



Microsoft Research

Faculty  
Summit

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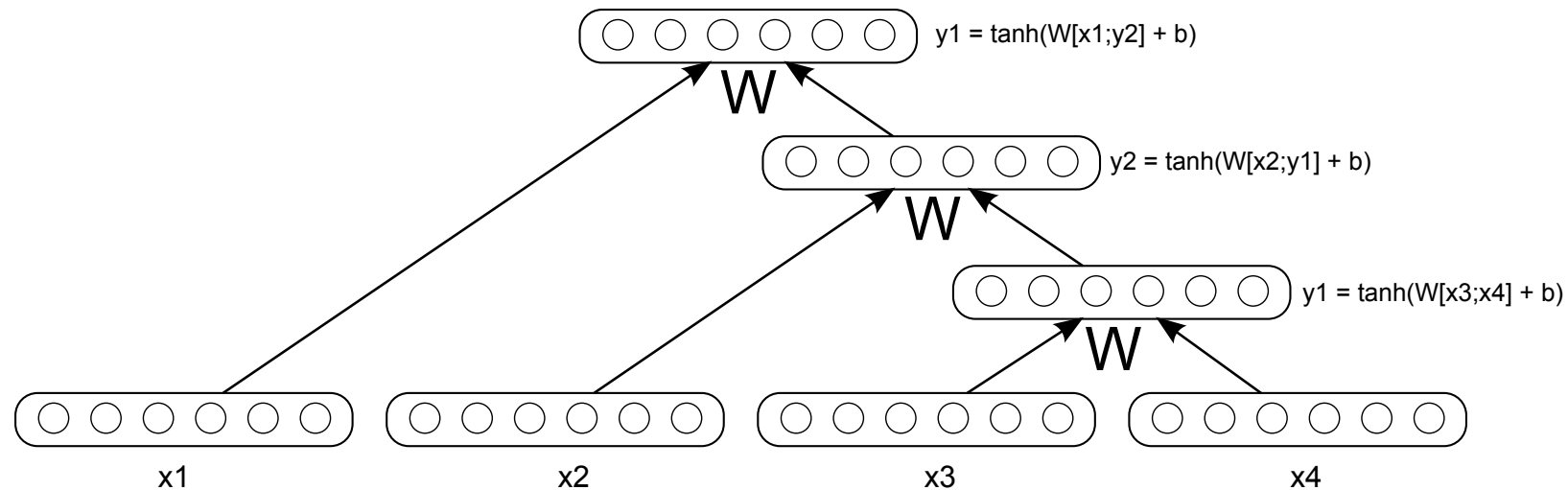
# Symbolic roles in vectorial computation

# Vectorial encoding of symbolic *structure*

— in contrast to hybrid symbolic/vectorial representations

A single vector encodes (i) all the (vectorial) labels  
**and** (ii) the (discrete) structure in which they reside

Cognitive motivation:  
vector  $\sim$  neural state



Socher, Manning & Ng 2010

# Vectorial encoding of symbolic *structure*

**TYPE:** Decompose structure into roles  $\{r_k\}$

Approach 1: Absolute position

[Approach 2: Contextual ( $\sim n$ -gram)]

Each  $r_k$  is assigned a vector encoding  $\mathbf{r}_k \in R$  (linearly indep.)

— designed or learned

Can be non-orthogonal:

- $\mathbf{r}_k \cdot \mathbf{r}_l \equiv \text{sim}(\mathbf{r}_k, \mathbf{r}_l) \neq 0$
- interaction of  $\mathbf{r}_k$  &  $\mathbf{r}_k$
- generalization

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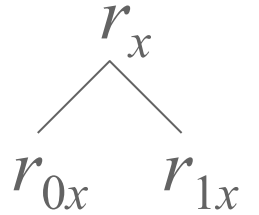
**INSTANCE:** Specific fillers for roles

