

MONA-LISA

MONA-LISA:  
Multimodal Ontological Neural Architecture for  
Linguistic Interactions and Scalable Adaptations  
 $\cong$  Toward Massively-Parallel N.L.P.

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**Motivation:** Existing Models of Massively-Parallel AI/NLP seems inadequate for solving Natural Language Problems

**More Concretely:** Existing models assume spreading activation and marker-passing on semantic memory – Is this enough?

**More Practically:** Is the limitation of the current models theoretical or is it simply due to the availability of adequate machines?

**More Philosophically:** Is there a philosophical stand that allows a possible answer?

## A Brief Look at Our Past Attempts – A Typical Massively-Parallel NLP Model

- Direct Memory Access Paradigm (DMAP, Riesbeck&Martin 1985).
- Following the tradition of Quillian 1966, spreading activation of nodes in semantic memory is used to recognize the input.
- Developed as a model of MT in DMTRANS (Tomabechi 1987).
- Extended as a speech-to-speech translation system in  $\Phi$ DMTRANS (Tomabechi 1988) and recently into a dialog translation system in DM-DIALOG (Kitano 1990).
- Also extension in a different direction (propagating more information) in HMCP (Tomabechi&Levin 1989).
- Typically, spreading activation marker-passing is used to 1) predict the next element of the phrasal templates; 2) activate nodes connected via relational links (normally via isa links).



## What is Lacking in These Existing Models?

- By definition, the network as a whole represents the semantic knowledge, and their organization represents the conceptual definition of the nodes in memory which is *apriori* given.
  - Nodes must be a part of semantic memory (conceptual inheritance), nothing else.
  - Arcs must be a relational links between nodes (conceptual relation), nothing else.
  - Any organization of nodes that are not purely semantic cannot be allowed.
- Thus, knowledge with other nature cannot be represented.
  - Syntactic knowledge such as notion of head or dynamic assignment of cases cannot be captured. I.e., these features do not belong to semantic memory, also these features are not decided *a priori*, instead they are decided at the time of utterance.
  - Pragmatic knowledge such as point-of-view, topic, focus, etc. cannot be captured. – This kind of knowledge does not constitute semantic definitions instead these are parametric features specific to particular utterance environments.

- **Further more**, the spreading activation marker-passing architecture assumes strictly local interactions.

Constraints are specified as links and therefore, constraints can be postulated only for the nodes that are immediately connected by links.

A node cannot look inside other node's templates – i.e., no cross constraint formulation into other templates.

- Finally, knowledge is restricted to symbolic ones.

## A Simple Example

- *Sue said that Mary ran.*
- This requires two concept sequences: [\*PERSON \*MTRANS-word that \*ACTION] and [\*PERSON \*RUN].
- There is no way to ensure that if the \*MTRANS-word is *said*, then the set of entities that caused the activation of \*ACTION contain (be headed by) a finite verb.
- Thus, concept sequence schemes would not be able to capture the grammaticality of *John said Mary runs* and the ungrammaticality of *John said Mary run* (or *John said Mary to run*).

## More Examples

### SUBCATEGORIZING FOR HEAD FEATURES OF COMPLEMENTS

(1)

a. I believe John studies at CMU.

b.\*I believe John study at CMU.

c.\*I believe John studying at CMU.

- The contrast between (1)a, (1)b, and (1)c, is that *believe* is subcategorized for an embedded clause whose head verb takes finite form but not the base form or the present participle form.
- Correct treatment of grammaticality in these examples requires the non-local operation of passing up the head features from *study* to *believe*.



## AGREEMENT OF ANAPHORS AND CONTROL

- (2)
- a. He tried to wash himself/\*herself.
  - b. He promised her to wash himself/\*herself.
  - c. She persuaded him to wash himself/\*herself.
  - d. She believed him to be washing himself/\*herself.
  
  - e. She appealed to him to wash himself/\*herself.

- There is no way to specify generalizations about behavior of groups of syntactic constituents.
- There is no way for the main verb to determine anything about the subject of the embedded clause because the template containing the main verb cannot see inside the template corresponding to the controlled clause.

