Evolution of Soar

based on "The Evolution of the Soar Architecture" Mind Matters, 1992 Laird and Rosenbloom

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Outline

- Revisit Soar versions 1-8
- Technical and research ideas
- Representative systems knowledge
 - Representative applications and research

Research Methodology

- 1. Pick basic principles to guide development
- → 2. Pick desired behavioral capabilities
 - 3. Make design decisions consistent with above
- + 4. Build/modify architecture
 - 5. Implement tasks
 - 6. Evaluate performance

Principles

- Draw from "intelligence" in humans and machines
- Start with architecture
 - The fixed mechanisms that support general intelligence
- Attempt to create a uniform, universal architecture
 - Use task independent representations and processes.
 - Architectural mechanisms shouldn't constrain system to specific approaches for all problems
- Minimal architectural mechanisms

Desired Behavioral Capabilities

- Interact with a complex world limited uncertain sensing
- Respond quickly to changes in the world
- Use extensive knowledge
- Use methods appropriate for tasks
- Goal-driven
- Meta-level reasoning and planning
- Coordinate behavior and communicate with others
- Learn from experience
- Integrate above capabilities across tasks
- Behavior generated with low computational expense

Pre-Soar

- Logic Theorist (LT) (1955)
 - First symbolic problem solver with heuristics
- GPS (1958)
 - Means-Ends Analysis and Recursive Goals
- Problem Spaces (1965)
 - Uniform Task Structure
- Production Systems (1967)
 - Uniform, Incremental, Context-sensitive Knowledge Representation
- Weak Methods (1969)
 - Organization of General Control Knowledge

Soar 1 – 1982 Goals

- Develop an architecture that supports multiple methods
 - Use different methods for different tasks
 - Use different methods for different subtasks
 - Methods determined by available knowledge

Soar 1: Approach

- Develop an AI architecture that supports problem spaces
 - Explicit representation of goals, problem spaces, states, operators
 - All tasks cast as decision making in a problem space
 - All knowledge supports problem space functions
- Use a parallel production system for long-term memory
 - Working memory contains current and proposed
 - goals,
 - problem spaces,
 - states,
 - operators.
 - Productions encode problem space knowledge
 - Propose object, vote on objects, apply operators.
 - Decision procedure tallies votes for selecting objects

Soar 1

Production Memory

Conditions Actions

Conditions — Actions

Conditions — Actions

Conditions — Actions

Working Memory

Type: Slot Stock

Goal [G1] G2, G3

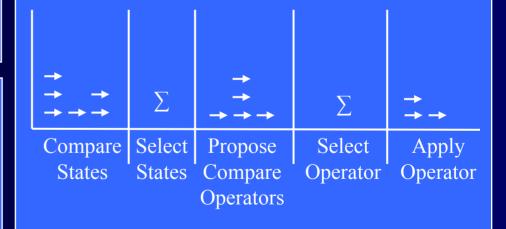
Problem Space [P2] P4

State [S13] S10, S11, S1

Operator [] O32, O33

Process

Elaboration, Decision, Application Cycle



Working memory is a set, not a graph Special slot for selected goal, problem space, state, operator Votes are tallied to select current object

Contrast with Other Approaches

- STRIPS for each operator, single representation of
 - operator preconditions and actions
- GPS for each operator, single representation of
 - operator preconditions, actions
 - table of connections
- Soar
 - Operators are first-class objects
 - Independent knowledge for
 - Proposal
 - Selection
 - Application
 - Can be disjunctive, conditional

