



Relevance Estimation for Evidence Marshalling

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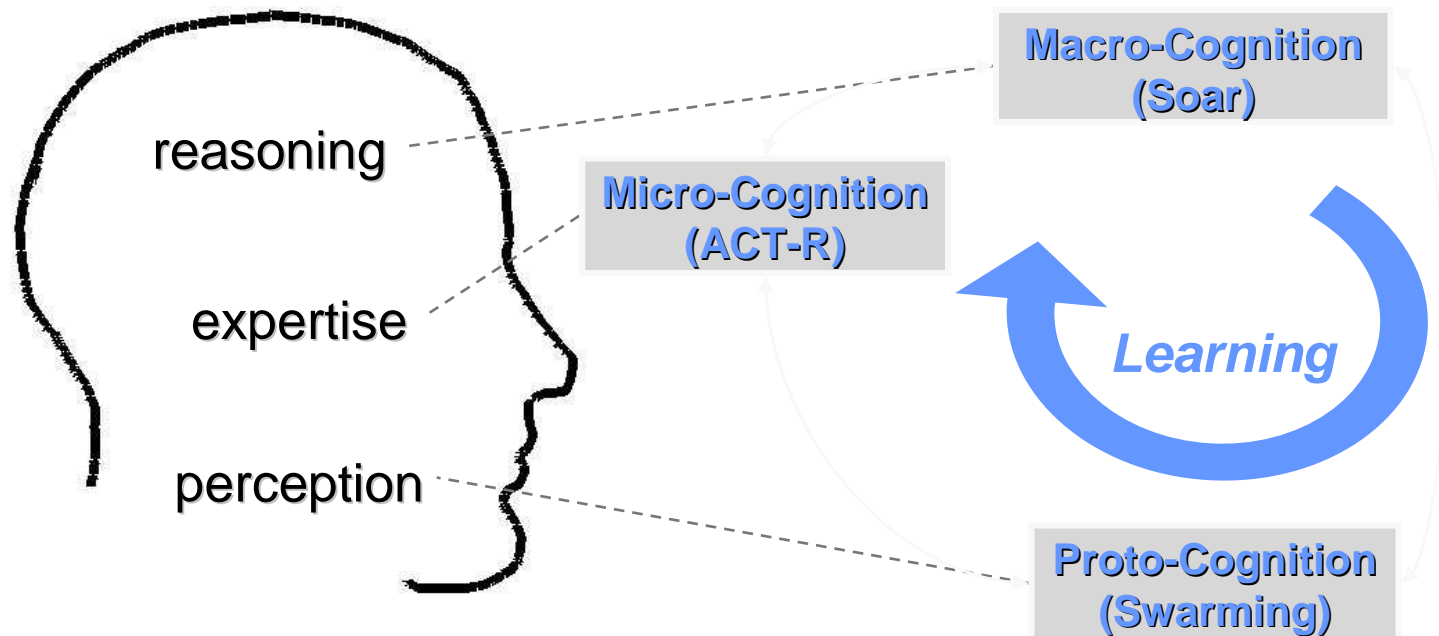
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Background/Review: ACIP



- Architectures for Cognitive Information Processing (ACIP)
 - New general “cognitive” architectures for DARPA-hard problems
 - Cognitive layer: proposed (strong) integration of Swarm, ACT-R, Soar
 - Soar Tech role: macro-cognitive architecture module
 - Using Soar as platform for knowledge-based reasoning
 - Example problem: Evidence marshalling



Outline

- Goal:
 - Support evidence marshalling (EM) with automated reasoning
- Problem:
 - Infinite search spaces
 - Difficult to know if/when progress is being made
 - One step from “Eureka!”
- Proposed Solution: Relevance Estimation
 - Algorithms that guide EM searches and get better with experience
- Methods:
 - Test bed for evaluating relevance estimation and evidence marshalling
- Warning:
 - Not a lot of Soar in this story; mostly laying groundwork...