## WORD ORDER CONSTRAINTS BASED ON OBLIQUENESS AND THE HEAD POSITION

- In English, the order of a verb's arguments is partly determined by their relative obliqueness; less oblique complements precede more oblique phrasal complements.
- In the examples in (3) the constraint is that “the adverb phrase is the most oblique sister of the post-verbal complements, and hence must follow them all”.

- (3)
- a. He looked up the number quickly.
  - b. He looked the number up quickly.
  - c.\*He looked the number quickly up.
  - d.\*He looked quickly up the number.
  - e.\*He looked quickly the number up.
  - f.\*He looked up quickly the number.

## More Knowledge Required

- Thus purely semantic massive-parallelism is inadequate for handling realistic natural language constraints.
- Then, how can we represent the rest?



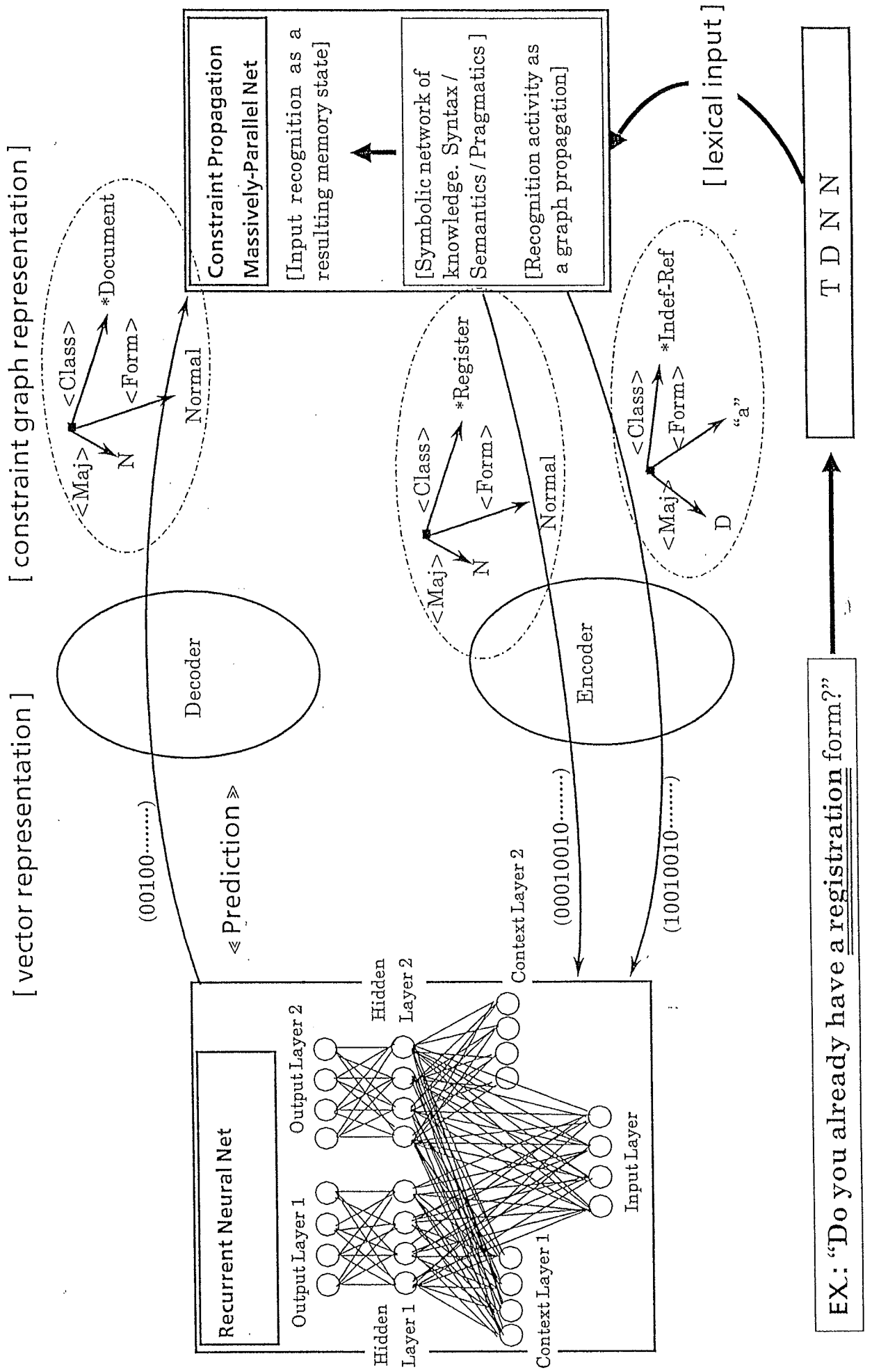
## Our Idea for Interaction of Three Kinds of Knowledge