Weak Methods in Soar 1

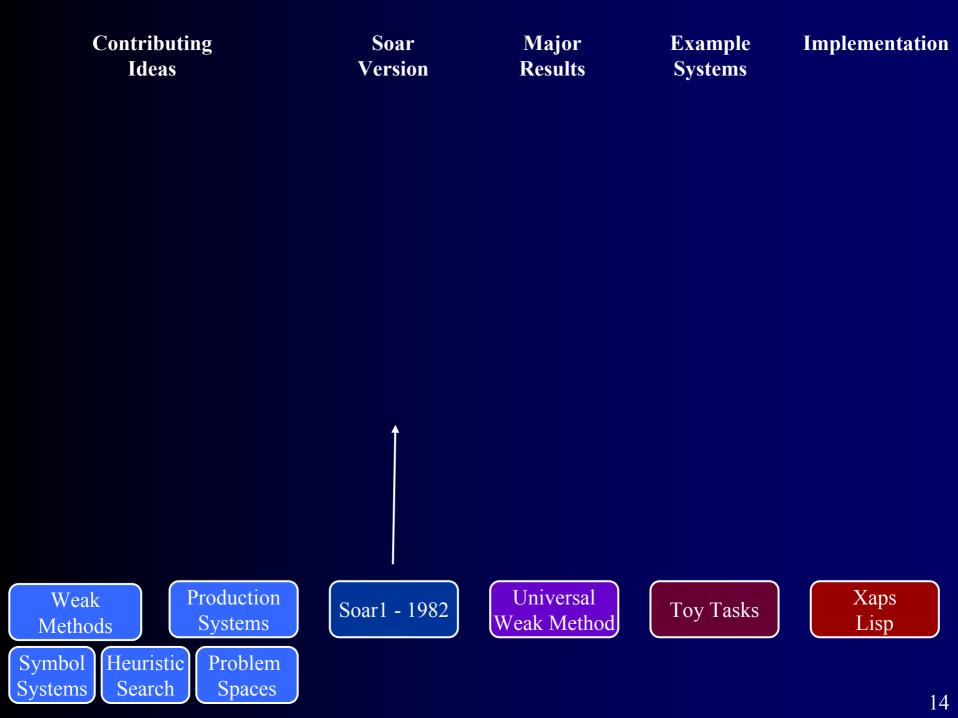
- By adding rules about task, could change methods
 - Blind search
 - Avoid duplicate states
 - Heuristic search task specific heuristics
 - Means-ends analysis
 - Hill climbing
 - Steepest ascent hill climbing
 - Breadth-first search
 - Depth-first search
 - Best-first search
- Not a big switch where method is selected explicitly

Soar 1 Achievements

- Unified problem spaces and production systems
- Basis for Universal Weak Method
 - Separate representation of control knowledge
 - Decisions based on dynamic integration of knowledge
- Systems built: Variety of simple puzzles and toy tasks
- Users: 1
- Implemented in XAPS 2
 - Rosenbloom's eXperimental Activation Production System

Soar 1 Shortcomings

- No subgoals
- No meta-level reasoning
- Voting results may not reflect knowledge
 - More votes ≠ more evidence, more knowledge
 - Limited expressability of knowledge no partial orders.



Soar 2 - 1983

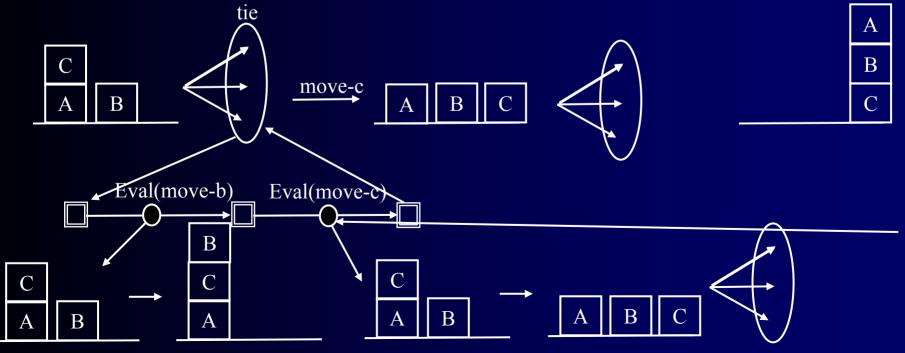
- Any goal principle
 - System can generate any and all types of goals
- Universal subgoaling
 - Single mechanism for creating all types of goals
- Automatic subgoaling
 - All subgoals generated automatically
- Preference-based decision procedure

