Connections and symbols II

AT1
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summary of preceding session

- "computational reduction" :
  - reduction of unboundedly complex behavior to the combination of simple ones
    - simple set of primitive processes
    - finite set of data types
    - a finite set of operations that combine the primitive processes to make more complex ones
  - what computational mechanisms underly complex behaviors (like language, reasoning, etc)?
    - Symbolic IA: (sequential & deterministic) computations with symbols and rules
      - eg: Turing machines, rewrite rules, finite state automata
    - Connexionist IA: (parallel & stochastic) computation with (continuous valued) neurone-like units
      - eg: Multilevel Perceptrons, Boltzman machines
- The Fodor & Pylyshyn challenge:
  - (current) connectionist architectures fail to capture complex behaviors
  - (future) connectionist architectures are 'mere' implementation of symbolic architectures

The Fodor & Pylyshyn argument

- mental representations have a constituent structure
  - they are not atomic or hollistic but have parts with specific roles
    - eg: the red cow; cheese or desert, Vx R(x), A->B
  - Some constituents can be recursive
    - eg: P. thinks that « M. is nice » -> J thinks that « P thinks that « M is nice » »
- mental processes are structure sensitive
  - eg: combinatorial semantics
    - semantics of « J. loves M. » derived from semantics of « J. », « loves » and « M. »
  - eg: logical inferences:
    - A->B, A entails B ; this does not depend on the meaning of A and B but on the structure of the representations
- as a result, mental computations are
  - systematic
    - all humans are mortal -> John is moral, Mary is mortal, etc.
    - « Paul likes fruits » grammatical -> « Paul likes fruits » also grammatical, etc
  - productive (achieve discrete infinity)
    - the list of thoughts/sentences is not finite (I can construct new thoughts with old ones)
- connectionist representations have none of these properties

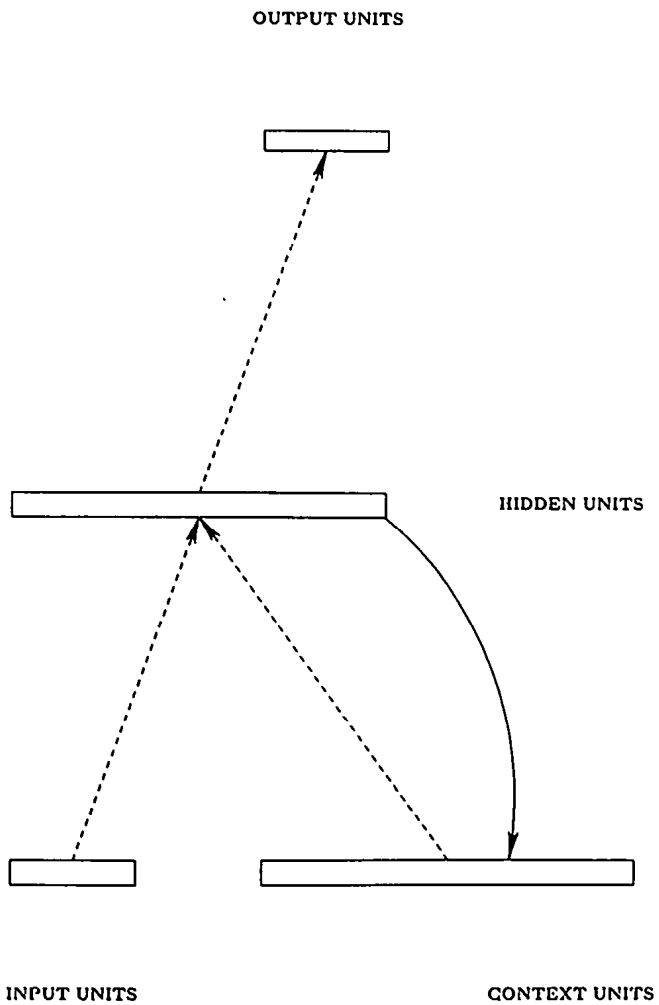
Possible responses to the Fodor & Pylyshyn critique

