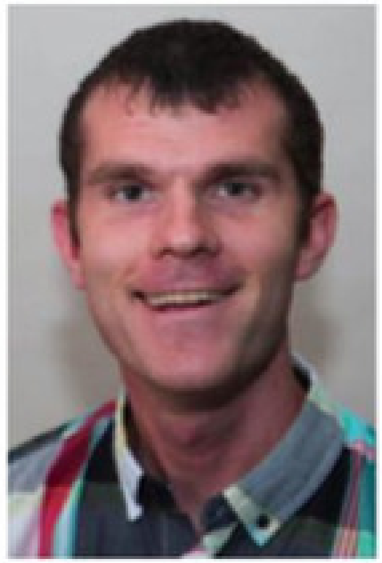
Discovering the Compositional Structure of Vector Representations with Role Learning Networks

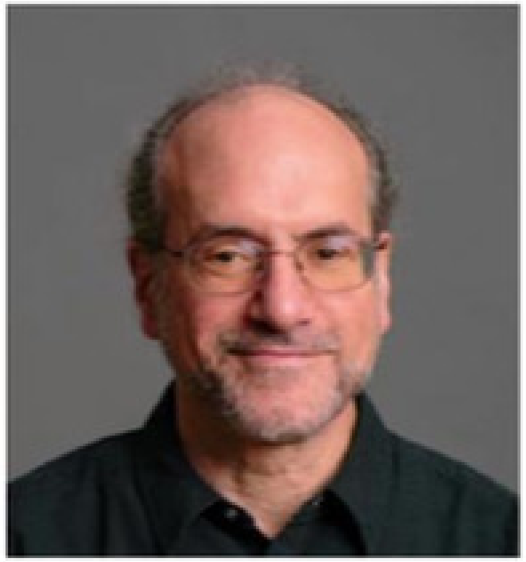
Paul Soulos[1]

Tom McCoy[1]



Tal Linzen[1]

Paul Smolensky[2,1]



1 Johns Hopkins University

2 Microsoft

tl;dr

- Our technique can uncover latent compositionality in vector representations
- Interpreting compositional structure sheds light on how these models function
- We understand the inner workings well enough to write down a symbolic algorithm to produce the neural encoding
- Our approximation allows us to directly manipulate the internal representations to produce desired behavior.

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- A set of fillers (tokens)
  - Example: {4, 2, 7, 9}

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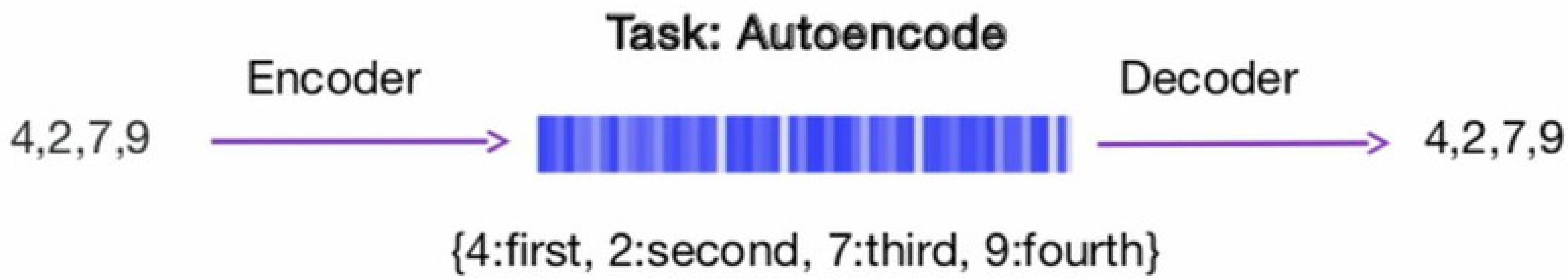
How can neural networks represent compositional structure?



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Tensor Product Representations (TPRs)

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Smolensky (1990)

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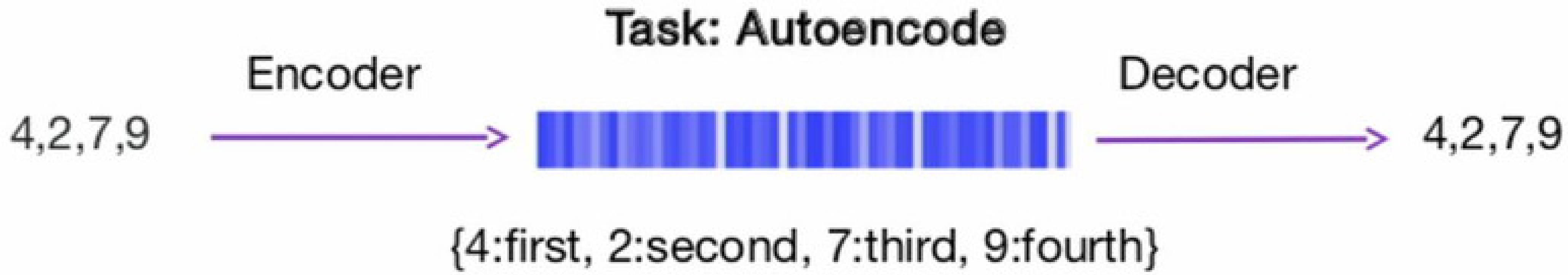


Tensor Product Representations (TPRs)

- A set of fillers (tokens)

Every filler f_i is vector

- A set of roles (positions in the structure)

Every role r_i is vector

- A binding operation (placing a filler in a specific role filler:role)