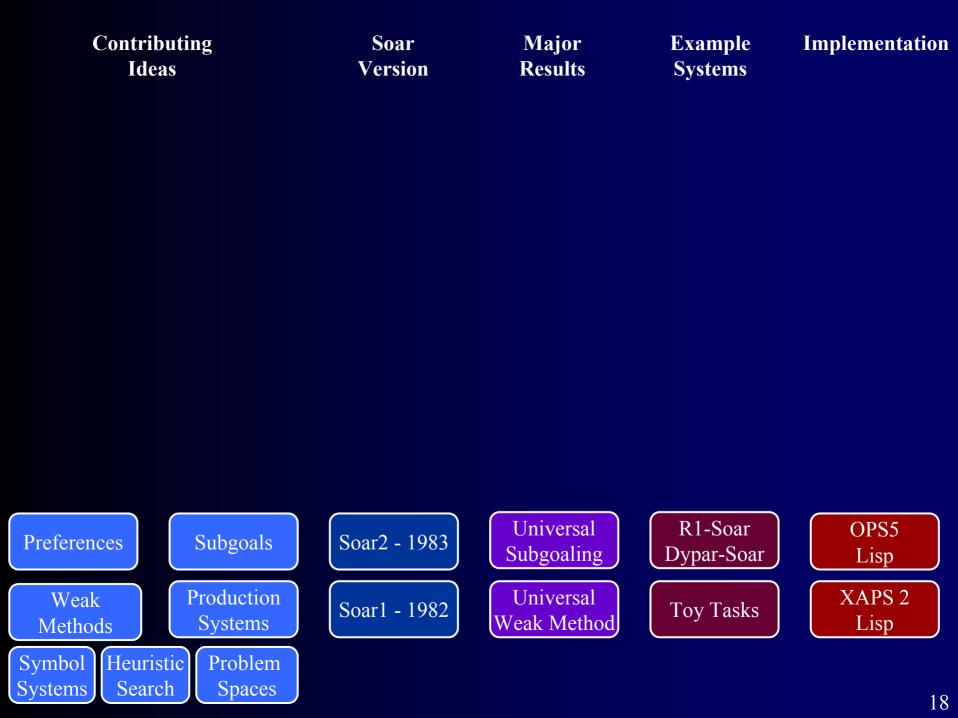
Soar 2 Approach

- Symbolic preference scheme replaces voting
 - Acceptable, reject, better, worse
- Detect inability to make decisions automatically:
 - Impasses: tie, conflict, no-change in decision
- Create subgoal automatically to resolve impasse
 - Recursively use problem spaces in subgoal
 - Subgoal parameters and results are determined dynamically by problem solving
- Working memory becomes graph structure rooted in goals

Soar 2: Selection Space

- Meta-level reasoning with evaluation
- Basis of many weak methods
- Depth-first search, mini-max, alpha-beta, iterative deepening, progressive deepening, ...





Soar 2 Shortcomings

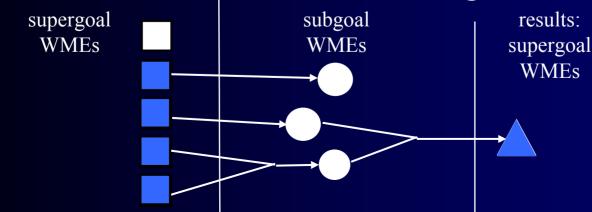
- No learning
- Must resolve same impasse multiple times during a task

Soar 3 - 1984

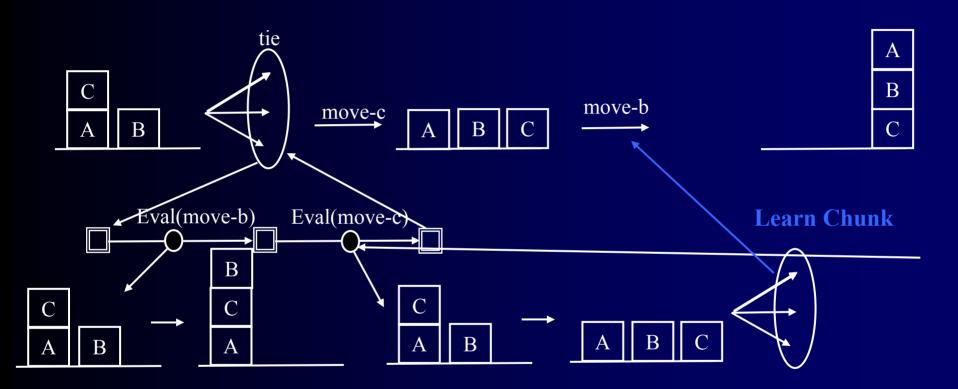
- How can learning be integrated with problem solving?
 - Learn when knowledge is incomplete: impasses
 - Learn when knowledge becomes available: results
 - Connect situation where learning is needed to when it is available
 - Knowledge transfer depends on similarity of situation

Soar 3 Approach

- Inspired by "chunking" as developed in XAPS.
- A rule is learned that summarizes processing in a subgoal.
- Conditions based on working memory elements tested by productions fired in subgoals.
 - Later restricted to just those tested on path to results.
 - Also inspired by goal-regression learning Mitchell, DeJong
- Actions are based on results of subgoal.