- level confusion
  - F&P talk about a descriptive level not a computational one; the descriptive level is compatible with many architectures including connectionnist ones; indeed, none of the physical implementations of symbol structures would satisfy the F&P criteria (eg, a physical computer).
- process confusion
  - F&P talk about conscious deliberative explicit thought processes (which are symbolic), not intuitive ones (which could be subsymbolic)
- Implementation matter
  - constructing a neurally plausible implementations of symbol manipulation is non trivial and interesting, and could reveal unexplained phenomena (eg graceful degradation)
- artificial dichotomy
  - There are many systems intermediate between classical architectures and connectionnist ones. It is an empirical issue which one is appropriate to modelling human cognition.
- F&P criticize some classes of connectionist architectures, they do not demonstrate their points for all possible architectures.
  - Potential counterexamples:
    - Recurrent Networks (Elmann)
    - Tensor products (Smolensky)

Elman

- structure of the paper
  - representing time
  - SRN architecture
  - xor through time
  - badiiguuu
  - word segmentation (15 words)
  - part of speech (13 categories, 29 words, 15 sentence templates)

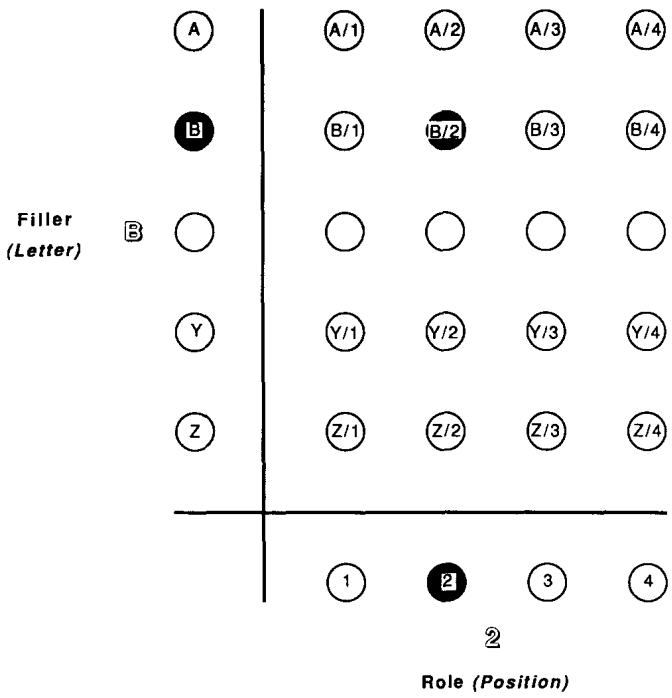
Backprop applied



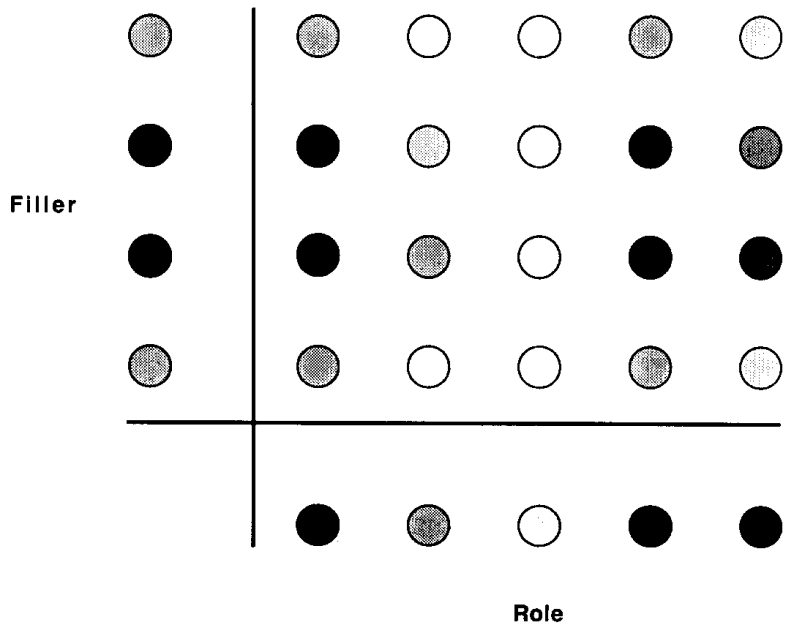
- structure of Smolensky
  - representing structures by fillers and roles
    - examples: trees, lists, etc
  - tensor products and filler/role binding (definition)
    - local, semilocal and distributed
  - unbinding (exact and selfadressed)
  - capacity and graceful saturation
  - continuous and infinite structures
  - binding and unbinding networks
  - analogy between binding units and hebb weights
  - example of a stack
  - structured roles