- Graph-based Representation into non-semantic space.
- Graph  $\iff$  Vector, Encoding/Decoding for symbolic/subsymbolic interaction.

## MONA-LISA: A Small but a New Step

- Spreading Activation Memory-Network
  - Semantics.
- Graph-based Constraint Propagation
  - Syntax/Pragmatics.
- Symbolic net/Subsymbolic (Neural) Net interaction via graph/vector conversions.

# MONA-LISA Architecture



## MONA-LISA: Actual Implementation

- A joint ATR/CMU effort.
- Speech recognition using Time-Delay Neural Net and Linear Prediction Neural Net.
- Symbolic massively-parallel constraint processing based upon graph propagation.
- Subsymbolic neural net contextual learning and prediction through recurrent neural network (modified Elman net).
- Graph/Vector encoding/decoding for designated conceptual nodes through an explicit vectorization of inheritance.



# Massively-Parallel Symbolic Processing: Graph Propagation Architecture

- The notion of propagating graphs instead of markers.
- Constraints are represented using graphs.
- Expressivity of graphs seems sufficiently strong. (Virtually all existing linguistic and inferential constraints are representable using graphs. – Such as subsumption-ordering feature structures of unification based grammar constraints. Constraints such as postulated in HPSG and LFG can be captured trivially. – Strength of syntactic constraint representation is as strong as these theories.
- Singular and uniform constraint processing based upon propagation of graphs and operations on them (i.e., graph unification).

## The methodology

- The graphs are attached to the memory-network nodes.
- Copies of these graphs are propagated.
- The graphs for instances of complement-nodes are unified against the graphs of head nodes.

# Sample node definitions

```
(def-frame *JOHN
  (inherits-from *MALE-PERSON)
  (type :lex-comp)
  (spelling John)
  (synsem
    (def-path
      (<0 loc cat head maj> == n)
      (<0 loc cat marking> == unmarked)
      (<0 loc cont para index> == [[per 3rd]
                                   [num sng]
                                   [gend masc]]))
      (<0 loc cont restr reln> == *JOHN)
      (<0 loc context backgr> == [[reln naming]
                                   [name JOHN]])
      (<0 loc context backgr bearer> == <0 loc cont para index>)
      (<0 mem> == <0 loc cont para index iden>))))
```

```

(def-frame *GIVE
  (inherits-from *GIVE-ACTION)
  (type :lex-head)
  (spelling give)
  (synsem
    (def-path
      (<0 loc cat head> == [[maj v]
                          [vform bse]
                          [aux -]
                          [inv -]
                          [prd -]]))
      (<0 loc cat marking> == unmarked)
      (<0 loc cat subcat 1> == <1>)
      (<0 loc cat subcat 2> == <2>)
      (<0 loc cat subcat 3> == <3>)
      (<0 loc cont reln> == *give-action)
      (<1 loc cat head maj> == n)
      (<1 loc cat head case> == nom)
      (<0 loc cont agent> == <1 loc cont para index>)
      (<1 loc cont restr reln> == *person)
      (<2 loc cat head maj> == n)
      (<2 loc cat head case> == acc)
      (<0 loc cont goal> == <2 loc cont para index>)
      (<2 loc cont restr reln> == *person)
      (<3 loc cat head maj> == n)
      (<3 loc cat head case> == acc)
      (<0 loc cont theme> == <3 loc cont para index>)
      (<3 loc cont restr reln> == *matter))))