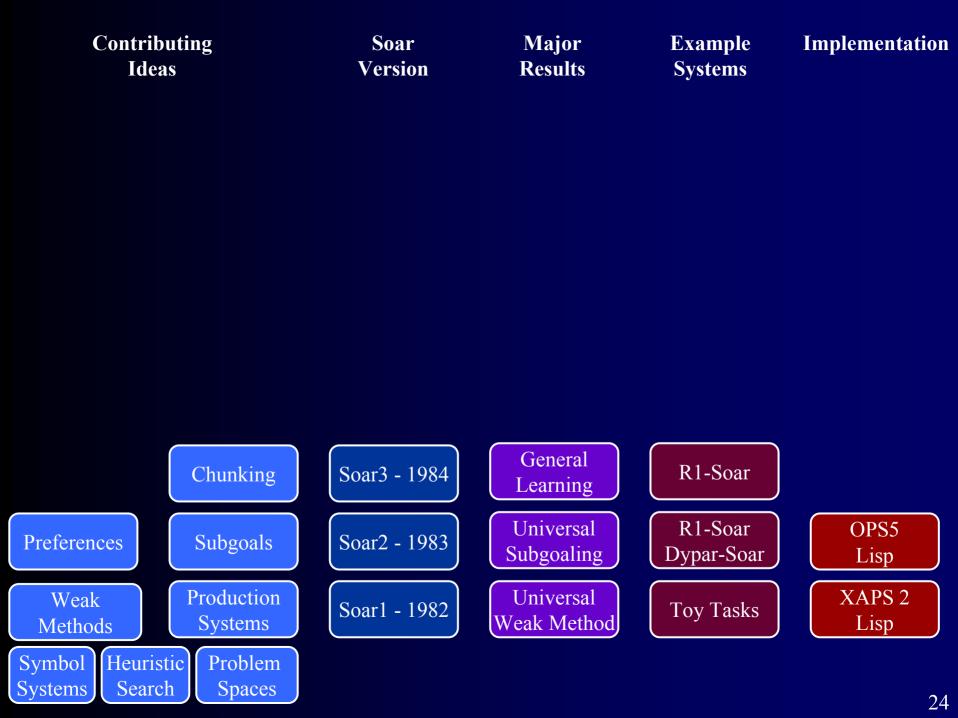
Soar 3: Chunking Example



Within Task Transfer: chunk learned in subgoal applies to avoid future search Across Task Transfer: chunk learned in one problem transfers to another

Soar 3 Results

- General learning method integrated with problem solving.
 - Learns incrementally and continually on all tasks.
 - Learns from both success and failure.
 - Learns a variety of types of knowledge:
 - Selection knowledge, operator application, operator creation, state refinement, problem formulation
 - Automatically converts deep knowledge to shallow knowledge
 - R1-Soar
- Users: 8



Soar 4 – 1986

- First version prepared for external release
 - Manual published, ported to Common Lisp, first Soar Workshop
- Explosion in applications and users
 - > 50 by 1988
- Explosion in types of learning and problem solving
- Newell proposes Unified Theory of Cognition

Soar 4 Results Knowledge-based Systems

- Algorithm design (Designer-Soar, Cypress-Soar)
- Medical Diagnosis (NeoMycin-Soar, Red-Soar)
- Production Line Scheduling (Merl-Soar)
- Chemical Process Modeling
- Natural Language Understanding (NL-Soar)
- Intelligent Tutoring (ET-Soar)

Unified Theories of Cognition

Allen Newell, 1989:

"I mean a single set of mechanisms for all of cognitive behavior."

- Problem solving, decision making, routine action
- Memory, learning, skill
- Perception, motor behavior
- Language
- Motivation, emotion
- Imagining, dreaming, daydreaming, ..."

"Our ultimate goal is a unified theory of human cognition. This will be expressed, I have maintained, as a theory of the architecture of human cognition—that is, of the fixed (or slowly varying) structure that forms the framework for the immediate processes of cognitive performance and learning."