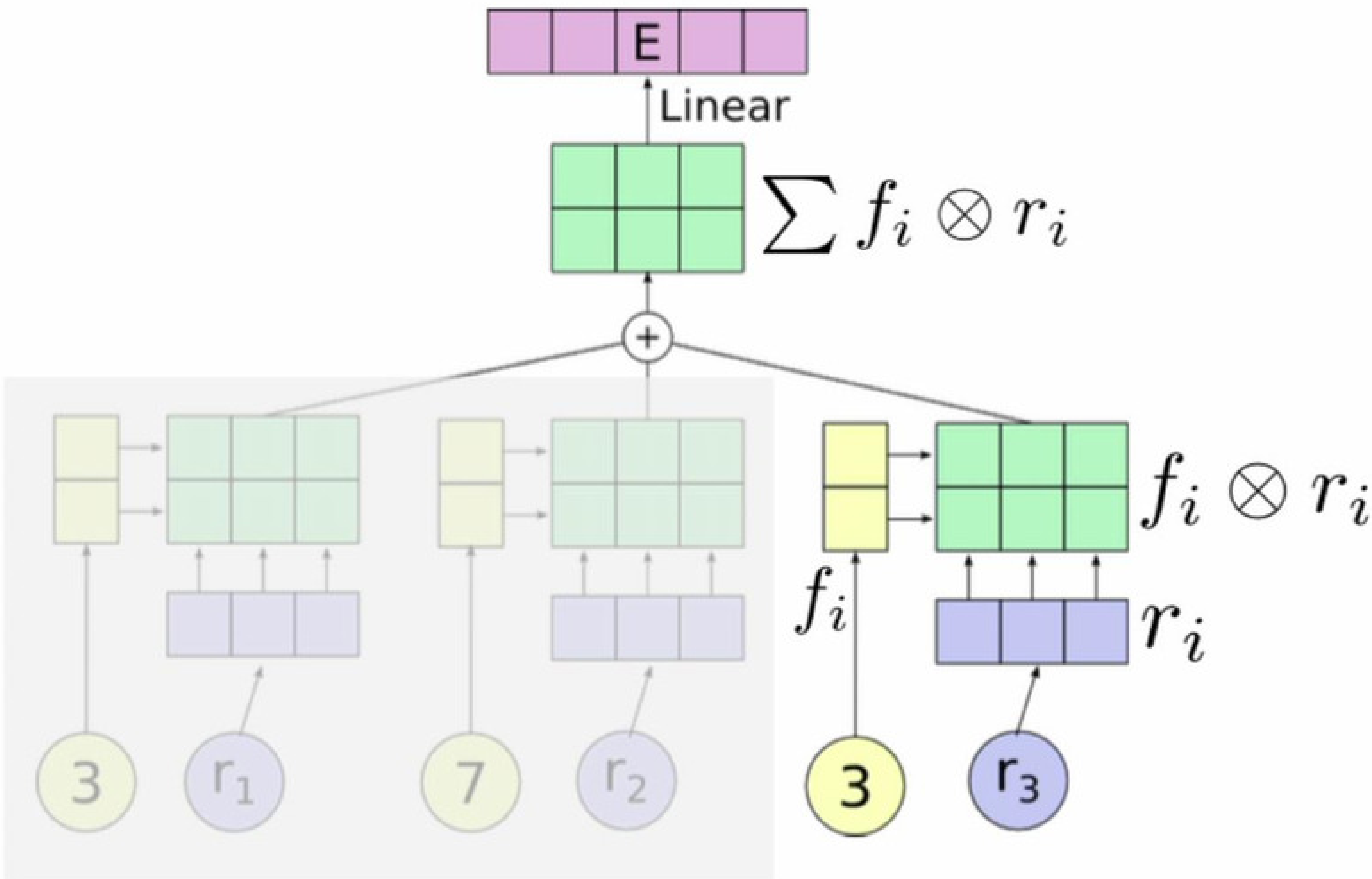
Tensor product: $f_i \otimes r_i$

- A composition operation (stitching all of the bound filler:roles together

Sum: $\sum f_i \otimes r_i$

Smolensky (1990)

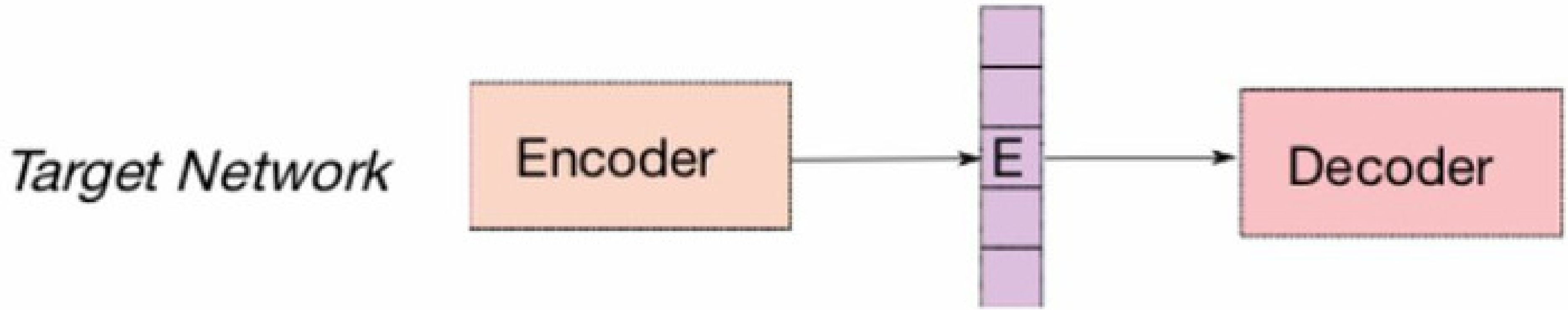
Tensor Product Encoder



McCoy, Linzen, Dunbar, and Smolensky (2019)

Dissecting Compositionality in Vector Representations (DISCOVER)

Goal: Discover implicit compositional structure in learned encodings E



$$E \stackrel{?}{=} \sum f_i \otimes r_i$$

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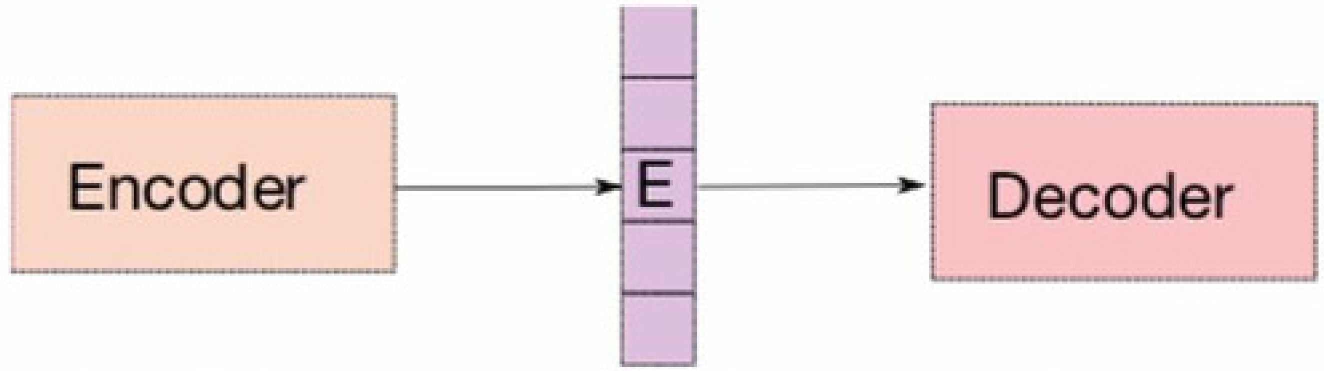
Target Network