```

```

(def-frame *PERSUADED
  (inherits-from *PERSUADE-ACTION)
  (type :lex-head)
  (spelling persuaded)
  (synsem
    (def-path
      (<0 loc cat head> == [[maj v]
                           [vform inf]
                           [aux +]
                           [inv -]
                           [prd -]]))
      (<0 loc cat marking> == unmarked)
      (<0 loc cat subcat 1> == <1>)
      (<0 loc cat subcat 2> == <2>)
      (<0 loc cat subcat 3> == <3>)
      (<1 loc cat head maj> == n)
      (<1 loc cat head case> == nom)
      (<1 loc cont restr reln> == *person)
      (<0 loc cont agent> == <1 loc cont para index>)
      (<0 loc cont persuadee> == <2 loc cont para index>)
      (<0 loc cont persuadee> == <0 loc cont circumstance agent>) ;;; obj control
      (<2 loc cat head maj> == n)
      (<2 loc cat head case> == acc)
      (<2 loc cont restr reln> == *person)
      (<3 loc cat head maj> == v)
      (<3 loc cat head vform> == inf)
      (<3 loc cat head aux> == +)
      (<3 loc cat subcat 1 loc cat head> == [[maj n]
                                             [case nom]])
      (<3 loc cat subcat 2 loc cat head> == saturated) ;;; must not unify
      (<3 loc cat subcat 3 loc cat head> == saturated) ;;; must not unify
      (<0 loc cont circumstance> == <3 loc cont>)
      (<0 loc cont reln> == *PERSUADE-ACTION)
      (<3 loc cont restr reln> == <3 loc cont reln>)
      (<3 loc cont restr reln> == *action))))

```

## Control handling in *persuaded*

(⟨ 0 loc cont persuadee ⟩ == ⟨ 2 loc cont para index ⟩)

(⟨ 0 loc cont persuadee ⟩ == ⟨ 0 loc cont circumstance agent ⟩)

# Actual graph propagation recognition algorithm

- 5 types of nodes: conceptual-class nodes, lexical-head nodes, lexical-complement nodes, memory-instance nodes, (and phonological-activity nodes.)

```
function sentential-recognize (input-stream)
  create-process (recognize-lexical (input-stream));
  invoke-global-incidents;
  for all NODE in DecayingLayer do
    print-node NODE;

function recognize-lexical (input-stream)
  reset activities in Activation Layer and Decaying Layer
  for word-hypothesis in input-stream do
    create-process (activate-lex-node (word-hypothesis));
  invoke-global-incidents;

function activate-lex-node (word-hypothesis)
  create instance of word-hypothesis
  and make a copy of constraint graph with addition of an 'mem'
  arc pointing to the created instance;
  if the node type is lexical-complement
    then propagate copied (and modified) constraint graph upward;

function invoke-global-incidents ()
  for head-instance in ActivationLayer do
    create-process (grab-subcats (head-instance)) ;

function grab-subcats (head-instance)
  for arcs specified in subcat graph (i.e, <0 loc cat subcat>) do
    if conceptual restriction node exists
      (i.e, <loc cont rest reln> has value)
    and if that node has received the constraint graph propagation
      then unify the subcat graph with the propagated graph
        if unify succeeds and obliqueness order is met
          then store result destructively in head-instance;
          propagate synsem graph upward;
```