Evidence Marshalling

- Process of “connecting the dots” to form a coherent narrative about a collection of evidences
 - Pop-culture Examples:
 - Sherlock Holmes
 - Procedural TV shows (Perry Mason, Law & Order)
 - Specialized human techniques for EM
 - Wigmorean analysis
- Many potential applications for automated methods:
 - Police investigations
 - Insurance fraud
 - Intelligence analysis

Automating EM

- Automated reasoning techniques have been demonstrated as effective tools for EM in very restricted problem domains
 - cause-of-death conclusions from evidence
 - insurance fraud detection
- Limits to automated EM in open-ended domains
 - Hypothesis generation
 - Knowledge sources
 - Efficient control of search process

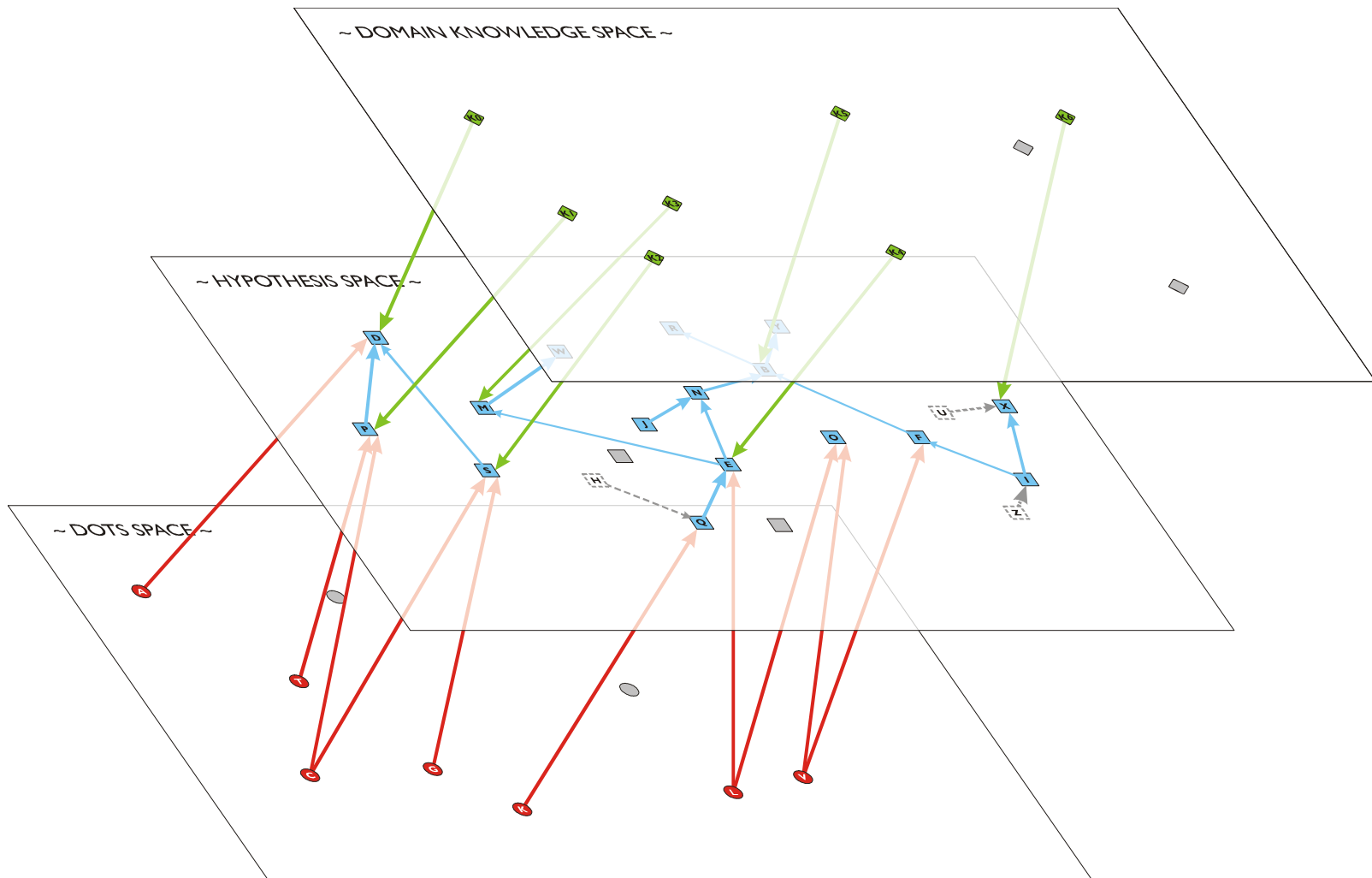
Automating EM: Near-term solutions

- Hypothesis generation:
 - In the near- to mid-term, no automated approach is likely to challenge human creativity
 - Our approach leverages user insight and experience by capturing their notions and “hunches” and then searching for confirming or disconfirming evidence
- Sources of knowledge
 - Trifles
 - Many existing automated sources: data extraction tools
 - Domain knowledge
 - Facts and inferences from applicable domain(s)
 - Increasing stores of general knowledge resources: Cyc, Semantic Web
- Efficient search
 - Must find intermediate hypotheses/assertions that can connect trifles to user hypotheses

Challenge: Search Space is Infinitely Large

- Domain knowledge and trifles combine in infinitely many possible ways
 - Bill Clinton was POTUS in 1996
 - Hillary Clinton is Bill Clinton's spouse
 - ...
- Difficult to judge if any individual intermediate hypothesis is getting closer to the goal
 - Hillary Clinton lived in the White House in 1996
- Multiple, simultaneous searches
