conditions for performing acts), Self- knowledge, Meta-knowledge; 2) Perceptuo Motor Layer containing implementations of primitive actions, perceptual structures that ground KL symbols, deictic and	semantic, episodic, procedural, e iconic (I/O); plus: cognitive map, reward system, the engine	neocortex and thalamus. HTM models cortex related to sensory perception, learning to infer and predict from high dimensional sensory data. The model starts with a hierarchy of memory nodes. Each node learns to pool spatial pattern using temporal contiguity (uising variable order sequences if appropriate) as the teacher. HTMs are inherently modality independent. Biologically the model maps to cortical regions, layers of cells, columns of cell across the layers, inhibitory cells, and non-linear dendrite properties. All representations are large sparse distributions of cell activities.	At the level of gross functional anatomy, most Leabra models employ a tripartit view of brain organization. The brain is coarsely divided into prefrontal cortex, r hippocampus and associated medial-temporal areas, and the rest of cortex "posterior" areas. Prefrontal cortex provides mechanisms for the flexible retenti and manipulation of activation-based representations, playing an important rol- working memory and cognitive control. The hippocampus supports the rapid weight-based learning of sparse conjunctive representations, providing central mechanisms for episodic memory. The posterior cortex mostly utilizes slow statistical learning to shape more automatized cognitive processes, including sensory-motor coordination, semantic memory, and the bulk of language processing. At a finer level of detail, other "components" regularly appear in Lea based models. Activation-based processing depends on attractor dynamics utilizing bidirectional excitation between brain regions. Fast pooled lateral inhibition plays a critical role in shaping neural representations. Learning arises from an associational "Hebbian" component, a biologically plausible error-drive learning component, and a reinforcement learning mechanism dependent on the brain's dopamine system.	theacting as a cognitive atom. Higher level processes implemented as behavior streams.integrated memory and control mechanismionCognitive cycle includes sensory memory, perceptual associative memory, workspace, transient episodic memory, declarative memory, global workspace, procedural memory, action selection, sensory motor memoryintegrated memory and control mechanismabra-s enintegrated memory and control mechanism	Learning, Reasoning, Imagining, Attention Focus, Time awareness Expectation generation and matching	procedural knowledge encoded as reactive rules; episodic and spatial memory encoded within a set of graph based structures	the flow of attention and thus inference. Specialized modules for representing and making inferences about specific concepts.	Condition definition and detection (cortex);Task-Method-Knowledge (TMK) modelsSelection of similarity circumstances to be changed in each experience (hippocampus);provide functional models of what agentSelection of sensory and other information to beknow and how they operate. They describe components of a reasoning	represented as rules organized as operators; semantic memory; episodic memory; menal imagery; o reinforcement learning ne a ne	nteracting ERE Gat Guardian H-Cogaff Homer Imprint MAX Omar PRODIGY PRS Psi-Theory R-CAST RALPH-MEA Society of Mind Subsumption architecture Teton Theo
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Implementation	http://www.isd.mel.nist.gov/projectLisp, TCL/TkNonlinear neural networks (feedback, multiple spatial and temporal scales)MATLAB, Python	Implemented in the Soar.Net Framework, codeLisp, JavaJavaframeworkwritten in C#. Runtime	The OpenCogPrime system implements CogPrime within overlay to JACK® the open-source OpenCog AI framework, see	Disciple was initially implemented in Lisp and is currently implemented in JavaOriginal version: Common Lisp; EPIC-X: C++Common Lisp, Java	Common Lisp Matlab, Python	NuPIC development environment available "Emergent" open source software written largely in C++ (runs on many for PC and Mac. It is available under a free platforms)	Extensible framework in Java. Open source, in Java an	l Prolog In Progress (C++, Java, Perl, Java, Prolog) bind	a, Python; features ACT-R Java Smalltalk ding and Emergent	Common Lisp, using Loom as theC with interfaces to almost anyCommonLisp, C, C++, 8 networked computers, sensingunderlying knowledge-engine; Java versionlanguage; Javahardware
	C++, Windows Real-time, VXworks,	based on CCR	http://opencog.org. The implementation is mostly C++			research license and a paid commercial			ding	in development
	Neutral Messaging Language	(Concurrency and	for Linux, some components in Java; also a Scheme shell			license.				
	(NML),	Coordination Runtime)	is used for interacting with the system.							
	Mobility Open Architecture	and DSS (Decentralized								
	Mobility Open Architecture Simulation and Tools (MOAST)	Software Services), part of								
	http://sourceforge.net/projects/mo	Robotics Developer								
	ast/	Studio 2008 R2.								
