Tensor Product Representations and Holographic Reduced Representations

Smolensky, 1990 & Plate, 1991

Tiwalayo Eisape, Joey Velez-Ginorio, Pedro Colon-Hernandez {eisape, joeyv, pe2517}@mit.edu

Neuro-symbolic Models for NLP (6.884), October 2, 2020

Outline

Introductions (us + 3 others) (11:35 - 11:40)

TPRs - why/what? (11:40 - 11:55)



Break out room (11:55 - 12:10 mins) Discussion (12:10 - 12:20 mins) [Early] Break (12:20 - 12:35)

TPR tutorial (12:35 - 12:50)



Discussion (12:50 - 12:55)

TPR Shortcomings; HRRs (12:55 - 1:10)



Discussion (1:10 - 1:25)

Outline

- 1. Is variable binding necessary?
- 2. Do humans use a TPR-like mechanism?
- 3. Do current models approximate faithfulness?
- 4. Small group technical questions

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A one-sentence summary of the implications of this view for AI:

connectionist models may well offer an opportunity to escape the brittleness of symbolic AI systems ...

... This paper offers an example of what such a collaboration might look like.

Jay is loved by Kay. Who loves Jay? Kay.

- ✤ Jay in role: subject of passive sentence
- ✤ Jay in role: object of wh-question
- ✤ Kay in role: object of passive by-phrase
- ★ Kay in role: answer to wh-question





[Paul Smolensky HLAI Keynote (2019); Newell, A. (1980)]





[Smolensky 1990, pg. 169]



(1) Decomposing the structures via roles



(1) Decomposing the structures via roles



(2) representing variable/value bindings





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[Soulos et al. 2019]

(3) representing conjunctions

Tensor Products

'Faithful' 👼 Tensor Product Representations



'Faithful' 👼 Tensor Product Representations

















Variable Binding

- L. Is Variable Binding Necessary?
- 2. Do humans use a TPR-like mechanism?
- 3. Do current models approximate faithfulness?
- 4. Small group technical questions



Gary Marcus @GaryMarcus · Feb 6, 2018

completely agreed, **@tdietterich**! lots of cases where **variable binding** is absolutely necessary. no **binding**, no AGI.

Thomas G. Dietterich @tdietterich · Feb 6, 2018

Replying to @tdietterich @jahendler and @GaryMarcus

There are lots of cases where binding appears to be necessary. Ex 1: If you put X into your pocket and then walk to work, you will be able to take X out of your pocket at work. Ex 2: If I ask you query X and you know X, you will tell me X, forall X.

2

1, 5

y g

⊥

Break





TPR Tutorial

(1) Symbolic Structure

TPR Tutorial

(1) Symbolic Structure(2) Encoding w/ TPRs

TPR Tutorial

(1) Symbolic Structure(2) Encoding w/ TPRs(3) Representation Proofs





Examples
(Give)
(Give (Give 🗌))
(Give (Give 🗌))





(2) Encoding w/ TPRs : Give, the programming language

A TPR is a mapping, [p]: Give₄ $\mapsto \mathbb{R}^{4\times3}$, from a set of symbols to a vector space via filler/role decompositions. Here, Give₄ denotes the set of all Give programs up to length 4.
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 $Give_4 = \{ \square, (Give \square), (Give (Give \square)), (Give (Give (Give \square))) \}$

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Fillers	
$f = \{i_1, i_2, i_3, i_4\}$	

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= { Give, \square , ε }

Roles

(Give (Give (Give))) = $(i_1:Give) \land (i_2:Give) \land (i_3:Give) \land (i_4:$

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$\begin{array}{c ccccc} \hline \textbf{Fillers} & [1] & [0] & [0] & [0] \\ [0] & [1] & [0] & [0] \\ f & = & \left\{ \begin{array}{c} [0] & [0] & [1] & [0] \\ [0] & [0] & [0] & [0] & [1] \end{array} \right\} \\ & & \mathbf{i_1} & \mathbf{i_2} & \mathbf{i_3} & \mathbf{i_4} \end{array} \end{array}$	$ \llbracket (Give (Give (Give))) \rrbracket = \llbracket (i_1:Give) \land (i_2:Give) \land (i_3:Give) \land (i_4: \square) \rrbracket $
$\frac{\text{Roles}}{r} = \{ \text{Give}, \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \$] }

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(3) Representation Proofs : Give, the programming language

<u>Theorem.</u> The following linear transformation is a representation of the instruction Give.