 - Trifles: Which “trifles” are relevant
 - Domain knowledge: Which facts about the world are relevant?
 - Hypotheses: Which intermediate hypotheses are on the right track?
 - Confidence: Which assertions are more likely/probable?

Simultaneous searches



Hypothesis:

Efficient search for EM is a solvable challenge

■ Evidence:

- Although the search space is infinitely large, people perform evidence marshalling adequately
- How?
 - Training & experience, tools (Wigmorean analysis)
 - “Natural” pruning of the search space
 - Humans generate heuristic choices (“hunches”) that can guide them thru very large search spaces

■ Goal: explore computational methods for:

- Generating and assessing “hunches” (relevance estimation)
- Learning from experience to improve the relevance estimation process

Proposal: Relevance Estimation

- Goal: Evaluate the relevance/importance of each new assertion
 - Cannot assume system already “knows” the answer or knows that some new inference is an important “dot”
 - Many potential assertions can be generated
 - May not be obvious which assertions will actually be valuable or “relevant” to the problem (Avoid “wishful thinking”)
 - Relevance estimation is the “strategy” for prioritizing direction(s) of reasoning and establishing “sufficiency” of a potential direction of reasoning
 - Context is important: Not evaluating in isolation
- Contributing methods:
 - Domain neutral: analogy, deduction, classification, etc.
 - Extant computational models: Information scent (Pirolli), Conceptual fluidity (Hofstadter)
 - Domain specific: social network analysis, model of user’s interest
- Metrics for relevance determination:
 - complexity-based (Occam’s razor)
 - graph-based (path length)
 - knowledge-based
 - information scent
 - ontological relationships