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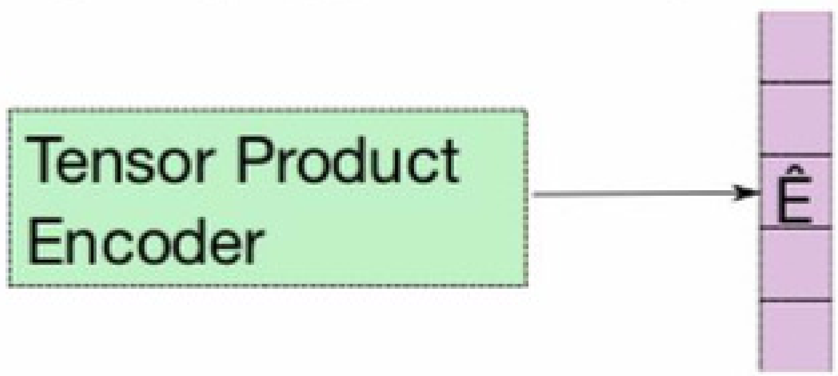
Approach: Discover implicit compositional structure in the target network's learned encoding E by approximating E with Ê



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Minimize MSE(Ê, E)

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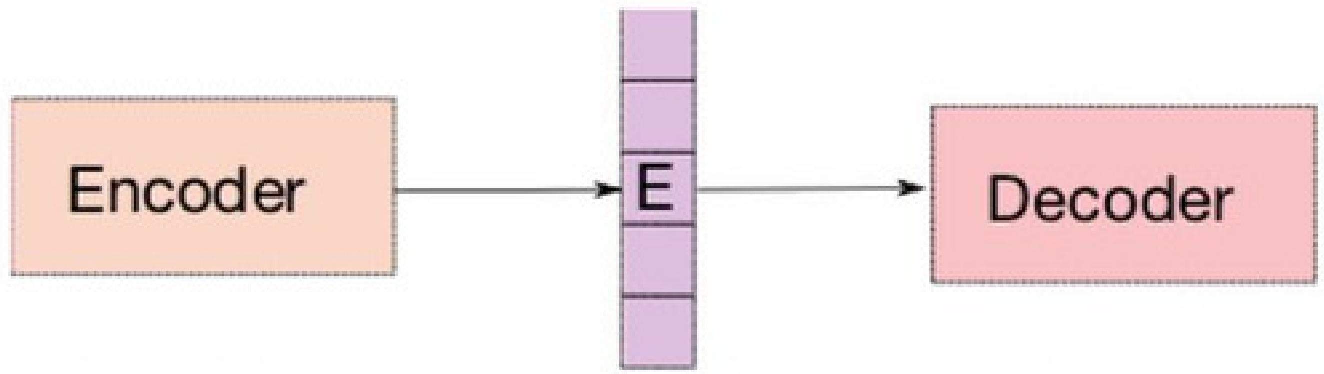

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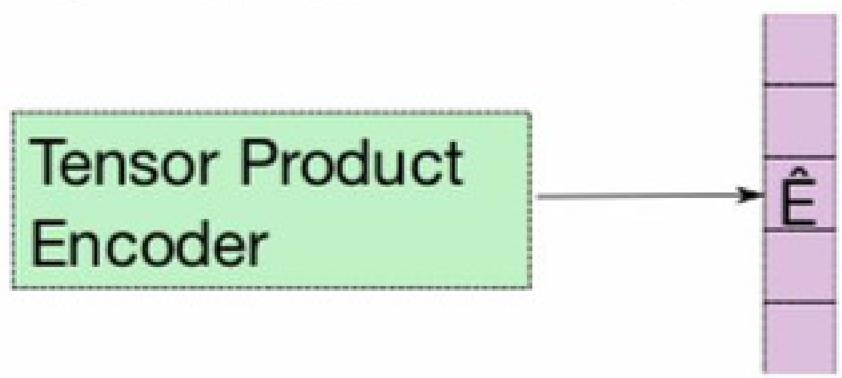

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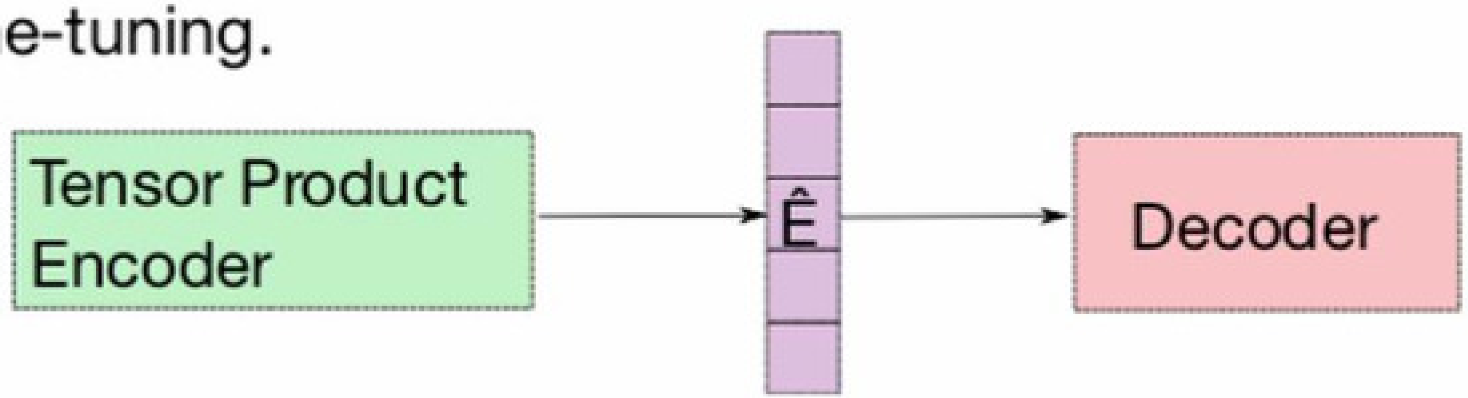
Minimize MSE(Ê, E)

Evaluation: Pass the compositional encoding to the non-compositional decoder. There is no fine-tuning.



$$\hat{E} \stackrel{?}{\approx} E$$

What structure is the target network learning?

Task: Autoencode

{4:first, 2:second, 7:third, 9:fourth}

Left-to-right (LTR) seems intuitive for copying. We want a FIFO queue to maintain the order.