	Urban Search and Rescue	http://www.conscious-								
	Simulation (USARSim)	robots.com/en/robotics-								
	Urban Search and Rescue Simulation (USARSim) http://sourceforge.net/projects/usa	studio/2.html								
	rsim/									

Funding program, project and environment in which the architecture was applied	Please see the long list: http://members.cox.net/bic	<u>bica2009/</u>		andia National Labs, internal R&D funding								Office of Naval Research	National Science Foundation		DARPA IPTO BICA, virtual indoor/outdoor environments	Numenta licesnses its software to various commercial partners.							NSF Science of Design program; Self Adaptive Agents project; Turn-based strategy games		
(added by Jim Albus) Support for Common Components																									
Working memory?	yes	Not explicitly defined	5	ecent percepts are folded together with a decayed version ecent percepts. This creates a short history of salient percepts th unctions as working memory.	3 3 7	, ,	Yes, although we call it short-term memory. Auditory short-term memory and visuo- spatial short-term memory are implemented.	separate structure yes			The framework of Disciple supports features and components that are common for many cognitive architectures, including working memory (reasoning trees), semantic memory (ontologies), episodic memory (reasoning examples), and procedural memory (rules). Communication is		Yes		<u>ves: includes mental states of</u> <u>the Self</u>		current situation	cluded as a workspace with t nternal structure including a ational model with both real and ows, ans a conscious contents	he active part of the memory	Yes d	eclarative	Each specialist implement its own.	Yes. Frequency modulation placed on neuron spike outputs, with different modulation phase for different objects in working memory.	n structure Functional Sketchboard, Content Blackboard, Motor Feedback Blackboard, Frames	ck
Semantic memory?	yes	Encoded as chuncks		es. Semantic information for a feature is obtained from the istory of the agent's experience.	n	•	-	yes. in both implicit and yes explicit forms (chunks/rules and NNs)			based on natural language patterns learned from the user.	Not explicitly	In many descriptives	Yes, in SNePS	yes: includes schemas		Many Leabra models of the learning and use of semantic knowledge, abstracted from the statistical regularities over many experiences, have been published. These include some language models.	· ·	he whole memory is semantic	frames n	one	Each specialist implement its own.	Yes. Similarity circumstances (= cortical column receptive fields) that are often detected at the same time acquire ability to indirectly activate each other.	n structures Frames	
Episodic memory?	yes	Not explicitly defined		'es. Individual transitions from experience to experience are an pisode.	n	•		yes. in both implicit and yes explicit forms (chunks and NNs)		Not explicetly defined, but would be encocoded as beliefs in beliefsets.		No	Yes, in task history and summary measurements	Yes, temporally-related beliefs in SNePS	YS yes: includes frozen mental state assemblies		Many Leabra models of episodic memory have been published, mostly focusing on the role of the hippocampus in episodic memory. Both declarative distributed me	mory encoded via sparse t	· ·		eclarative or a spreading tivation network	own.	Yes. Similarity circumstances (= cortical column Yes: Defined as traces through the Encoded as g	ph structures Functional Sketchboard, Content Blackboard, Motor Feedback Blackboard	:k
Procedural memory?	yes	Explicitly defined	Yes. Multiple explicitly defined neural systems for learning, planning ,and control of action	'es. Common sequences of transitions are reinforced and are mo kely to be executed in the future.	re Extends Soar's procedural y memory to diagrammatic g components c	generate single or		yes. in both implicit and yes explicit forms (chunks/rules and NNs)		Plans and intentions with activation levels			Yes, Advisors can be weighted by problem progress, an repeated sequences of actions can be learned and store		d be yes: includes primitives		A fair number of Leabra models of automatized sequential action have been produced, with a smaller number specifically addressing issues of motor control. Most of these models explore the shaping of distributed patterns of synaptic strengths in posterior brain areas in order to produce appropriate action sequences in novel situations. Some work on motor skill automaticity has been done. A few models, integrating prefrontal and posterior areas, have focused on the application of explicitly provided rules.	r	the part of memory that is directly related to executable operations	Yes (Implicit)	les		Yes. Recommendation weights associated in the basal ganglia with cortical column receptive field detections instantiate procedural memory Hereins and methods, which are behavioral elements Hereins and methods are behavioral elements Hereins are behavioral eleme	Frames, Action Modules, (limited implementation)	
cognitive map?	yes		Yes. Networks that learn entorhinal grid cell and hippocampal place field representations on line	•	Cognitive map emerges y p n	yes. Mission-specific processors build 2D maps.	No.	yes							yes		Leabra contains the mechanisms necessary to self-organize topographic representations. These have been used to model map-like encodings in the visual system. At this time, it is not clear that these mechanisms have been successfully applied to spatial representation schemes in the hippocampus.	đ	as part of the memory	g			No. Requirement to conserve resources by using any one similarity circumstance (= receptive field) to support multiple behaviours precludes the existence of unambigous cognitive maps	Limited body-centric spatial layout of selected objects	