Soar 4 Results: Unified Theory of Cognition (1987)

- Immediate Reasoning Tasks
- Syllogisms
- Balance Beam
- Cryptarthmetic
- Towers of Hanoi
- Transcription Typing
- Instruction for simple tasks
- Verbal learning
- Series completion



Soar 4 Shortcomings

- Limited interaction with external environments
- Excessive copying of state structures during operator application

Soar 5 - 1989

- Add interaction with external environments
- Improve efficiency by eliminating state copying

Soar 5 Approach

- Modify problem space computational model
- Only a single state per goal
 - State changes through operator application or perception
- Operator productions destructively modify current state
 - Retractable entailments: i-support
 - Automatic classification of rules into entailments/destructive
 - i-support vs. o-support
- Operators stay selected until terminated with a reconsider preference: @
- Justifications built for results
 - Not required in Soar 4 because everything o-supported

Soar 5 Results

- Integrates interaction, reaction, planning, learning
- Four level architecture
 - Motor programs: innate not subject to cognition
 - Parallel Production System: Reflexes
 - Operators: Deliberation
 - Subgoals: Planning and Hierarchical Reasoning
- Used worldwide at over 15 sites, 100 researchers

Soar 5 UTC Applications

- Number conservation (Q-Soar)
- Concept learning (SCA)
- Visual Attention (NOVA)
- Sentence parsing (NL-Soar)
- Learning Physics (Dyna-Soar)
- Browsing (Browser-Soar)
- Highly interactive tasks (HI-Soar)
- Decision modeling (NTD-Soar)
- Learning task-action mappings (TA-Soar)

Contributing Ideas	Soar Version	Major Results	Example Systems	Implementation
Single State Destructive Operators	Soar5 - 1989	External Tasks	HI-Soar Hero-Soar	
	Soar4 - 1986	UTC	ET-Soar NL-Soar	External Release
Chunking	Soar3 - 1984	General Learning	R1-Soar	
Preferences Subgoals	Soar2 - 1983	Universal Subgoaling	R1-Soar Dypar-Soar	OPS5 Lisp
Weak Methods Production Systems	Soar1 - 1982	Universal Weak Method	Toy Tasks	XAPS 2 Lisp
Symbol Heuristic Problem Spaces				35

Soar 5 Shortcomings

- Software rot
 - Difficult to maintain and extend
 - Code is > 10 years old
- Significant efficiency problems with big systems and long runs
 - Having impact on initial versions of Air-Soar

Soar 6 – 1992

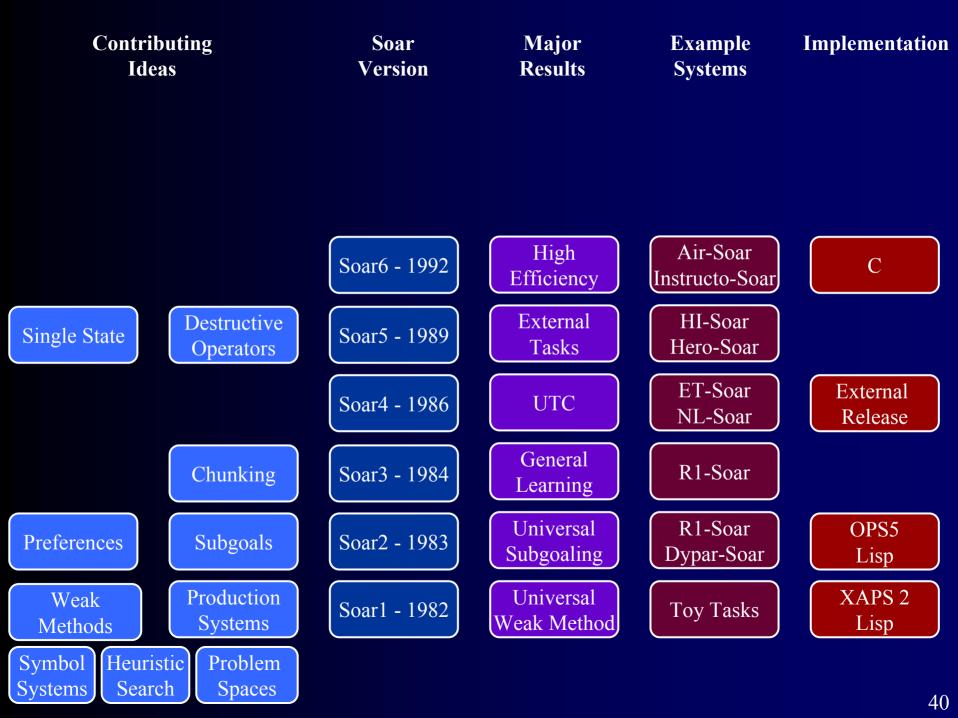
• Significantly improve efficiency, portability, correctness maintainability