Test bed for RE/EM Research

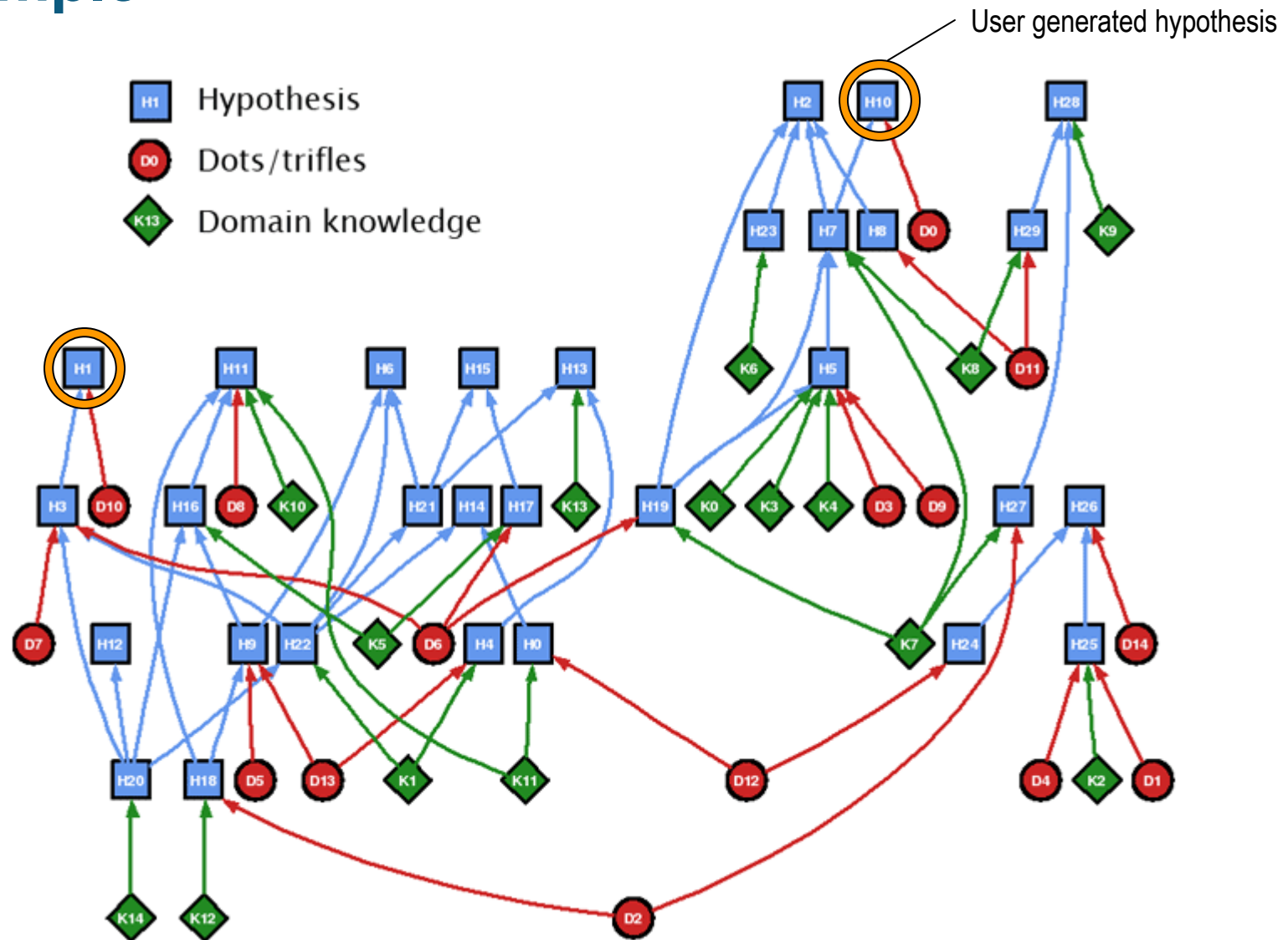
■ Problem:

- Need large bodies of encoded knowledge to evaluate approaches to RE/EM
- Access to “real” data is difficult for research purposes
 - security, sensitivity, size, etc.