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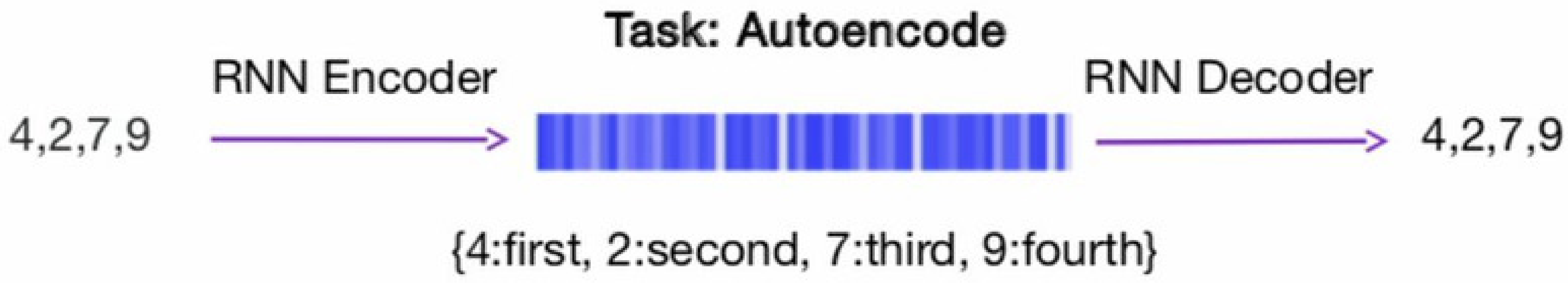
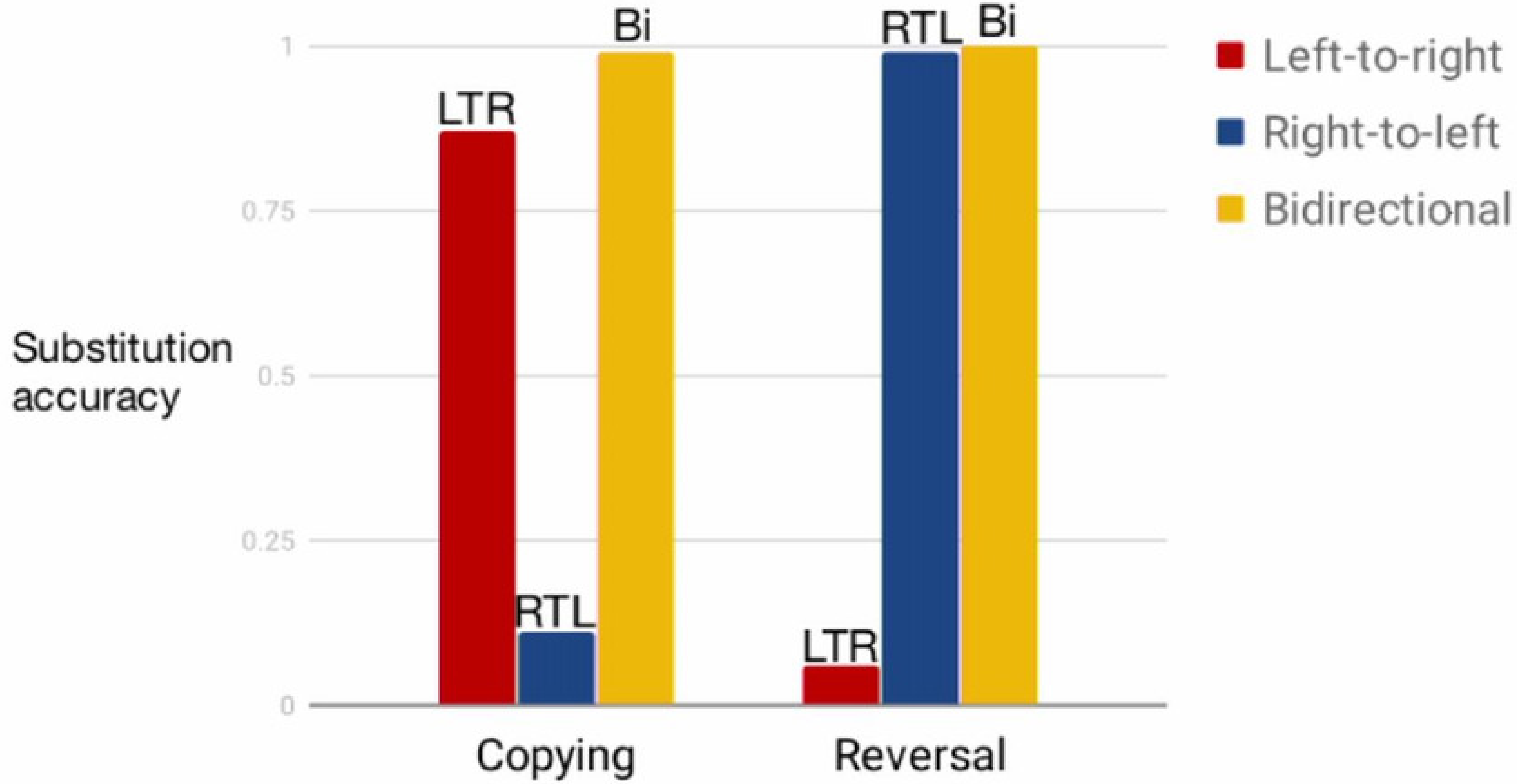


Left-to-right (LTR) seems intuitive for copying. We want a FIFO queue to maintain the order.

Right-to-left (RTL) seems intuitive for reversal. We want a LIFO stack to reverse the order.

Engineered Roles



McCoy, Linzen, Dunbar, and Smolensky (2019)