reward system?	Yes, Value Judgment proces compute cost, benefit, risk	k	,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	es. Reward is specified in the definition of the task. It can be an rbitrary function of observed and unobserved states.		yes. Status assessment mechanism in core layer.		yes. in the form of a Yes, Va motivational subsystem risk and a meta-cognitive subsystem (MCS determines rewards based on the MS)	alue Judgment processes compute cost, benefit,	Uses ACT-R memory equations, so memories and plans get strengthened.		No	Yes; Advisor weights are acquired during self-supervise learning.	ed	yes		Leabra embraces a few alternative models of the reward-based learning systems dependent on the mesolimbic dopamine systems, including a neural implementation of temporal difference (TD) learning, and, more recently, the PVLV algorithm. Models have been published involving these mechanisms, as well as interactions between dopamine, the amygdala, and both lateral and orbital areas of prefrontal cortex.	· · ·	experience-based and context-				Yes. Some receptive field detections are associated with recommendations to increase or decrease recently used behavioural recommendation weightsFunctional descriptions of tasks allow agents to determine success or failure of those tasks by observing the state of the world. Success or failure can then be used to reinforce decisions made during execution.appraisal-bas user-defined reward		
Iconic memory (including Interface and Imagery)?	d Yes, image and map representations	Propositional (Based on chunks)	Emerges from role of top-down attentive interactions in laminar models of how the visual cortex sees	lo explicit. An implicit iconic memory emerges from the transisio istory between vision-based features.	n n	no (to be implemented)	Yes.	sensor	ed to emerge implicitly via combination of ry, declarative and simulative memory. Not nented/tested yet.	not particularly, would be application and IO system specific.		Part of visual perceptual processor	Yes, in some descriptives		yes (imagery was not implemented)		In Leabra, iconic memory can result from activation-based attractor dynamics or from small, sometimes transient, changes in synaptic strength, including matrices mechanisms of synaptic depression. Imagery naturally arises from patterns of bidirectional excitation, allowing for top-down influences on sensory areas. Little work has been done, however, in evaluating Leabra models of these phenomena against biological data.	ng various processed pixel		Not directly implemented. n Extension possible.			AtYes. Maintained on the basis of indirect activation of cortical columns recently active at the same timeSpatial relationships are encoded using the underlying knowledge engine.Explicitly define the underlying knowledge engine.	d No	
Perceptual memory (if understood separately from iconic and working memory)?	.,			es. All different sensory modalities and combinations of nodalities are treated the same within BECCA.	elements of perceptual p	• •	Yes.		t currently only for vision. Further modalities will lemented later.			Yes			yes: input-output buffer (in psychology, very short-term perceptual memory and iconic memory are synonyms)		Different aspects of perceptual memory can be supported by activation-based learning, small changes in synaptic strengths, frontally-mediated working memory processes, and rapid sparse coding in the hippocampus.	, ,				has some of this	Yes. Based on indirect activation of cortical columns on the basis of recent simultaneous activity	Perceptual representations at multiple levels (complexity) and timescales (see "visual input" and "auditory input" below).	
Attention and consciousness	Yes, can focus attention on regions of interest. Is aware in relation to the environme other agents.	are of self	Yes. Clarifies how boundary, surface, and prototype attention differ and work together to coordinate object and scene learning. Adaptive Resonance Theory predicts a link between processes of Consciousness, Learning, Expectation, Attention, Resonance, and Synchrony (CLEARS) and that All Conscious States Are Resonant States.	'es. The most salient feature at each time step is attended.	s c le C c c r r	implemented as a bias	Attention plays an important role in the architecture, as it for example determines the next eye fixation and what will be learnt.	interes	an focus attention on regions and topics of it. Is aware of self in relation to the environment her agents.			Emergent Phenomenon of working memory	Yes, some Advisors attend to specific problem features	S	described by a special attribute	mechanisms within HTMs although this is not in currently released product.	In Leabra, attention largely follows a "biased competition" approach, with top-down activity modulating a process that involves lateral inhibition. Lateral inhibition is a core mechanism in Leabra, as is the bidirectional excitation needed for top-down modulation. Models of spatial attention have been published, including models that use both covert shifts in attention and eye movements in order to improve object recognition and localization. Published models of the role of prefrontal cortex in cognitive control generally involve an attention-like mechanism that allows frontally maintained rules to modulate posterior processing. Virtually no work has been done on "consciousness" in the Leabra framework, though there is some work currently being done on porting the Mathis and Mozer account of visual awareness into Leabra.	broadcasts recruiting possible eponse to the current contents odulating the various forms of		Atttntion via expectation generation and matching.			Yes. Cortical columns have receptive fields defined by groups of similar conditions that often occurred at the same time in past sensory experiences, and are activated if the receptive field occurs in current sensory inputs. Attention is selection of a subset of currently detected columns to be allowed to communicate their detections to other cortical areas. The selection is on the basis of recommendation strengths of active cortical columns, interpreted through the thalamus, and is implemented by placing a frequency modulation on the action potential	Within-utterance attention span. Situated spatial model of embodied self (but no semantic representation of self that could be reasoned over).	