■ Proposed Approach:

- Test bed for RE/EM
 - Automatically generate potential search spaces
 - Capture size and complexity of the space
 - Systematically vary parameters that represent the “connectedness” of possible hypotheses in the example
 - Simulate relevance across a number of orthogonal and over-lapping dimensions

Example

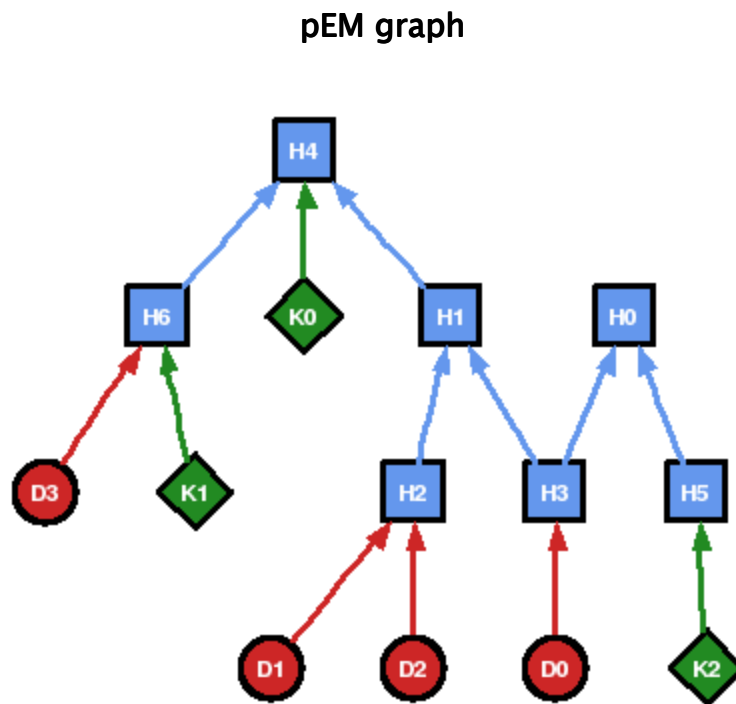


Simulating relevance in the test bed

- Relevance:
 - Predicts the likelihood of a relationship between m and n
 - Estimated by aggregating multiple knowledge sources
 - $RE = f(re_0, re_1, re_2, \dots re_n)$, where re_i is a source of knowledge about the relationship between m and n
- Contributing knowledge sources, re_i , can include:
 - ontological relationships between m and n
 - semantic and syntactic similarity between m and n
 - completeness of analogical mapping between m and n
 - “cognitive” distance between m and n
 - expectation of success of getting to m and n
 - recognition of m in the context of n

Simulating relevance in the test bed, cont'd

- Some sources can be simulated using graph theoretic operations, e.g., transitive closure in graph implies perfect knowledge of relations between dots, domain facts, and hypotheses.

