On neural networks and compositionality

Dieuwke Hupkes

Institute for Logic, Language and Computation
University of Amsterdam

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Neural networks and Compositionality

- Why do I care about neural networks?
- Why do I care about compositionality?

Neural networks and Compositionality

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- Why do I care about compositionality?
- What do these two things have to do with each other?

The appropriateness of neural models

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- "[. . .] neural networks are essentially very large correlation engines that hone in on any statisctical, potentially spurious pattern" (Hudson and Manning, 2018)
- Neural networks are data-hungry because they don't develop re-usable representations (almost everyone)

The rest of the team

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What is compositionality

The principle of compositionality

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The meaning of a whole is a function of the meanings of the parts and of the way they are syntactically combined.
Partee (1995)

What is compositionality

What does it mean that neural networks are not compositional?

- They find different parts than we expect
- They find different rules than we expect
- They find other aspects of the data more salient
- They cannot represent hierarchy

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- They favour modelling exceptions over learning rules
- They are not getting the right signal from the data
- The 'test' data is distributionally too different from the training data
- ...

The appropriateness of neural models

Our approach: "dissect" compositionality:

- Does a model find the right parts and rules?

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Data

PCFG SET

Unary functions: `reverse`, `swap`, `copy`, ...
Binary functions: `prepend`, `append`, `remove_first`, ...
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```
reverse A B C        ⇒    C B A
copy D E             ⇒    D E
append C B A , D E
```

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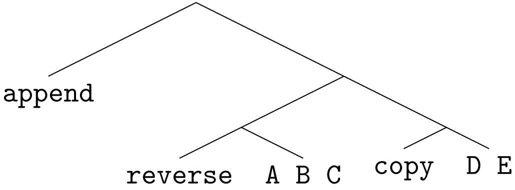
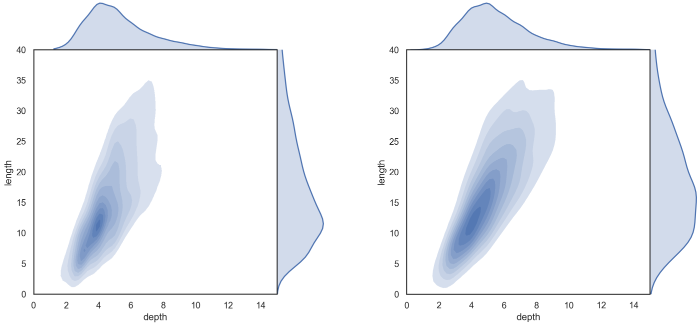


PCFG SET

Data Naturalisation



(a) PCFG SET   (b) WMT 2017

Figure: Distribution of sentence depth and length in the PCFG SET and WMT2017 data.

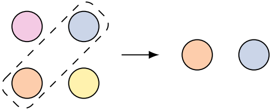
Models

1. **LSTMS2S** Recurrent encoder-decoder model with attention
2. **ConvS2S** Convolutional encoder and decoder with multistep attention
3. **Transformer** Fully attention based model

Results

Experiment	LSTMS2S	ConvS2S	Transformer
PCFG SET*	0.769 ± 0.006	0.841 ± 0.014	0.925 ± 0.007

Systematicity



Can models systematically recombine unseen pairs of functions?

Results

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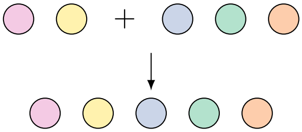
Productivity



Can models productively combine functions to generate longer sequences?

- Newly formed sequences (generalisation)
- Combinations of known sequences (concatenation)

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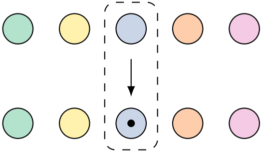
Productivity, *generalisation**	0.293 ± 0.010	0.322 ± 0.002	0.561 ± 0.015
concatenation†	0.196 ± 0.006	0.295 ± 0.030	0.539 ± 0.012

Substitutivity



Do models support substitution of synonyms?

- Equal distributions in training data
- Only in ‘primitive’ condition in training data

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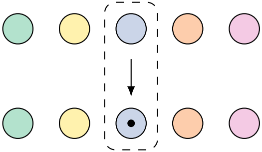
Substitutivity, *eq. distributed*†	0.763 ± 0.010	0.962 ± 0.005	0.984 ± 0.003
***primitive*†**	0.606 ± 0.038	0.612 ± 0.027	0.877 ± 0.043

Substitutivity

Cosine distances

	LSTMS2S	ConvS2S	Transformer
Equally distributed	0.389	0.142	0.079
Primitive	0.408	0.461	0.373
Other	0.960	0.862	0.772

Localism



Do models build representations incrementally?

`append reverse A B C , copy D E`

$\equiv$

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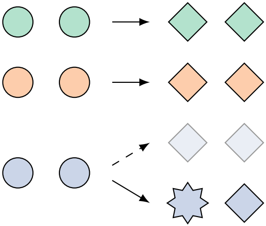
Localism†	0.447 ± 0.007	0.574 ± 0.044	0.561 ± 0.025

Overgeneralisation



Do models overgeneralise during training?

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Overgeneralisation

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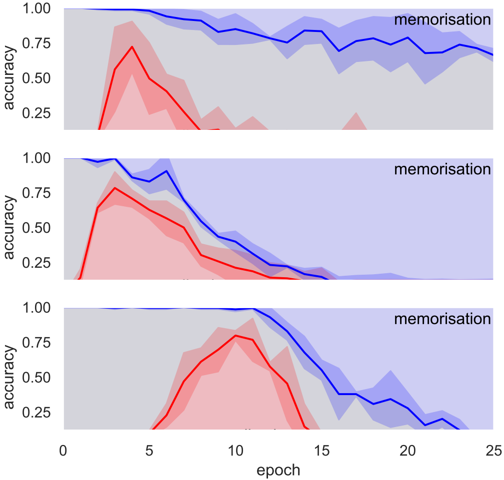
Localism†	0.447 ± 0.007	0.574 ± 0.044	0.561 ± 0.025
Overgeneralisation*	0.727 ± 0.175	0.783 ± 0.116	0.843 ± 0.023

Overgeneralisation

LSTM2S

ConvS2S

Transformer



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