Visual input?	Yes, color, stereo	chunks)	Natural static and dynamic scenes, psychophysical displays. Used to develop emerging architecture of visual system from retina to prefrontal cortex, including how 3D boundaries and surface representations form, and how view-dependent and view- invariant object categories are learned under coordinated guidance of spatial and object attention.	Υes	visual input. s	Yes, both real cam and synthetic images from the simulator.	Visual input is currently coded as list structures or arrays.	proces	tly handled via interfacing with external vision sing tools. Tighter interlinkage with a hierarchical ion system is a topic of current research.			Interaction of visual motor and visual perceptual processors	Possible but not implemented	perceptual structures in PML		HTMs are inherently modality independent although we have applied them to vision tasks. We offer a Vision Framework for programmers and a Vision Toolkit requiring no programming skills.	An advanced Leabra model of visual object recognition has been produced which receives photographic images as input.	t not implemented			•		Currently implemented by emulation of action potential outputs of populations of simulated sensory neurons Not implemented, but would be handled by the underlying knowledge engine Propositional	r relational Yes. Temporally and spatially accurate vector model of upper human body, including hands, fingers, one eye. Via body- tracking suit, gloves and eyetracker.	

Auditory input? No, not yet Proposit chunks)	itional (based on Natural sound streams. Used to develop emerging architecture of visual system for auditory streaming and speaker-invariant speech recognition	No no (to be	e implemented) Auditory input is currently coded as text input (segmented either as words, phoner or syllables).			cts, Yes. FORRSooth is an extended version that conducts Has been done using off-the recognition	•		While a few exploratory Leabra models have taken low-level acoustic features as possible but not implemented input, this modality has not yet been extensively explored. possible but not implemented	No. none		Not implemented, but would be handled Support for text-based by the underlying knowledge engine communication	Yes. Speech recognition (BBN Hark), custom real-time prosody tracker with H* and L* detection.
Special modalities? Yes, LADAR, GPS, odometry, inertial	Yes. SAR, LADAR, multispectral IR, night vision, etc. BECCA is modality agnostic. It can handle inputs originating any sensory modality.	g from SONAR, Finder.	Laser Range	Reads text from the Internet ;-)		Accepts data from external databases agents have used speech a		HTMs have been applied to vision, audition, network sensors, power systems, and other tasks.		no built-in modalities, but allow plug-in sensors and actuators Possible to extend.		No	Multimodal integration and realtime multimodal communicative act interpretation
	r productions (linear nt version) Yes: CogEM and TELOS models of how amygdala and basal ganglia interact with orbitofrontal cortex etc		d be implemented No. ic processors)	yes Yes. St	Strengthening/weakening of olansAn expert interacts directly with a Disciple cognitive assistant, to teach it to solve problems in a way that is similar to how the expert would teach a lessNo	Yes	yes (a version of it)		Leabra embraces a few alternative models of the reward-based learning systems dependent on the mesolimbic dopamine systems, including a neural implementation of temporal difference (TD) learning, and, more recently, the PVLV	I Not decided.			Yes, in a recent implementation (RadioShowHost)
Bayesian Update Not implemented, but could be. Yes, for r	r memory retrieval No, sort of: Includes some Bayes effects as emergent properties No		d be implemented No. Tic processors)		experienced collaborator. This process is based on mixed-initiative problem solving (where the expert solves the more creative parts of a problem and the agent solves the more routine ones), integrated learning and teaching (where the expert helps the surrent intentions agent to learn by providing examples, hints and multiplications and the expert helps the supret to	Yes	no	HTM hierarchies can be understood in a belief propagation/Bayesian framework.	algorithm. Models have been published involving these mechanisms, as well as interactions between dopamine, the amygdala, and both lateral and orbital areas of prefrontal cortex.While Leabra does not include a mechanism for updating knowledge in a Bayes- optimal fashion based on singular experiences, it's error-driven learning mechanism	Yes.	rewards.	within a methods state-transition machine. Not implemented, but could be. No	No