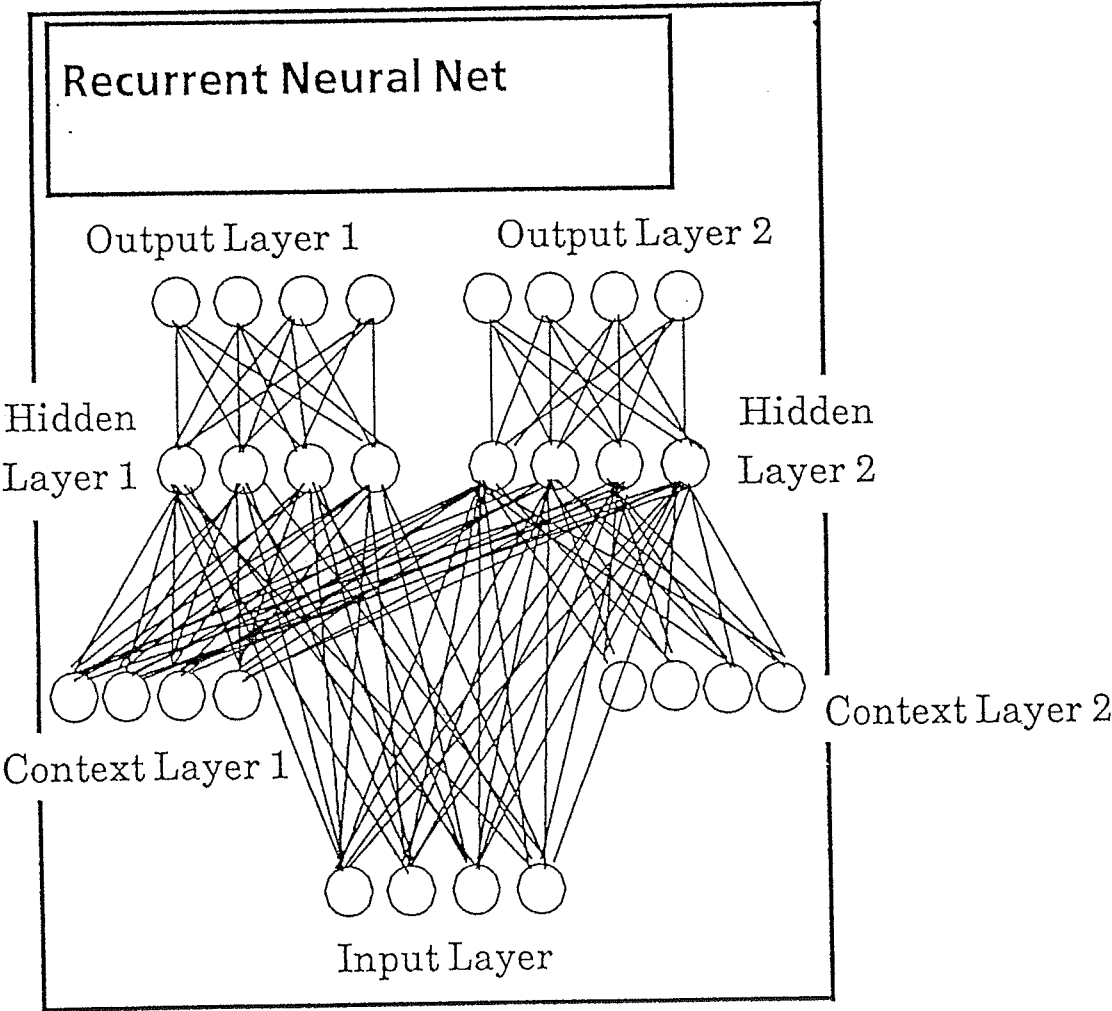
Resulting global memory state with 1 node(s) in the Decaying Layer:

```
(*PERSUADED2356
(INHERITS-FROM *PERSUADED)
(TYPE
(VALUE
(COMMON :INST-HEAD)))
(SYNSEM
(VALUE
(COMMON
X01[[0 X02[[MEM X03 *PERSUADED2356]
[LOC X04[[CONT X05[[RELN X06 *PERSUADE-ACTION]
[CIRCUMSTANCE X07[[RELN X08 *GIVE-ACTION]
[AGENT X09[[PER X10 3RD]
[ NUM X11 SNG]
[GEND X12 FEM]
[IDEN X13 *MARY2384]]
[GOAL X14[[PER X15 3RD]
[ NUM X16 SNG]
[GEND X17 FEM]
[IDEN X18 *SANDY2524]]
[THEME X19[[IDEN X20 *SUS12607]
[GEND X21 NEUT]
[PER X22 3RD]]
[RESTR X23[[RELN X08]]]
[PERSUADEE X09]
[AGENT X24[[IDEN X25 *JOHN2265]
[GEND X26 MASC]
[ NUM X27 SNG]
[PER X28 3RD]]]
[CAT X29[[SUBCAT X30[[NIL ]]
[MARKING X31 UNMARKED]
[HEAD X32[[PRD X33 -]
[INV X34 -]
[AUX X35 +]
[VFORM X36 INF]
[MAJ X37 V]]]]]
[1 X38[[MEM X25]
[LOC X39[[CONTEXT X40[[BACKGR X41[[BEARER X24]
[NAME X42 JOHN]