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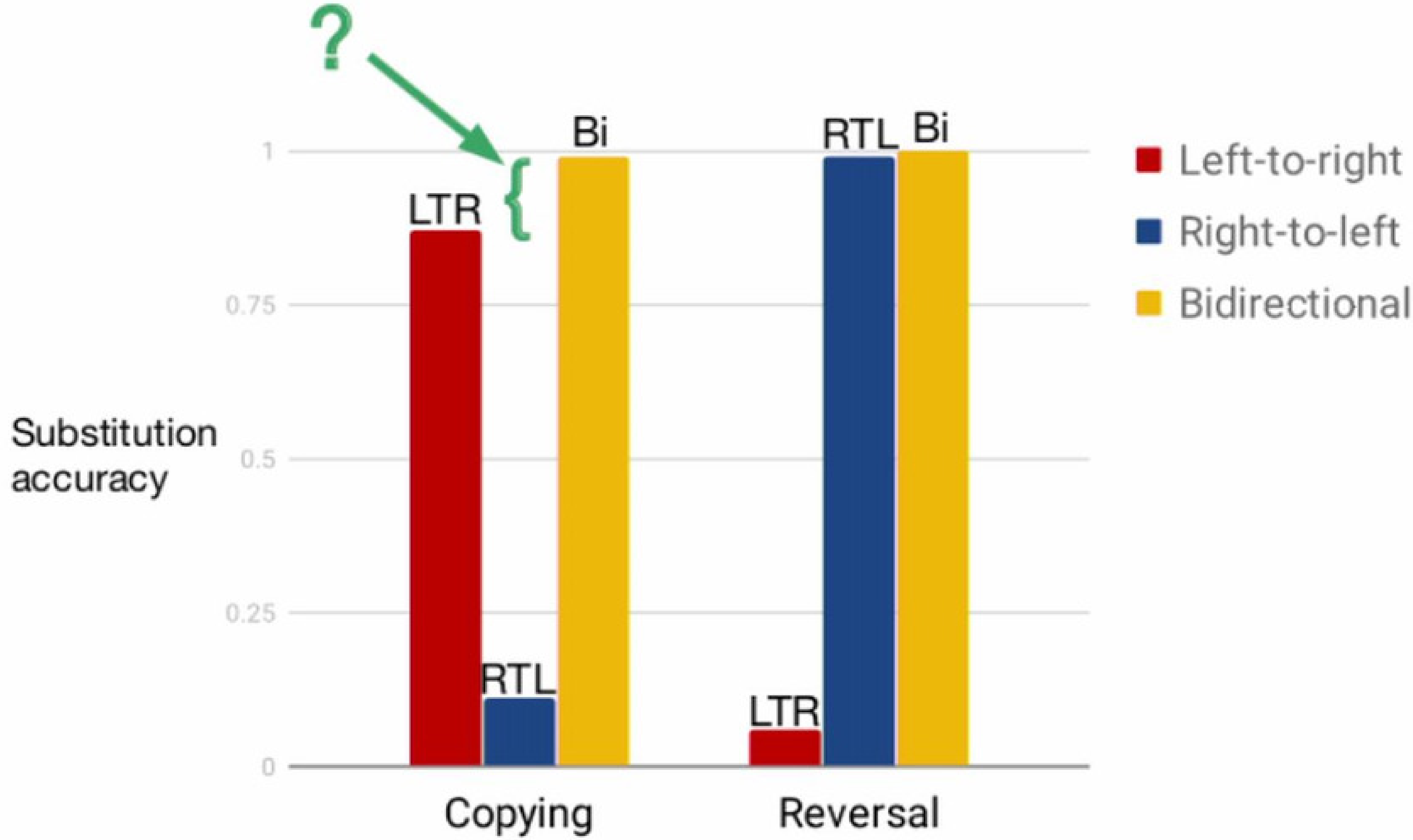

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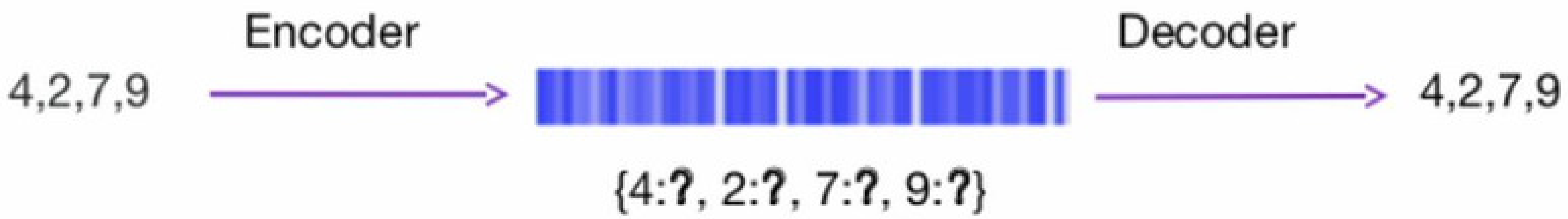
Differentiable Role Assignment



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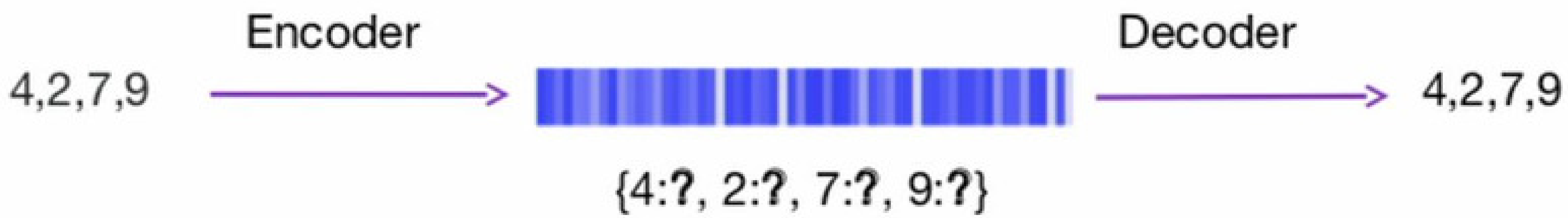