Hebbian Learning Not implemented, but could be No Gradient Descent Methods (e.g. Not implemented, but could be No	Yes, sort of: Hebbian learning law is insufficient. Both Hebbian and anti-Hebbian properties are needed.Not formally, although the principle of associating co-occur signals is used extensively.Yes, but not BackpropagationNo. BECCA does not use artificial neural networks.	in specifi	d be implemented ic processors) d be implemented No.	yes Yes Via dan't use this sort of algorithm explicitly, no	explanations, and the agent helps the expert to teach it by asking relevant questions), and multistrategy learning (where the agent integrates complementary learning strategies, such as learning from examples, learning from explanations, and learning by analogy, to learn general concepts and	Yes, with respect to groupings of Tier-3 Advisors.	yes	Yes	does approximate maximum a posteriori outputs given sufficient iterated learning. An associational learning rule, similar to traditional Hebbian learning, is one of the core learning mechanisms in Leabra. A biologically plausible error correction learning mechanism similar in performance.	No. the episodic memory for hebbian learning	eatures Yes, but with an overlay management that determines whether Hebbian learning will oc at any point in time		No
	res, but not backpropagation No. BECCA does not use altificial neural networks. res, but not backpropagation Yes. Multiple kinds of self-organization new productions) Yes. Multiple kinds of self-organization	in specifi	ic processors)		No No	Yes, can learn new Advisors	yes	Yes	A biologically plausible error-correction learning mechanism, similar in performance to the generalized delta rule but dependent upon bidirectional excitation to communicate error information, is one of the core learning mechanisms in Leabra. All "active" representations in Leabra are, at their core, patterns of neural firing rates. These vectors of activity may be interpreted encoded and decoded in different ways, however. By analogy, all digital computer representations are strings of bits, but they may be interpreted as structures and pointers and the like. The way in which vectors of activity at "hidden" layers of neural units are interpreted is			Yes. Learns refinements of methods for existing tasks and can respond to a specification of some new task by adapting the methods for some similar task.	
Common General Paradigms Modeled									almost always a matter of learning in Leabra models. In this way, internal representations are always learned from experience.				
Main general paradigms	Visual and auditory information processing Goal-directed behavior		Vorkspace Theory. dal sensory Learning (e.g. implicit learning, verbal learning); acquisition of first language (syntax, vocabulary); expertise; memory; so problem solving; concept formation	ome Control of virtual-world agents. Natural language processing. We are now starting to work with humanoid robots but that's early-stage.		ci- r traffic Constraint solving; game playing; robot navigation; spoken dialogue	voluntary perception, cognitio and action			reasoning with insufficient knowledge and resources Expectation generation and matching via learing and reasoning on stored knowledge and sensory inputs.	ReasoningAll cognitive processes are implemented three sequences of receptive field activations, including both direct detections and indirect activations. At each point in the sequence the behaviour with the predominant recommendation weight across the currently activated receptive field population is perfor This behaviour may be to focus attention on particular subset of current sensory inputs of implement a particular type of indirect activat (prolong current activity, or indirectly activated the basis of recent simultaneous activity, past simultaneous receptive field change). Recommendation weights are acquired throw rewards that result in effective sequences for cognitive processing. Frequently used sequences for <b< td=""><td>ed. to on on h tes</td><td>Integrated behavior-based and classical AI; blackboards; distributed implementation</td></b<>	ed. to on on h tes	Integrated behavior-based and classical AI; blackboards; distributed implementation
other general paradigms Image: Constraint of the second	Perception, abstraction Yes, depending on what is meant Yes	Yes, problem solving is yes, impl the main application.	licit. Yes. At moment, CHREST solves problems mostly by pattern recognition.	yes Yes Ye	Verbal working memory, working memory verbal working memory	isual Yes reasoning without a goal	self-regulated learning (at the stage of design) yes		Tripartite brain organization. In the traditional AI meaning of "problem solving", involving the generation of a sequential plan to meet a novel goal, little work has been done in Leabra. Some Yes		Modle finding A simple example is fitting together two objective fields often Yes A simple example is fitting together two objective fields often	 Planning, Reinforcement learning s. Yes Yes 	Modular architecture ("schema-style") allows easy expansion of common and custom features and principles. Solves to some extent the scaling problem.
									Leabra models of sequential action can generalize when performing in a novel situation, but none of these models have addressed the traditional AI planning problem.		active in the past shortly after fields directly activated by one object were active. Because objects have often been seen in the past in several different orientations, this indirect activation is effectively a "mental rotation". Receptive fields combining information from indirect activation derived from one object a the direct activation from the other object recommend movements to fit the objects together. A bias is placed upon acceptance of such behaviours by taking on the task.		