Soar 6 Approach

- Port to C
 - Rewrote from scratch by Bob Doorenbos
- Provide efficiency for large highly interactive systems.
 - 8-10 times faster than Soar 5 for medium size tasks (1000 rules)
 - 20-80 times faster for large tasks and long runs.
 - Dispatcher-Soar learning > 100,000 chunks without significant slowdown

Soar 6 Applications

- Cognitive Modeling, many with learning
 - Play Super Marios (HI-Soar)
 - Solve Electric/Magnetic Physics Problems (EFH-Soar)
 - Natural Language Processing (NL-Soar)
 - Medical Diagnosis using abduction (Red-Soar)
 - Air Traffic Controller (ATC)
- Learning Systems
 - Learning by Instruction (Instructo-Soar)
 - Learning from interaction with environment (IMPROV)
 - Symbolic Category Learning (SCA-2)
- Performance Systems
 - Fly SGI flight simulator (Air-Soar)
 - First versions of military simulation agents (TacAir-Soar, RWA-Soar, Debrief)
 - Teamwork (STEAM)
 - Training and Instruction (STEVE)



Soar 6 Shortcomings

- No runtime environment in C like in Lisp
- Difficult to integrate Soar with other applications

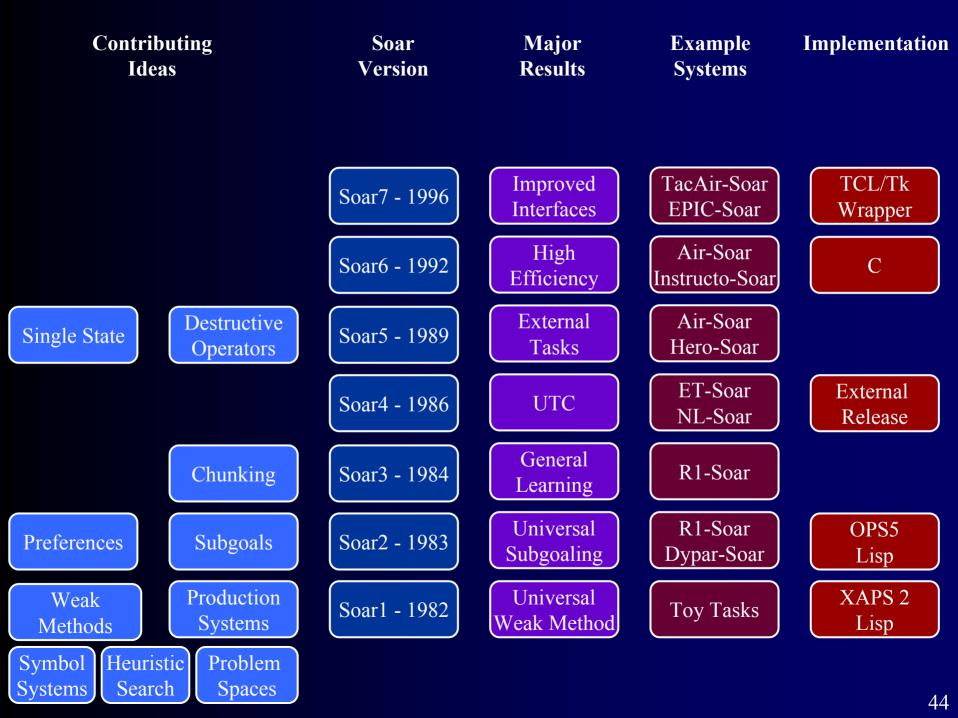
Soar 7 - 1996

- Make easier to:
 - create runtime tools
 - connect to external environments
 - run multiple agents
- Integrated Soar with Tcl/Tk

- Two companies use Soar
 - ERS: ExpLore Reasoning Systems
 - KB Agent
 - Soar Technology, Inc.