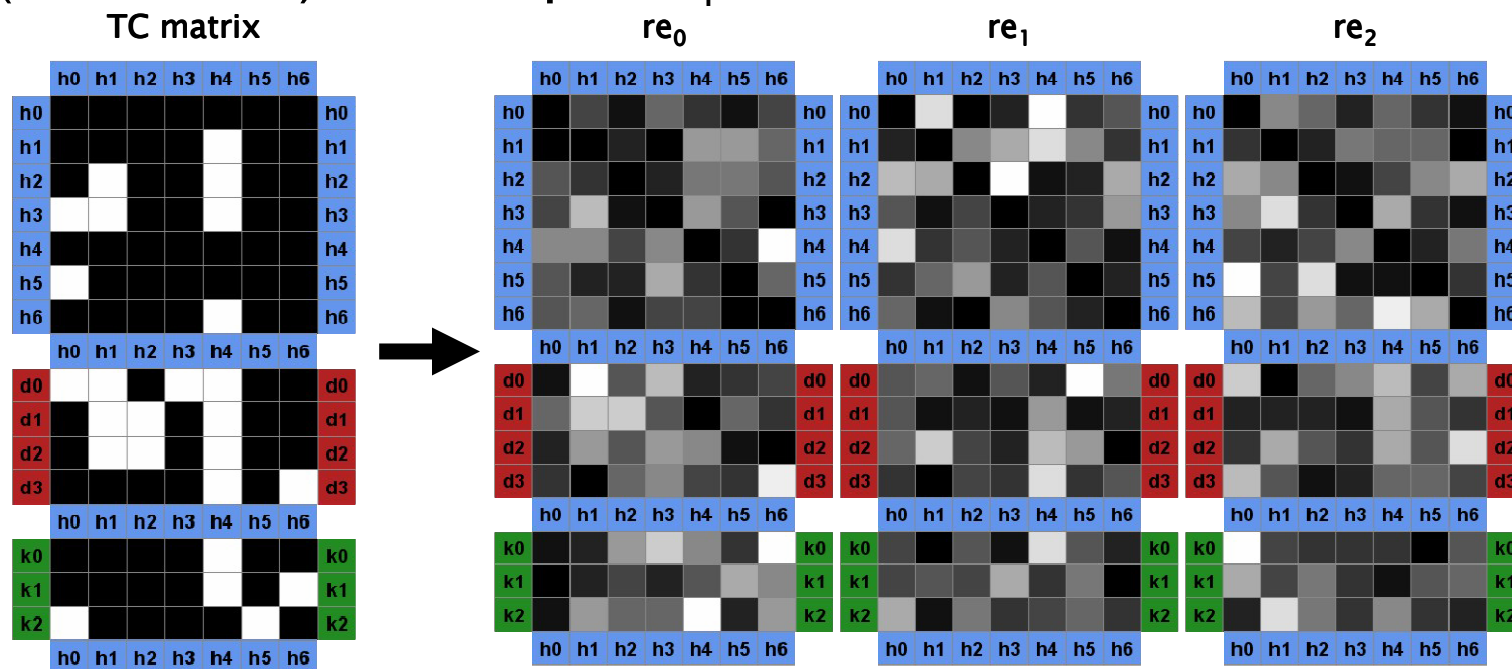


TC matrix

	h0	h1	h2	h3	h4	h5	h6	
h0								h0
h1								h1
h2								h2
h3								h3
h4								h4
h5								h5
h6								h6
	h0	h1	h2	h3	h4	h5	h6	
d0								d0
d1								d1
d2								d2
d3								d3
	h0	h1	h2	h3	h4	h5	h6	
k0								k0
k1								k1
k2								k2
	h0	h1	h2	h3	h4	h5	h6	

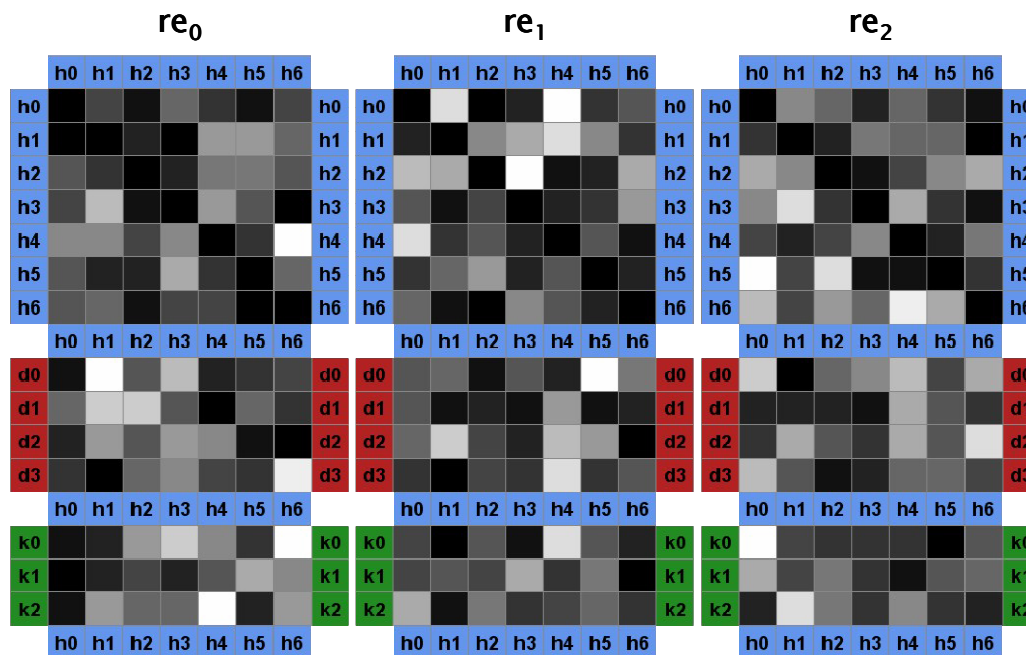
Simulating relevance in the test bed, cont'd