example of tensor product representations

Paul loves Mary-> loves(Paul,Mary)
-> pred=loves, arg1=Paul, arg2=Mary
-> pred*loves+arg1*Paul+arg2*Mary

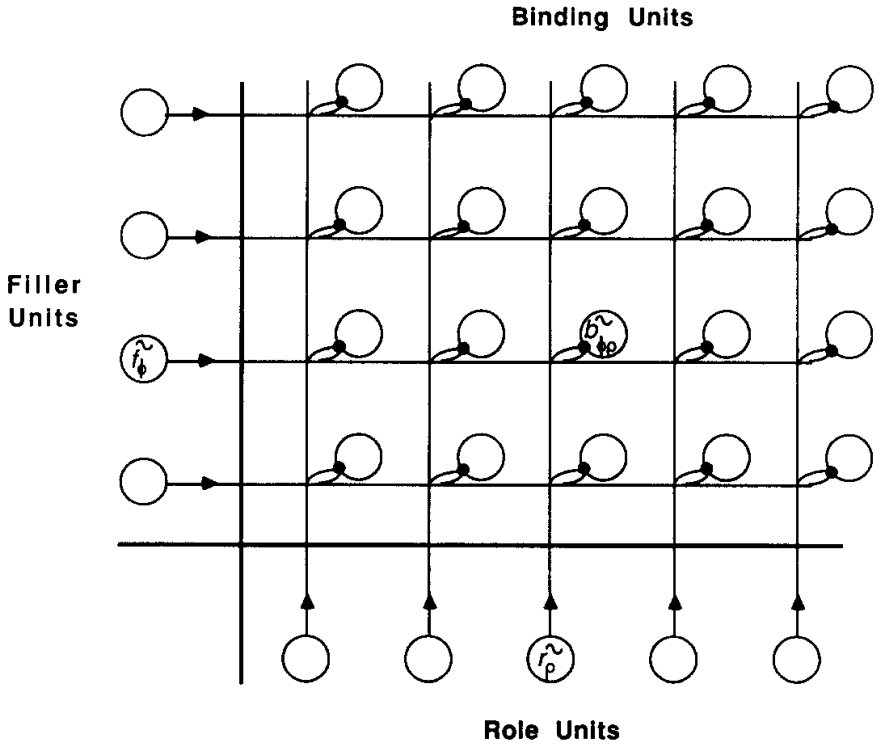


Local

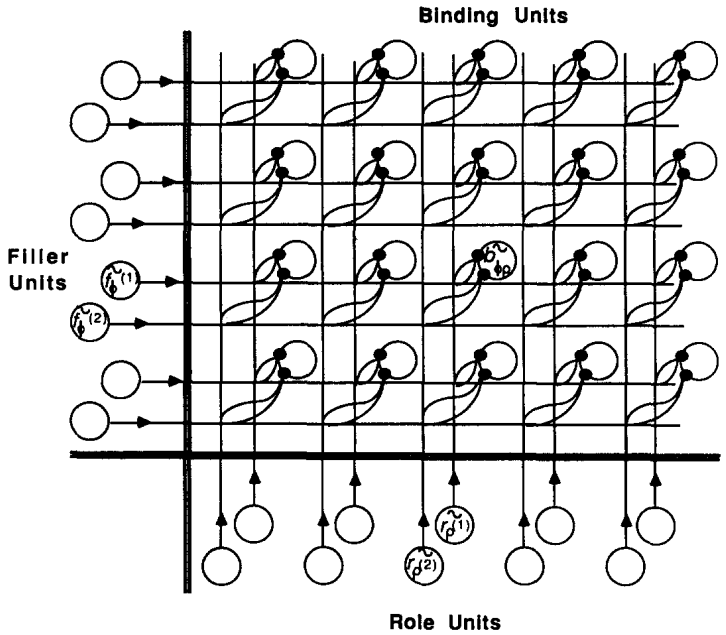


Distributed

binding and unbinding

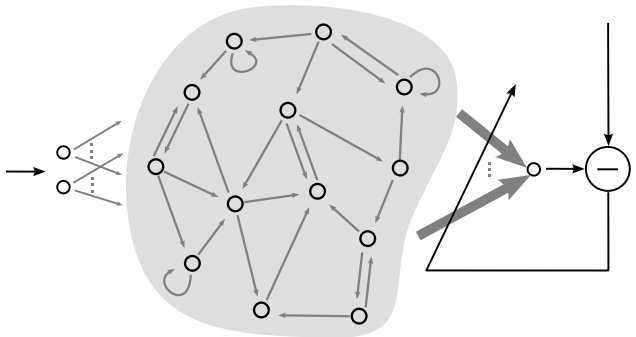


Binding network



Parallel Binding network (N=2)

- extensions of Elman's SRN
  - computational capacity of SRN
    - Servan-Schreiber, D., Cleeremans, A., & McClelland, J.L. (1988). Encoding sequentialstruc- lure in simple recurrent networks (CMU Tech. Rep. No. CMU-CS-88-183). Pittsburgh, PA: Carnegie-Mellon University, Computer Science Department.
    - Lawrence, S., Giles, C. L., & Fong, S. (2000). Natural language grammatical inference with recurrent neural networks. IEEE Transactions on Knowledge and Data Engineering , 12(1), 126–140.
    - Pollack, J. B. (1991). The induction of dynamical recognizers. Machine Learning , 7(2–3), 227–252. R