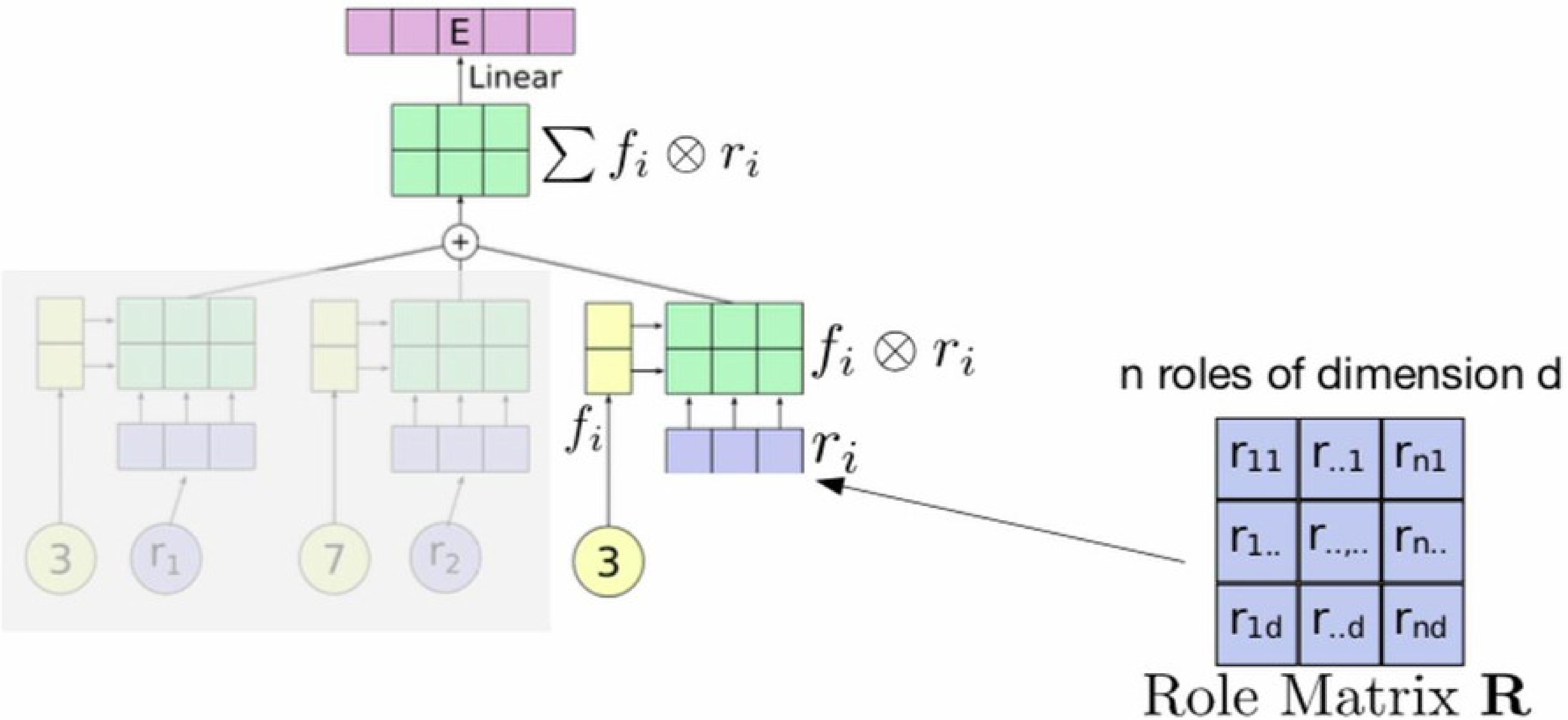

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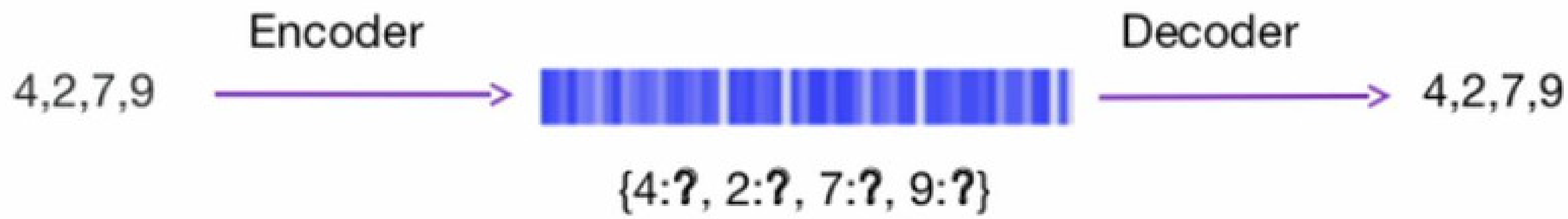
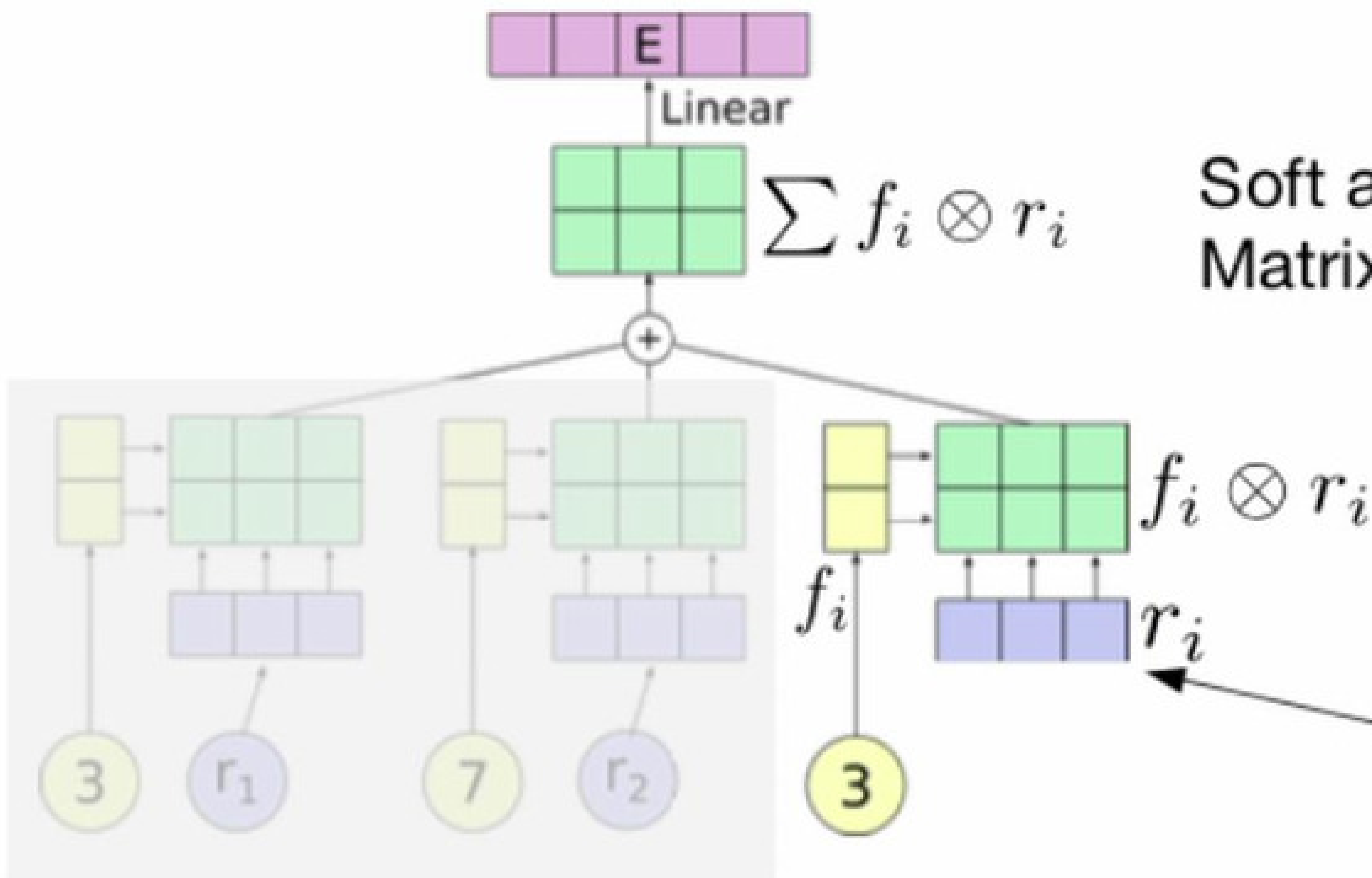
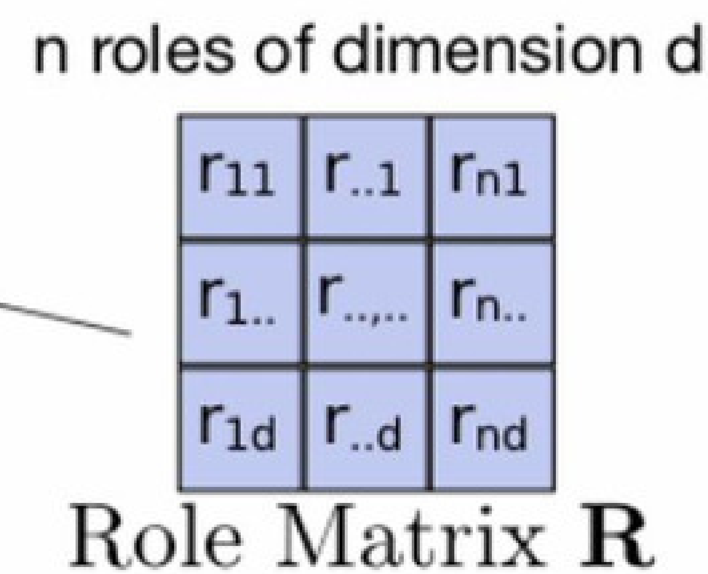