Let  $\mathbf{f}_k \in F$  (linearly indep.) be the label in role  $r_k$   
—  $\mathbf{f}_k$  may be a vector encoding of a symbol  $f_k \in A$   
— designed or learned

**ENCODING:**  $\mathbf{v} = \sum_k \mathbf{f}_k \otimes \mathbf{r}_k$

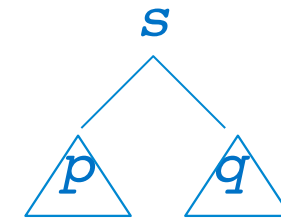
Can be recursive:

$$\forall x \in \{0, 1\}^*$$



$$\mathbf{r}_{0x} = \mathbf{r}_0 \otimes \mathbf{r}_x$$

$$R = \bigoplus_d R^{(d)}$$



$$\mathbf{s} = \mathbf{p} \otimes \mathbf{r}_0 + \mathbf{q} \otimes \mathbf{r}_1$$

$\Rightarrow$  exact computation of recursive functions

Size: linear in number of roles

Tensor Product Representations (TPRs: 1990)

# Summary: TPRs

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N.B.: Turns out to have important (indirect) implications for grammatical theory

# Computability theory over TPRs

What symbolic functions can be computed over TPRs using neural computation?

The functions in the following classes are computable in a linear neural network:

$\mathcal{B}$  = base of in-place symbol mappings

$\mathcal{C}$  = closure under composition of  
[ tree-manipulating primitives  $\cup \mathcal{B}$  ]

$\mathcal{P} \sim$  “primitive recursive”

‘Primitive recursive’:

$$\mathcal{C} \subset \mathcal{P}$$

$g, h \in \mathcal{P} \Rightarrow f \in \mathcal{P}$  when

$$f(s) = \begin{cases} g(s) & \text{if } \text{atom}(s) \\ h(f(\text{ex}_0(s)), f(\text{ex}_1(s))) & \text{otherwise} \end{cases}$$

# Decoding TPRs

## INSTANCE $\mathbf{v}$ : Inner product

$$\mathbf{f}_k = \mathbf{v} \cdot \mathbf{r}_k^+ \quad \text{— given } \{\mathbf{r}_k\}$$

## SAMPLE $\{\mathbf{v}^{(\alpha)}\}$ : Generative model

Hypothesis:  $\{\mathbf{v}^{(\alpha)}\}$  is a collection of TPRs, each encoding an instance of a symbol structure of a single type

$$\mathbf{v}^{(\alpha)} = \sum_k \mathbf{f}_k^{(\alpha)} \otimes \mathbf{r}_k \quad \text{— where } \mathbf{f}_k^{(\alpha)} \text{ encodes a symbol } \mathbf{f}_k^{(\alpha)}$$

Learning algorithms: derived from generative model

TYPE: What are  $\{\mathbf{r}_k\}$  and  $\{\mathbf{f}_k\}$  ?

INSTANCE: For a given  $\alpha$ ,

which symbol  $\mathbf{f}_k^{(\alpha)} \in \mathcal{A}$  fills each role  $r_k$ ?

**APPLICATION:** Decoding neuroimages of combinatorial stimuli (e.g., sentences, words).

Instance bindings  $\{\mathbf{f}_k^{(\alpha)} / r_k\}$  of stimuli are known, so only need learn the TYPE encoding

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$R(\text{---}, Y)$   
Role

If  $X$  fills this role, vector encoding is:  $X \otimes (R \otimes Y)$

$\cong R \otimes X \otimes Y$   
(used in cognitive models)

Approach 1: [filler]  $\otimes$  [position]

Approach 2: [filler<sub>1</sub>]  $\otimes$  [filler<sub>2</sub>]