    - Rodriguez, P. (2001). Simple recurrent networks learn context-free and context-sensitive languages by counting. Neural Computation, 13(9).
  - reservoir computing
    - http://reservoir-computing.org
    - Jaeger H (2007) Echo state network. Scholarpedia 2(9):2330. http://www.scholarpedia.org/article/Echo_state_network



- extensions:
  - implementation of a phonological theory (Optimality Theory) in a tensor product network with energy relaxation
    - see the Harmonic Mind (Smolensky & Legendre)
  - Escaping the explosion in nb of neurons: holographic reduced representations
    - define A * B as an operation that preserves the dimensions (eg xor, circular convolution)

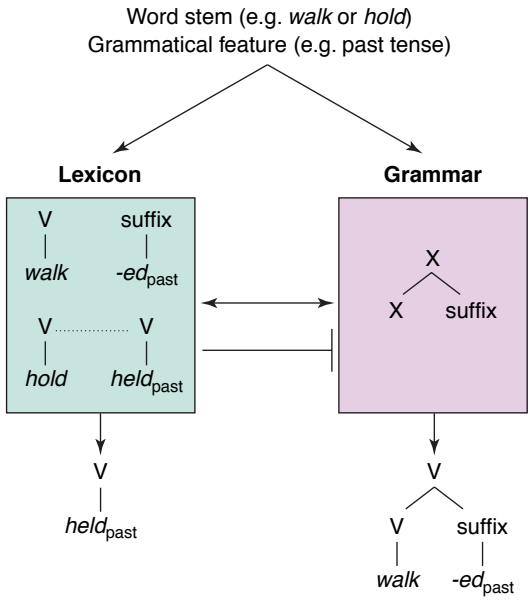
Conclusions

- What about the F&P Challenge?
  - tensor products are an interesting implementation/alternative to symbolic systems
  - recurrent networks could also be an alternative, but much less understood