[RELN X43 NAMING]]]
[CONT X44[[RESTR X45[[RELN X46 *JOHN]
[PARA X47[[INDEX X24]]]
[CAT X48[[MARKING X49 UNMARKED]
[HEAD X50[[CASE X51 NOM]
[MAJ X52 N]]]]]
[2 X53[[LOC X54[[CAT X55[[HEAD X56[[MAJ X57 N]
[CASE X58 ACC]
[MARKING X59 UNMARKED]
[CONT X60[[PARA X61[[INDEX X09]
[RESTR X62[[RELN X63 *MARY]]]
[CONTEXT X64[[BACKGR X65[[RELN X66 NAMING]
[NAME X67 MARY]
[BEARER X09]]]]
[MEM X13]]
[3 X68[[LOC X69[[CAT X70[[HEAD X71[[MAJ X72 V]
[VFORM X73 INF]
[AUX X74 +]
[INV X75 -]
[PRD X76 -]]
[MARKING X77 UNMARKED]
[SUBCAT X78[[2 X79[[LOC X80[[CAT X81[[HEAD X82 SATURATED]]]]]
;; SUBCAT moved for print [3 X83[[LOC X84[[CAT X85[[HEAD X86 SATURATED]]]]]
[1 X87[[LOC X88[[CAT X89[[HEAD X90[[CASE X91 NOM]
[MAJ X92 N]]]
[CONT X93[[PARA X94[[INDEX X09]
[RESTR X95[[RELN X96 *MATTER]]]]]]]]]
[CONT X07]]
[MEM X97 *TO2468]])))]
(S-TIME
(VALUE
(COMMON 1)))
(W-TIME
(VALUE
(COMMON 2)))
NIL
```