- Real knowledge is imperfect and from multiple, potentially contradicting, sources
- In the testbed, the perfect TC relationships are distributed (with noise) to multiple re_i matrices



Simulating relevance in the test bed, cont'd

- Test bed facilitates:
 - Easy use of knowledge sources represented as a matrices
 - Explorations of how to aggregate noisy and contradictory knowledge



Aggregation options:

$$RE(m,n) = \sum c_j * re_i(m,n)$$

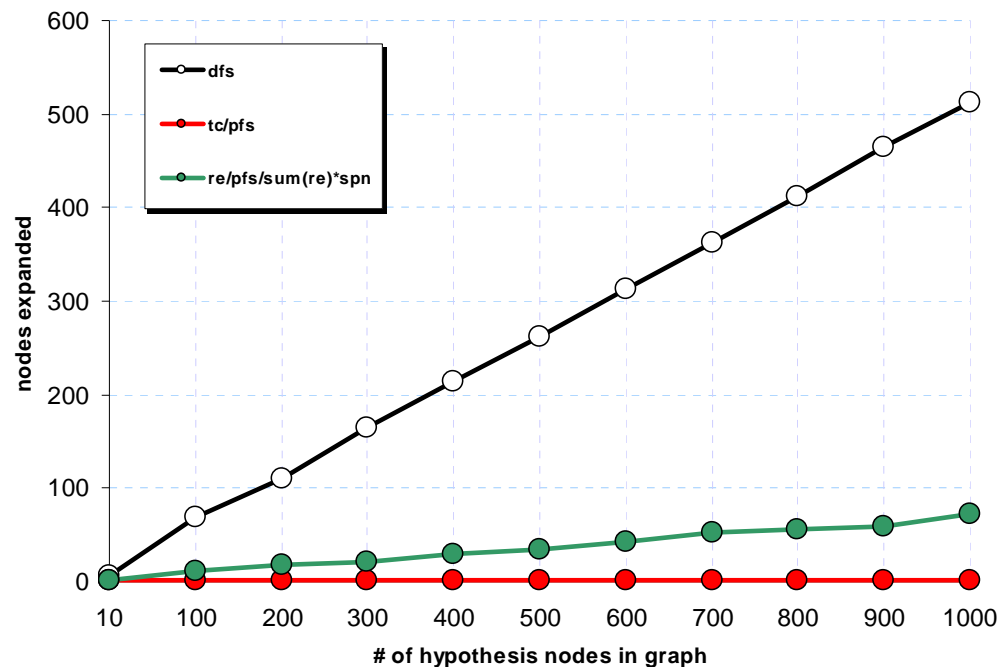
$$RE(m,n) = \max(re_i(m,n))$$

$$RE(m,n) = \text{avg}(re_i(m,n))$$

$$RE(m,n) = \dots$$

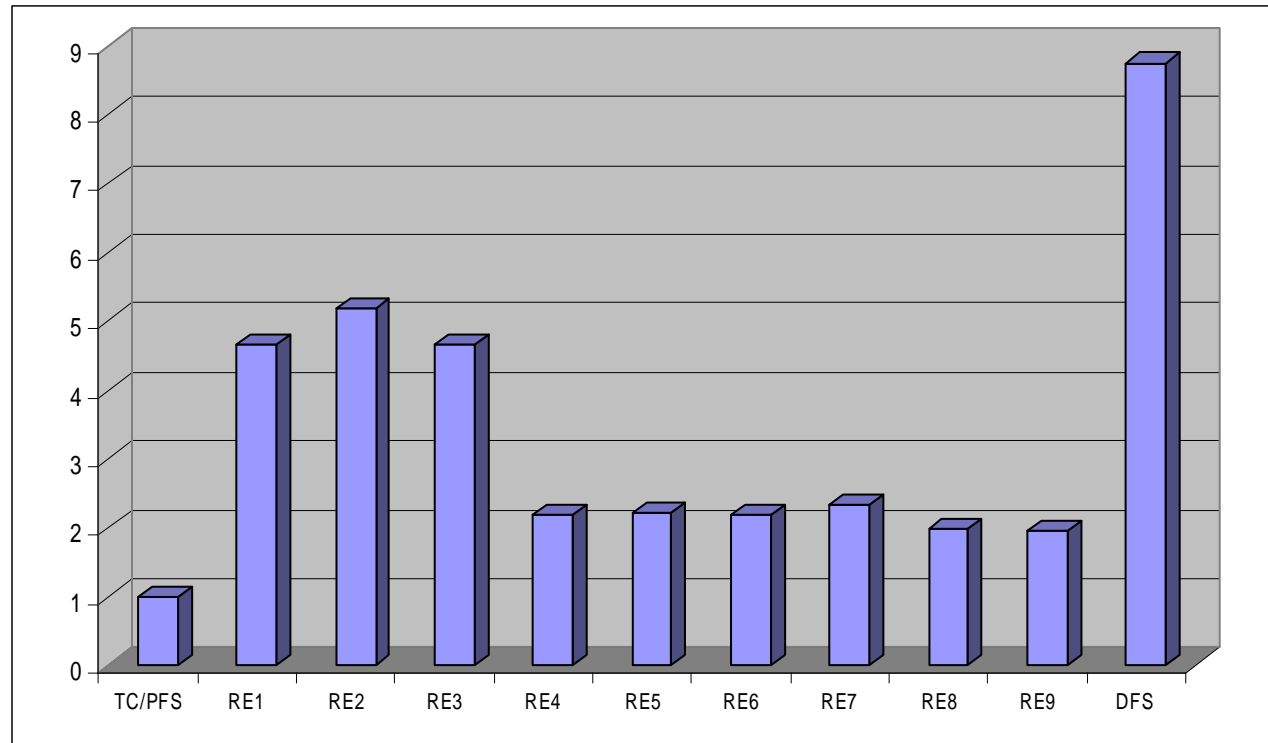
Initial Results (1)

- Search for all nodes in pEM graphs
 - DFS: exhaustive knowledge-free search; upper-bound
 - TC: perfect knowledge give direct path to goal; lower bound
 - RE: RE(m,n) guides priority-first search;
 - 90% fewer expanded nodes in comparison to DFS



Initial Results (2)

- Testbed enables systematic exploration of RE alternatives
 - vary patterns of domain/dot relationships
 - vary patterns of data-to-hypothesis relationships
- Graph shows search steps needed for a number of relevance estimation parameter settings (h=30, n=9000)



Conclusions

- Humans provide evidence tractable search for EM is feasible and clues for how to do it
- Test beds can be developed for exploring search challenge without large, a priori investments in knowledge encoding
 - Proof-of-concept test bed can generate problems automatically for exploring the consequences of RE design options
 - Plan: Complement with open-source, real-world datasets
 - Enron email, Center for Non-proliferation studies WMD data sets
- Nuggets:
 - Interesting ideas about how to attack this problem
 - Developed simple testbed for exploring computational approaches
 - Rich literature from which to draw inspiration
- Coal:
 - No feasibility implementation/exploration of solution (“idea ware”)

Extra Slides

RE is more than data screening...

- Data screening reduces the complexity somewhat
- The key to reducing effective complexity is dynamic adaptation to the specific search(es) at hand