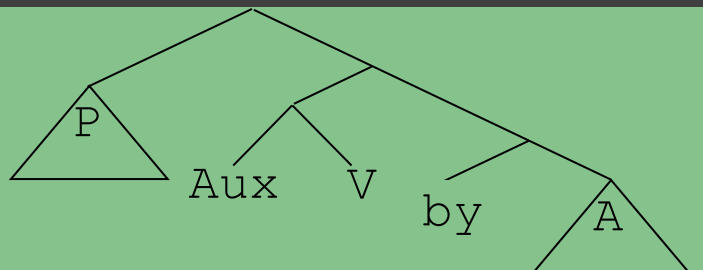
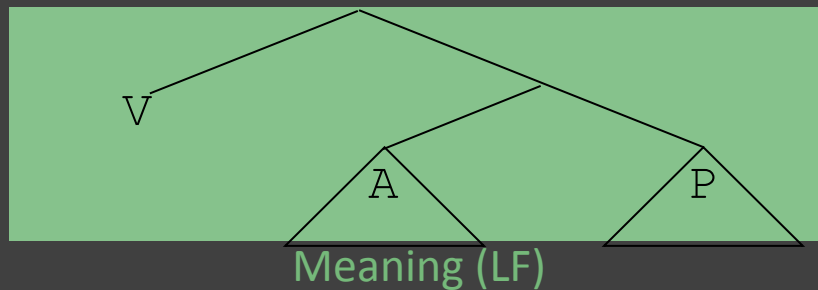
Few leaders are admired by George Bush



admire(George Bush, few leaders)

$$f(s) = \text{cons}(\text{ex}_1(\text{ex}_0(\text{ex}_1(s))), \text{cons}(\text{ex}_1(\text{ex}_1(\text{ex}_1(s))), \text{ex}_0(s)))$$

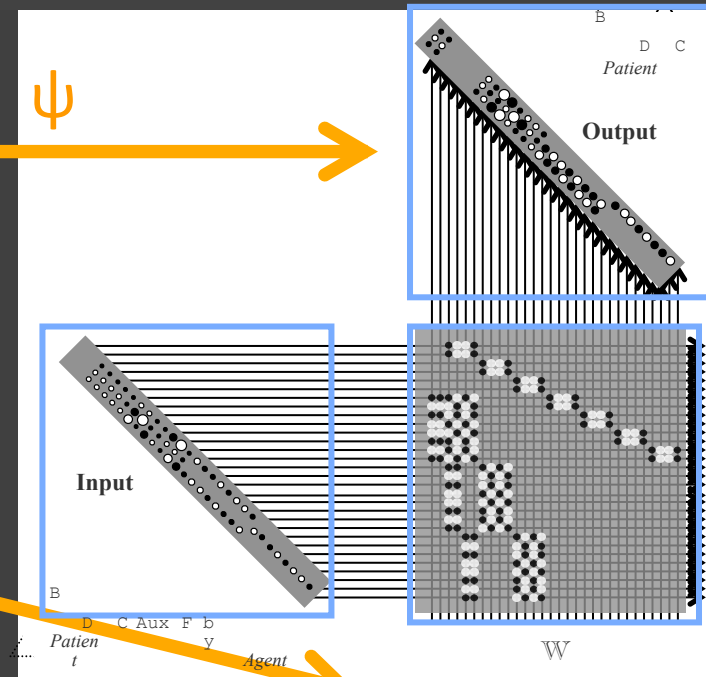
$$\mathbb{W} = \mathbb{W}_{\text{cons}_0}[\mathbb{W}_{\text{ex}_1} \mathbb{W}_{\text{ex}_0} \mathbb{W}_{\text{ex}_1}] + \mathbb{W}_{\text{cons}_1}[\mathbb{W}_{\text{cons}_0}(\mathbb{W}_{\text{ex}_1} \mathbb{W}_{\text{ex}_1} \mathbb{W}_{\text{ex}_1}) + \mathbb{W}_{\text{cons}_1}(\mathbb{W}_{\text{ex}_0})]$$



“Passive sentence”

$\psi$   
Isomorphism

$\mathbf{a}_{\text{Passive}}$



$\mathbf{a}_{LF}$

$\mathbb{W} \mathbf{a}_{\text{Passive}}$