Decision Making Makes decision based on Value Yes Judgment calculations	Yes	yes	Yes.	yes Yes Yes	Yes No	Yes	yes		Much work has been done on Leabra modeling of human decision making in cases of varying reward and probabilistic effects of actions, focusing on the roles of the dopamine system, the norepinepherine system, the amygdala, and orbito-frontal cortex.	Uses Inference (both statistical and logical).			Yes, using hierarchical decision modules as well as traditional planning methods
AnalogyNot implementedLanguage ProcessingNot implementedYes	Yes in rule discovery applications Yes Yes Yes		emented No. emented Only acquisition of language.	Yes Comprehension and generation fully implemented. Dialogue is something we're actively working on.	Image: Sector	Yes, via pattern matching yes Yes Yes			Some preliminary work has been done on using dense distributed representations in Leabra to perform analogical mapping. No Many Leabra language models have been produced, focusing on both word level and sentence level effects. Beginning stage	Somewhat Yes.	Yes Yes	Yes, using the functional specification (requirements and effects) of tasks. Limited Not implemented Yes	No Yes.
Working Memory Tasks?Yesperceptual illusions	Yes International Internationa		No.	yes Unclear exactly what this means. The system does many Ye tasks involving working memory.	/es Visual and Verbal WM Tas No	ks Unclear exactly what this means	yes: modeled perceived flipping of the Necker cube		Leabra models of the prefrontal cortex have explored a variety of working memory phenomena. Yes No		Yes Yes	Yes	Yes. No.
implicit memory tasks metacognitive tasks			Yes. No.	yes yes	No No	Yes	yes: modeled perceived flipping of the Necker cube		In principle NO		Yes. Depend on indirect receptive field activations on the basis of recent simultaneo	5 Yes	No.
social psychology tasks personality psychology tasks motivational dynamics			No. No. No.	yes yes yes yes	No Image: Second sec	Personality and emotion can be modeled through Advisors	yes: modeled perceived flipping of the Necker cube		No No No No				No.
	ultiple models) Yes Yes Yes	no	No.	We aren't doing modeling of human cognition and so we haven't tried the system on standard "cognitive modeling test problems. So no. yes See above Yes					Yes. Not yet	Voc (necoccon (feature for neuting)	Vas	No ? Not implemented ?	No.
Task SwitchingTest fillTower of Hanoi/LondonYesPRP?Dual TaskYesYesYes	No res res	not yet	No. No. No.	yes See above Yes yes See above Yes yes See above Yes yes See above Yes	ves no ves yes ves yes ves yes ves yes				Yes.Not yetI think there might have been some preliminary work on Tower of London, but I'm not sure.Not yetNot that I know of.Not yetNot that I know of.Not yet	Yes (necessary feature for nexting) No.	Yes	Not implemented Yes Yes Yes No Yes Not implemented Yes	No. ? No. .
N-Back ? Yes visual perception with comprehension Yes	Yes Yes	not yet	No. Yes.	See above We have done this in the virtual world. Currently research aims at doing it for humanoid robots also	yes		yes		Yes, but there is still work to be done, here. Not yet Not yet Not yet A powerful object recognition model has been constructed. Not yet	Yes.	Yes	No Not implemented	? Yes (see "special modalities" above)
spatial exploration, learning and Yes Yes. Search for targets in regions of interest.	Yes Yes		To some extent.	yes See above See above	no no	Yes	yes		Preliminary work only. Not yet Object localization naturally arises in the object recognition model. Not yet	yes.	Yes Yes.	Yes implemented but not comp human behavior	Yes.
learning from instructions Yes. Learn from subject matter experts. pretend-play No Meta-Theoretical Questions (added	No, unless you mean supervised learning Yes: Outline of architecture for teacher-child imitation	no Not imep	olemented No. No.	yes Yes, in the virtual world context See above Image: Context in the virtual world context in	no no no no	Yes Yes	quasi-implemented quali-implemented		Some preliminary work on instruction following, particularly in the domain of Not yet classification instructions, has been done in Leabra. Not that I know of. Not that I know of. Not yet	yes.	Yes. some	Yes, from new task specifications implemented but not comp human behavior	red to No. No.
by Stephen Grossberg)No. Uses information from battlefield information network, apriori maps, etc.Unsupervised learning?Yes. Updates control system	res. Can categorize objects and events of the res	yes	Yes. Yes.	No. Mix of local and global Yes.	Image: Sector	Yes Yes	yes yes	Yes, HTM is a biological model. Yes, uses time as primary learning method.	Yes, throughout the architecture Perceptual, episodic and procedural, each in	yes		Yes, in the existing implementation Yes. Adapts in response to failures	No.
parameters in real-time Supervised learning? Yes. Learns from subject matter experts.	alter spatial maps and sensory-motor gains without supervision. Ves. Can learn from predictive mismatches with environmental constraints, or explicit teaching signals, when they are available. No	not imple	emented Yes.	Yes.	no	Yes	yes	Yes, networks can be supervised at top node.	both instructionalist and selectionist modes No	yes		through situated action + reinforcement learning, or through generative planning + abstraction. Yes, from new task specifications	No.