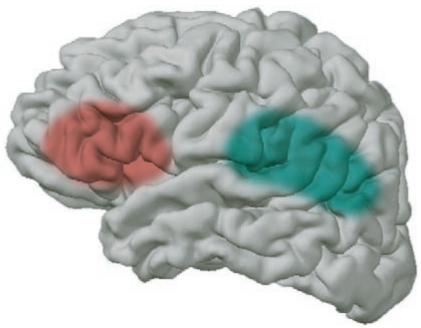
- The hidden debate
  - innate vs learner structures (to be continued…)

Conclusions

- empirical impact of the debate
  - past tense in English
    - rule: play->played, fax->faxed
    - exceptions: sing->sang, put->put
    - Pinker & Prince (1988)
    - procedural vs declarative memory (Ullman et al, 1997; Pinker & Ullman, 2002)



	Lexicon	Grammar
Used for:	roots, idioms, irregulars, some regulars	phrases, sentences, any regular form
Form of computation:	lookup, association	combination, unification
Subdivision of:	declarative memory	procedural system
Associated with:	words, facts	rules, skills
Principal substrate:	temporo-parietal cortex	frontal cortex, basal ganglia



Pinker, S. & Prince, A. (1988) On language and connectionism *Cognition*, 28, 73-193.
Ullman MT, Corkin S, et al. (1997). A neural dissociation within language: *Journal of Cognitive Neuroscience*, 9: 266–276.
Pinker, S. & Ullman, M. (2002) The past and future of the past tense. *Trends in Cognitive Science*, 6, 456-463.

Conclusions

- empirical impact of the debate (cont)
  - statistical learning vs algebraic learning in infants
    - Saffran et al, (1996), Marcus et al, (1999), Pena et al (2002)

Saffran, J., Aslin,R., Newport, E. (1996). *Science*, 274,1926.
Marcus, G.F., Vijayan, S., Bandi Rao, S., Vishton, P. M. (1999). *Science*, 283, 77
Peña, M., Bonatti, L., Nespor, M., Mehler J. (2002). Signal-Driven Computations in Speech Processing, Science, 298, pp. 604-607.

  - exemplar-based versus abstract representations
    - object recognition (Biederman & Gerhardstein, 1993), face recognition, speech recognition (eg Goldinger, 1988; Johnson 1997, Pierrehumbert 2001)

Biederman, I., & Gerhardstein, P. C. (1993). Recognizing depth-rotated objects: Evidence and conditions for 3D viewpoint invariance. Journal of Experimental Psychology: Human Perception and Performance, 19, 1162-1182.
Johnson, K. (1997). Speech perception without speaker normalization: An exemplar model. In K. Johnson & J.W. Mullennix (eds.), Talker Variability in Speech Processing, pp. 145-165. San Diego: Academic Press.
Pierrehumbert, J. (2001). Exemplar dynamics: Word frequency, lenition and contrast. In J. Bybee and P. Hopper (eds.), Frequency and the Emergence of Linguistic Structure, pp. 137-157. Amsterdam: Benjamins.
Goldinger, S.D. (1998). Echoes of echoes? an episodic theory of lexical access. *Psychological Review* 105:251-279.

Extensions

- computational reduction: finding the right architecture
- other connectionnist architectures
  - Kohonen's maps (competitive learning) (Kohonen, 1982)
  - Adaptive Resonance Theory (Grossberg, 1976)
  - Reinforcement learning (Barto, Sutton, Anderson, 1983)
- other computational frameworks
  - Probabilistic/Bayesian frameworks
  - Predictive Coding/Free Energy