Soar7 Applications

- Final TacAir-Soar, RWA-Soar
 - Attention modeling
- Teamwork applications using STEAM:
 - RWA-Soar, Robo-cup, Electric Elves (organization management and teamwork)
- Learning multi-tasking (EPIC-Soar)
- Modeling air-traffic controllers
 - Working memory decay model
- Vision-processing (Vision-Soar)
- Language Generation: (LG-Soar & continued work on NL-Soar)
- More games:
 - Descent-Soar, Quake-Soar
 - PACMAN
- Mission rehearsal bots
 - HTNs
 - Emotion Modeling
 - Social Interactions
- Organization modeling (Country Chaos)



Soar 7 Shortcomings

- Race conditions between rules and across subgoals
- Inconsistency in reasoning across subgoals possible
- Learning could create rules that would never fire
- Output could be inconsistent with selected operators

Soar 8 - 1999

- Fix problems with interactions with external environments
 - Across goal consistency
 - Goal dependency sets
 - Iterative instead of parallel processing of goals
 - Non-contemporaneous chunks
 - Change operator selection to be i-supported
 - Eliminate reconsider preference
 - Change Decision Cycle

Processing Across Substates

• Problem:

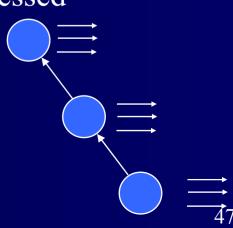
- Rules can fire in substates even though impasse is about to be resolved
- Run-away substate can generate results that are invalid

Approach

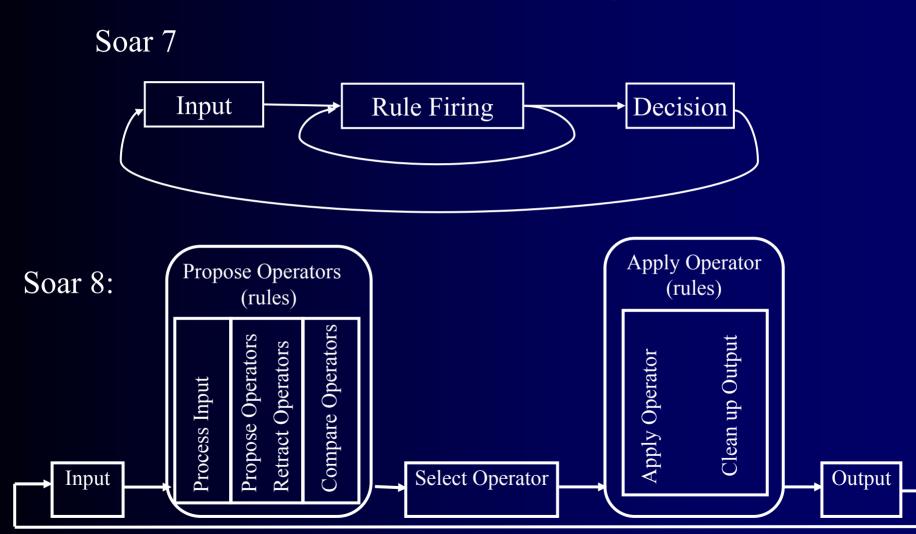
- Cascade rules from oldest to newest substate
- Remove substates if impasse is resolved
- Recompute match set after each substate processed

Implications

- Avoids firing rules that will be irrelevant
- Avoids some race conditions



Soar's Decision Cycle



Soar 8 Applications

- External Interaction
 - Play Quake (Quakebot)
 - Computer game non-player characters (Haunt II)
 - Adversaries for military simulations (MOUTBot)
 - Unmanned Air Vehicle (UAV) control
 - •
- Social Interaction Agents
- •

Contributing Ideas	Soar Version	Major Results	Example Systems	Implementation
Goal Decision Cycle	Soar8 - 1999	Substate Coherence	MOUTBOT QuakeBot	SGIO
	Soar7 - 1996	Improved Interfaces	TacAir-Soar RWA-Soar	TCL/Tk Wrapper
	Soar6 - 1992	High Efficiency	Air-Soar Instructo-Soar	C
Single State Destructive Operators	Soar5 - 1989	External Tasks	Air-Soar Hero-Soar	
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What's Next?

- Soar 8.5
 - Bug fixes
 - Numeric indifferent preferences
- Soar 9
 - Working memory activation
 - New architectural learning mechanisms
 - Reinforcement learning
 - Episodic learning?
 - Rule decay?

Biggest Surprises

- Lack of buy in AI to Soar's best ideas
 - Open decision making for operator selection
- Success of niche AI
 - Specialized techniques for specific problems
- Difficulty of finding applications that require humanlevel AI
 - Military Simulations
 - Computer Games

Where does Soar sit today?

 Best symbolic architecture for building complex, knowledge-rich performance systems.