Arbitrary mixtures of unsupervised and Yes supervised learning?	Yes. E.g., the ARTMAP family of models.	not imple	emented Yes.	Yes	no	Yes	yes		No	yes		Yes. Can develop a new method from a task specification and then later adapt that method based on experience.	No.
Can it learn in real time? Yes Search it do fast stable learning; i.e., Yes. Uses CMAC algorithm that	Yes. Both ART (match learning) and Vector Associative Map (VAM; mismatch learning) models use real-time local learning laws.YesYes, theorems prove that ART can categorizeYes	yes	Yes. Yes.	Yes Yes	no no	Yes	yes in short, yes. Learning in GMU	HTMs can learn on-line, meaning learning while inferring. Real time depends on size of network and nature of problem. Yes	Yes	Sometimes.		Yes	No.
adaptive weights converge on each trial without forcing catastrophic forgetting? When no errors, learning stops.	events in a single learning trial without experiencing catastrophic forgetting in dense non-stationary environments. Mismatch learning cannot do this, but this is adaptive in learning spatial and motor data about changing bodies.						BICA consists in storage of mental states and in creation o new schemas, without forgetting. Learning "weights" applies to the neuromorphic cognitive map. In most cases, learning occurs in one shot.						
Can it function autonomously? Yes. Operates machines and drives vehicles autonomously.	Yes. ART models can continue to learn stably about non-stationary environments while performing in them.	yes	Yes.	Yes.	Yes. Key motivation for selecting BDI	Yes	yes.	Yes	Yes			Yes	Yes; however, no actual implementations have yet pushed the architecture on this issue.
Is it general-purpose in its modality; i.e., is it brittle? It is general purpose and robust in real world environments.	ART can classify complex non-stationary data streams. The FACADE ₃ D vision model clarifies how multiple types of visual data (e.g., edge, texture, shading, stereo) are processed by laminar cortical circuits.	ge and yes	It is general-purpose and not brittle.	lt is general purpose and robust in real world environments.	no	General purpose	general-purpose.	Yes	General purpose			General purpose	The architecture to some extent addresses the brittleness problem, but not to full autonomy.
Can it learn from artbitrarily large databases; i.e., not toy problems? Yes. All applications are real-world and real-time.	Yes. Theorems about ART algorithms show that they can do fast learning and self- stabilizing memory in arbitrarily large non- stationary data bases. ART is therefore used in many large-scale applications http://techlab.bu.edu/	not teste	ed Yes. Simulations on the acquisition of language have used corpora larger than 35 utterances. Simulations with chess have us databases with more than 10k positions Discrimination networks with up to 300k chunks have been created.	sed	no	Yes	in principle, yes.	Yes	???			Yes, up to the limitations of the underlying knowledge engine	No.
Can it learn about non-stationary databases; i.e., environmental rules change upredictably?Yes. Battlefield environments change upredictably.Can it pay attention to valued goals?Image: Can it pay attention to valued goals?	Yes. See above. Yes Yes. ART derives its memory stability from Yes		Yes, through attention mechanisms.	Yes.		Untested but we believe so	in principle, yes.	It can be implemented for on-line learning.	??? 			Yes Yes. Goals are encoded as the intended	No. Yes.
	Yes. ART derives its memory stability from Yes matching bottom-up data with learned top- down expectations that pay attention to expected data. ART-CogEM models use cognitive-emotional resonances to focus attention on valued goals.	yes	i co, throogh attention mechanisms.		yes		yes.		res			Yes. Goals are encoded as the intended effects of tasks.	
Can it flexibly switch attention between unexpected challenges and valued goals?Yes. Makes decisions about what is most important based on rules of engagement and situational awareness.	Yes. Top-down attentive mismatches drive attention reset, shifts, and memory search. Cognitive-emotional and attentional shroud mechanisms modulate attention shifts.	yes	Yes.	Yes.	Yes. yes	Yes	yes: by switching roles of ment states.	al	Yes			Not implemented	Yes.
Can reinforcement learning and motivation modulate perceptual and cognitive decision-making? Can it adaptively fuse information from multiple types of sensors and modalities?	Yes. Cognitive-emotional and perceptual- cognitive resonances interact together for this purpose.YesART categorization discovers multi-modal feature and hierarchical rule combinations that lead to predictive success.Yes	yes yes	No. Yes.	Image: A state of the stat	/es, cognitive Image: mail of the second s	Yes Yes	yes. yes: by using / creating appropriate schemas.	Yes	Yes In principle, but not implemented			Yes In principle, but not implemented	Yes. Yes, although it depends on the particular use of the architectural features.