Soft attention over the learned Role Matrix for role assignment



SCAN

Input	Output
jump	JUMP
jump left	LTURN JUMP
jump thrice	JUMP JUMP JUMP
jump opposite left after walk around right	RTURN WALK RTURN WALK RTURN WALK RTURN WALK LTURN LTURN JUMP

Target network is a GRU seq2seq architecture

Lake and Baroni (2018)

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Target	**Learned**	LTR	RTL	Bi	Tree	BOW
98.5%	94.8%	6.7%	7.0%	10.7%	4.3%	4.5%

Table 1: Substitution accuracy for various encoders

Lake and Baroni (2018)

SCAN Role Scheme Interpretation

- Using manual analysis of the role predictions, we created a symbolic algorithm for assigning roles to fillers
- The algorithm matches 98.7% of the role learning network's predictions on the test set.

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- The algorithm matches 98.7% of the role learning network's predictions on the test set.
- Most roles are defined based on position in a subclause (e.g. *last element of the first subclause*)
- **Example roles:**
  - Role 30: Always assigned to *and*
  - Role 17: Only appears in sequences that contain the word *after*
- These two roles allow the decoder to understand the basic syntax of the command.

Differentiable API Design

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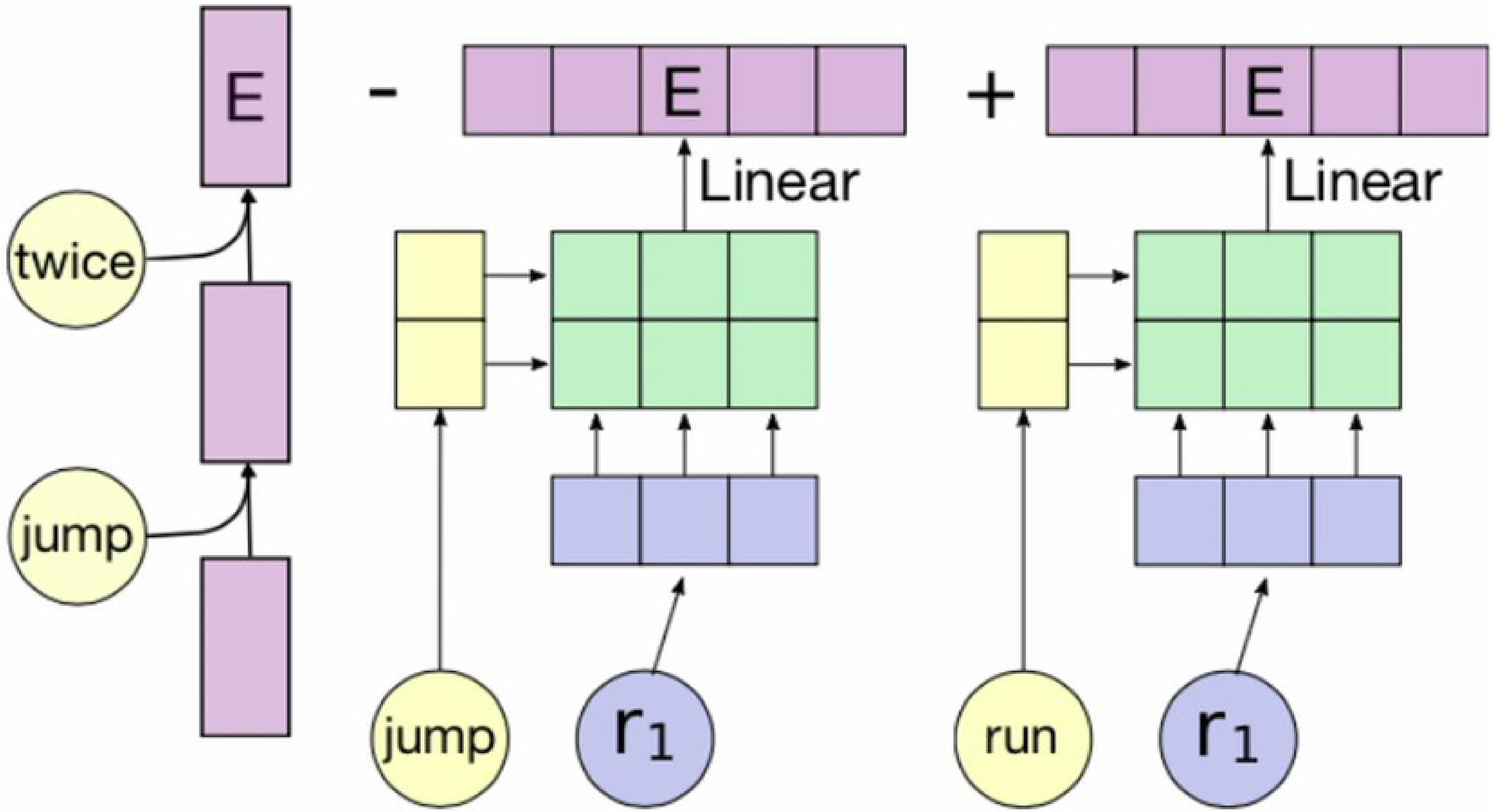
```
<isAnd, isAfter, subclauseOneAction, subclauseOneSecondWord...> encode(List<Input Tokens>)

List<Output Tokens> decode(<isAnd, isAfter, subclauseOneAction, subclauseOneSecondWord...>)
```