## Subsymbolic Connectionist Neural Network

- Recurrent Neural Network based on Elman's recurrent net.
- Time-sensitive learning captured in the hidden layer.
- Instead of decoding hidden layer learning, we explicitly encode and decode at input layer and output layer. – Hidden layer info is hard to get.

# Recurrent Network based on Elman network



## Connecting Subsymbolism with Symbolism

- Head-features and inheritance hierarchy explicitly vectorized.
- Encoding and decoding between vectors and graphs.
- Some nodes (one to two levels higher in abstraction than lexical ones) are designated as subsymbolic interaction nodes.

# Syntactic Head-Features are Vectorized

1st 2nd 3rd 4th 5th  
 Major form case/aux-inv-pred persn number (gender is in hier)

N THERE NOM FIRST SINGULAR  
 IT ACC SECOND PLURAL  
 NORM THIRD

V FIN AUX+ FIRST SINGULAR  
 BSE SECOND PLURAL  
 BSP INV+ THIRD  
 PRP  
 PAS  
 INF  
 GER

A PRD+

P OF PRD+  
 AT  
 IN  
 TO  
 FROM  
 FOR  
 OTHER

D THE  
 A  
 AN  
 MY  
 YOUR  
 THEIR  
 ANY  
 OTHER

ADV

# Inheritance Hierarchy is Vectorized

1st-level	2nd	3rd	4th	5th
object	physical-object	animate-object	person	male-persn
			female-per.	
		animal		
		plant		
		other-animate-obj		
	inanimate-object	natural-substance		
		artificial-subst.	document	
				book
				computer
food		other-inanimate-		object
	mental-object	theory&rule		
	abstract-tool	language	lisp	
			prolog	
			English	
			Japanese	
	abstract-material	title		
	intellectual-	thesis		
			product	
	other-mental-		object	
	social-object	institution	corporation	public corp.
			private corp.	
		educational-	university	
			institution	
	service			
	cost-of-service	fee		
phenomenon	physical-phenom.	action	atrans	give
			pay	
		ptrans	travel	
			send	
		mtrans	read	
			ask	
			greet	
		include	attend	
			register	
		other-action	assist	apply
			record	
try	persuade			
		event	atrans-event	
			ptrans-event	
			mtrans-event	
		include-event	attendance	
			registration	
		other-event		



naive-measurement ambiguous-size  
other-measurement

Decoding is left to right, stopping at ambiguous vector units. – Some generalization capability.





## Evaluation of Subsymbolic Predictions

- Trained on 12 dialogs of conference registration domain.
- One dialog is one epoch.
- Predictions such as *\*register* after *to*.
- and also ((MAJ V) (FORM BSE)).
- Some inductive generalization.

## An Observation about massively parallel hardware implementation

- It requires 1) Massively parallel processing 2) propagation of graphs 3) access to any location is the shared memory as a part of the graphs.
- No current massively parallel hardware seems to support this (cf. CM-2, IXM2, SNAP).
- Also, full graph-unification support with cycles, convergent arcs, negation and disjunctions seem non-trivial in the current massively parallel hardware.

## Current Implementation (as of Nov. 1990)

- Constraint Propagation Network implemented on a parallel CommonLisp using a vectorized frame representation. TDNN in parallel 'C'. Recurrent neural net in both parallel CommonLisp and parallel 'C'. Both serial and parallel versions of Quasi-Destructive graph unification algorithm (Tomabechi, 1991).
- Closely-coupled shared memory parallel hardware – 16 CPU Sequent/Symmetry.
- Simulated massive-parallelism through dynamic creation of light-weight processes.
- Division into three levels of processing:

**Node level:** this is the level where nodes receive and fire activations, i.e., the representational level of memory nodes. In the existing models of massively-parallel artificial intelligence, this is assumed to be the level of processing as well.

**Light weight process (lwp) level:** this is the level at which massively parallel processing is performed. Any number of *lwps* may be created during processing,

**Processing unit level:** this is the level of actual processing hardware. Any number of pro-

processors may be configured depending on the hardware architecture. One (or more) processing units may be dedicated to the scheduling of *lwps*.

## Future Possibilities

- Other modal channels, e.g. connecting visual neural network.
- What about symbolic learning? Case-based? Explanation-based?
- How about hardware?

## MONA-LISA: Philosophical Stand

- Material Representationalist View:  
“To be a person is to be a system of representations.”
- More specifically,  
“Speech Act is an action to modify the world to conform to our representations. Speech Recognition is to modify our representation to conform to the world.”
- One Distant Goal:  
“Unification of constraints across all of representational components regardless of nature of representations.”

## Kinds of Representational Questions to be Involved

- **Epistemological dichotomy**

- Some knowledge is *a priori* given [to an artificial intelligence].
  - Assumed in the symbolic knowledge representation schemes such as semantic networks, frames, script, etc..

- Some knowledge is *a posteriori* acquired.
  - Especially learning of neural network seems purely *a posteriori*.

- **Compositionality question** How is representational content interpreted? Frege/Montagovian view supports pure compositionality (*meaning of the whole is the function of the meaning of the parts*) . Is that true? Can we take out a part from the whole and call it a representation?

- **Monotonicity question** Pure Compositionality assumes pure monotonicity. Is that true?