Statement by the contributor Most statements included here were written as summaries of the BICA-2009 CogArch panel presentations. Their short versions will be included in the AI Magazine symposium report.	Biologically-relevant cognitive architectures should clarify how individuals adapt autonomously in real time to a changing world filled with unexpected events; should explain and predict how several different types of learning (recognition, reinforcement, adaptive timing, spatial, motor) interact to this end; should use a small number of equations in a larger number of modules, or microassemblies, to form modal architectures (vision, audition, cognition,) that control the different modalities of intelligence; should reflect the global organization of the brain into parallel processing streams that compute computationally complementary properties within and between these modal architectures; and should exploit the fact that all parts of the necortex, which supports the highest levels of intelligence in all modalities, are variations of a shared laminar circuit design and thus can communicate with one another in a computationally self-consistent way.	tem withattention to the lack ofIllysupport in the currenttate-of-family of cognitiveult,architectures forntsperceptual imagination,and cited his group's DRS		at the panel, I pointed out that the list of tasks needs to be greatly expanded, to include, for example, implicit learning tasks, meta-cognitive tasks, social psychology tasks, personality psychology tasks, motivational dynamics, and so on, all of which have been simulated using the CLARION cognitive architecture. The architecture described in this column was pioneered in the proprietary Novamente Cognition Engine, and is now being pursued in the Open-source OpenCogPrime system, build with in the OpenCog framework In my presentation in the BICA-2009 CogArch panel, I discussed the AGI Roadmap Initiative (see http://agi- roadmap.org) and also the need for a glossary of AGI terms to help us compare cognitive architectures.		FORR (FOr the Right Reasons) is highly modular. It includes a declarative memory for facts and a procedural memory represented as a hierarchy of decision-making rationales that propose and rate alternative actions. FORR matches perceptions and facts to heuristics, and processes action preferences through its hierarchical structure, along with its heuristics' real-valued weights. Execution affects the environment or changes declarative memory. Learning in FORR creates new facts and new heuristics, adjusts the weights, and restructures the hierarchy based on facts and on metaheuristics for accuracy, utility, risk, and speed.		Hierarchical Temporal Memory (HTM) is a model of neocortex and thalamus. It is highly constrained and guided by anatomy and physiology at the levels of cortical regions, cellular layers, cellular connectivity, local inhibitory neurons, and non-linear integration of synapses along dendrites. HTMs build hierarchical models of the spatial and temporal statistics in sensory data. The models can be used for inference and prediction. HTMs have been commercially applied to numerous commercial problems. Numenta aims to be a catalys t for commercial applications of neocortical models of compution and inference. It publishes its algorithms and code for research and commercial deployment.		Though NARS can be considered as a "cognitive architecture" in a broad sense, it is very different from the other systems. Theoretically, NARS is a normative theory and model of intelligence and cognition as "adaptation with insufficient knowledge and resources", rather than a direct simulation of human cognitive behaviors, capabilities, or functions; technically, NARS uses a unified reasoning mechanism on a unified memory for learning, problem-solving, etc., rather than integrates different techniques in an architecture. Therefore, accurately speaking it is not after the same goal as many other cognitive architectures, though still related to them in various aspects.	Nick Cassimatis argued that repositories should focus on standardizing task environments and problems within them rather than details about cognitive architectures themselves. Theoretical arguments indicate that any syst which must learn to perfom a large number of different behaviors will be constrained into t recommendation architecture form by a combination of practical requirements include the need to limit information handling resou the need to learn without interference with p learning, the need to recover from compone failures and damage, and the need to constr the system efficiently.	s ig es, t	The actual systems built in the Ymir architecture, notably Gandalf, the Cognitive Map for Asimo, and the SuperRadioHost systems, have shown the Ymir framework to be quite flexible and extensible. Ymir was not initially built to solve general- purpose intelligence, and it is become clear that none of the Constructionist methodologies (i.e. most efforts to date relying on "first order" manually-constructed software) will be able to handle the multitude of topics related to general intelligence, such as global attention, global learning, flexible task learning and integration, etc. For this we are working on new methodologies relying on Constructivist approaches, which emply self-organization and automatic architectural growth (see my keynote paper From Constructionist to Constructivist A.I. (2009), in AAAI Fall Symposium Series - Biologically Inspired Cognitive Architectures, Washington D.C., Nov. 5-7,175-183. AAAI Tech Report FS-09-01, AAAI press, Menlo Park, CA.).