 $Give : \sum_{i} f_{i} \otimes r_{i} \mapsto \sum_{i} f_{i} \otimes r_{i}$

(3) Representation Proofs : Give, the programming language

<u>Theorem.</u> The following linear transformation is a representation of the instruction Give.

Give :
$$\sum_{i} f_{i} \otimes r_{i} \mapsto \sum_{i} f_{i} \otimes r_{i}$$

Proof.

Recall that w/ TPRs we encode Give programs as conjunctions of filler/role decompositions, i.e. $[p] = \sum_i f_i \otimes r_i$. Additionally, recall that: (Give p) \rightarrow p

$$\llbracket (Give p) \rrbracket = \llbracket p \rrbracket$$
$$= \sum_{i} f_{i} \otimes r_{i}$$
$$= Give \sum_{i} f_{i} \otimes r_{i}$$
$$= Give \llbracket p \rrbracket$$

Discussion

- How does this scale to larger programs in Give?
- What if our programming language was more complicated?
- Other thoughts...

Benefits & Shortcomings of Tensor Decomposition

- + No impositions on structure
- + Faithful
- + Variable binding
- Scaling up can be memory and compute demanding
 - Using ConceptNet as an example, ~4M nodes, ~40 relations might need to play around with pretty large tensors



Holographic Reduced Representations

- Use Circular Convolutions and Correlations to associate/disassociate vectors that represent structures
- Requires a reconstruction system to sort through the noise
- Circular Conv. and Circular Corr. can be manipulated to query structure



Representations with HRR

Sequences

 $s_{abc} = a + a \circledast b + a \circledast b \circledast c$ $s_{de} = d + d \circledast e$ $s_{fgh} = f + f \circledast g \circledast h$

•

Representations with HRR

Sequences

Variable Binding

$$\tilde{\mathbf{t}} = \tilde{\mathbf{x}} \circledast \tilde{\mathbf{a}} + \tilde{\mathbf{y}} \circledast \tilde{\mathbf{b}}.$$

Binding a to X and b to Y

Representations with HRR

Sequences

Frame-Slots

Running frame: Spot runs

trunning = lrun + ragent Sfspot

Variable Binding

Seeing frame: Dick saw Spot run

$$t_{seeing} = l_{see} + r_{agent} \circledast f_{dick} + r_{object} \circledast t_{running}$$

= $l_{see} + r_{agent} \circledast f_{dick}$
+ $r_{object} \circledast (l_{run} + r_{agent} \circledast f_{spot})$

Frame:

Job Application:

- Name
- Date

Filler

• September 1, 2020



Binding Date & Filler

September 1, 2020

C[0]=0.1*0.05+-0.16*0.04+-0.22*0.06+=-0.0146



Binding Date & Filler

September 1, 2020

C[1]=0.1*-0.16+0.05*-0.22+0.04*0.06=-0.0246

C:	-0.0146	-0.0246
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Pairing Job Application + Date Field

September 1, 2020

C[2]=0.1*0.06+0.05*0.04+-0.16*-0.22=0.0432

C:	-0.0146	-0.0246	0.0432
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September 1, 2020

C:	-0.0146	-0.0246	0.0432
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C: {Date:September 1,2020}



September 1, 2020



C': {Date: September 1, 2020, Name}

C': {Jo

Add in Frame Label C': {Date: September 1, 2020, Name}+ Job Application C'':{Job Application: Date: September 1, 2020, Name}

C": {Job Application: Date:September 1,2020, Name}

Keep in mind representations are stored in a distributed manner We used the "decoder" implicitly to clean the noise Our representations are the result of an FFT



















Benefits of Holographic Representations

- Format for the two input vectors is not specified, only independently distributed
- **Space Efficiency:** you just need the 2 vectors rather than the whole Tensor, result is the same size as the input
- Can be calculated in O(n log n) with FFT
- HRRs could retain ambiguity while processing ambiguous input (New York as City and as Name)
- Easy analysis of capacity, scaling and generalization

Shortcomings of Holographic Representations

- Decoder/cleaner must store all the possible outputs. If it knows everything, then why not find a way to exploit it?
- Is the decoder static? How would you add some new domain?
- Elements of each vector must be independently distributed, but have meaningful features
- Hit until you decode the correct thing?
- Some operations to decode require additional machinery (recursive)



Encoding Methods?


Encoding Methods?



[END]