Constituent Surgery

$$\mathrm{emb}(\text{jump twice}) - \mathrm{TPR}(\text{jump}) + \mathrm{TPR}(\text{run}) \stackrel{?}{=} \mathrm{emb}(\text{run twice})$$



JUMP JUMP → RUN RUN

Constituent Surgery

run : 11 left : 36 twice : 8 after : 43 jump : 10 opposite : 17 right : 4 thrice : 46 →
TR TR JUMP TR TR JUMP TR TR JUMP TL RUN TL RUN
− run : 11 + look : 11 →
TR TR JUMP TR TR JUMP TR TR JUMP TL LOOK TL LOOK
− jump : 10 + walk : 10 →
TR TR WALK TR TR WALK TR TR WALK TL LOOK TL LOOK

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Constituent Surgery

$\texttt{run}: 11$ $\texttt{left}: 36$ $\texttt{twice}: 8$ $\texttt{after}: 43$ $\texttt{jump}: 10$ $\texttt{opposite}: 17$ $\texttt{right}: 4$ $\texttt{thrice}: 46 \rightarrow$
TR TR JUMP TR TR JUMP TR TR JUMP TL RUN TL RUN
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TR TR WALK TR TR WALK TR TR WALK TL LOOK TL LOOK
− `left`: 36 + `right`: 36 →
TR TR WALK TR TR WALK TR TR WALK TR LOOK TR LOOK
− `twice`: 8 + `thrice`: 8 →
TR TR WALK TR TR WALK TR TR WALK TR LOOK TR LOOK TR LOOK
− `opposite`: 17 + `around`: 17 →
TR WALK TR WALK TR WALK TR WALK TR WALK TR WALK TR WALK TR WALK TR WALK TR WALK
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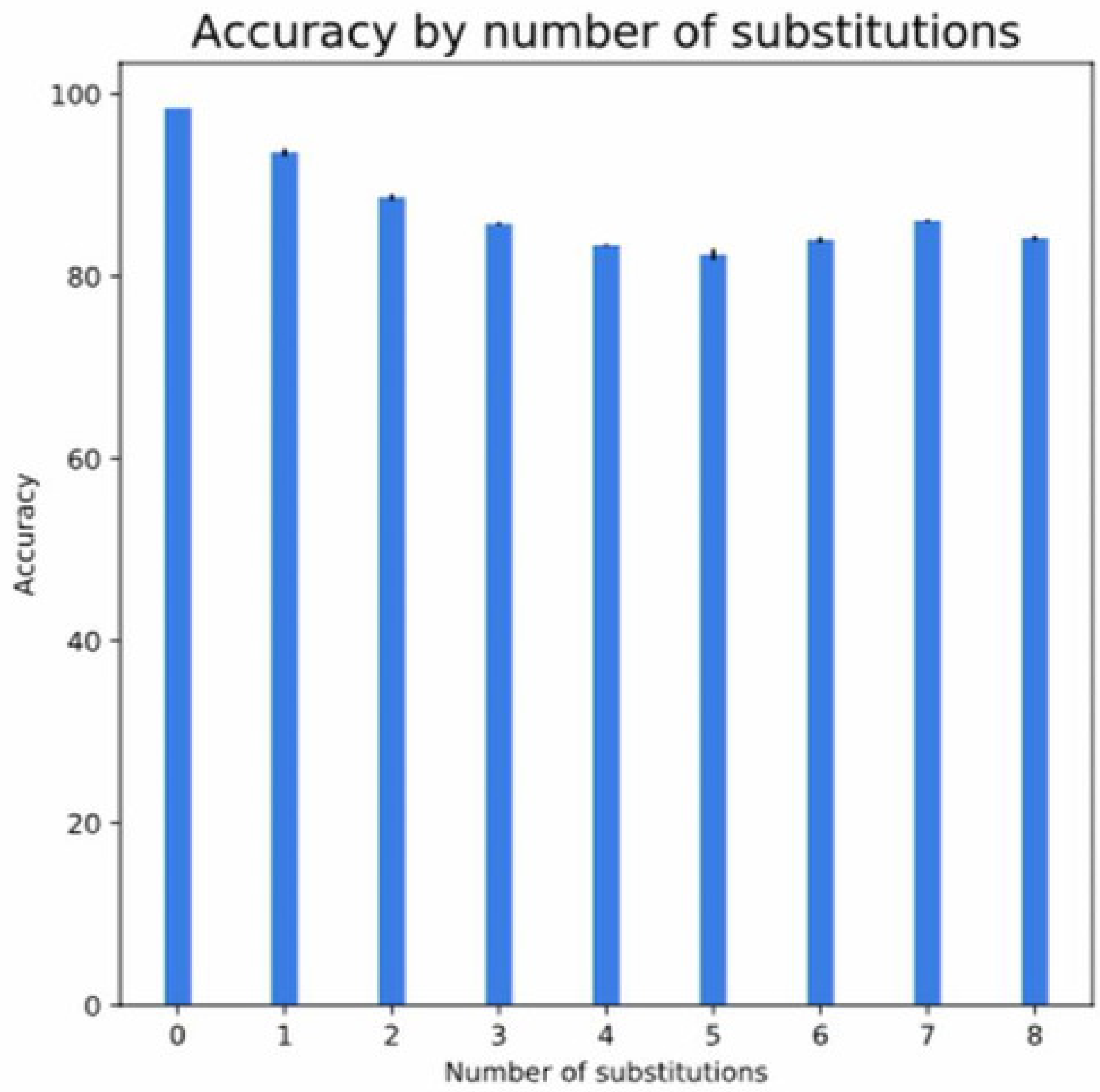
Constituent Surgery (Continued)



Sentence Embedding Models

	Learned	LTR	RTL	Bi	Tree	BOW
InferSent	**4.05e-4**	8.21e-4	9.70e-4	9.16e-4	7.78e-4	4.34e-4
Skip-thought	9.30e-5	9.91e-5	1.78e-3	3.95e-4	9.64e-5	**8.87e-5**
SST	**5.58e-3**	8.35e-3	9.29e-3	8.55e-3	5.99e-3	9.38e-3
SPINN	**.139**	.184	.189	.181	.178	.176

Mean-squared error for learned and engineered role schemes.

Future Directions

- Train the Tensor Product Encoder end-to-end
- Tensor Product Decoder
- Does a compositional bias improve training?
  - Train faster, fewer parameters, better generalization
- Improving natural language models with a compositional bias

Thank you!

- Run the code yourself
  - https://github.com/psoulos/role-decomposition

- Want more details?
  - Come by the poster
  - Check out the paper: https://arxiv.org/abs/1910.09113

Acknowledgements

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