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Grounded Graph Decoding improves Compositional Generalization in Question Answering

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ucbrise.github.io/graphdecoder

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Compositionality is a critical component of complex language

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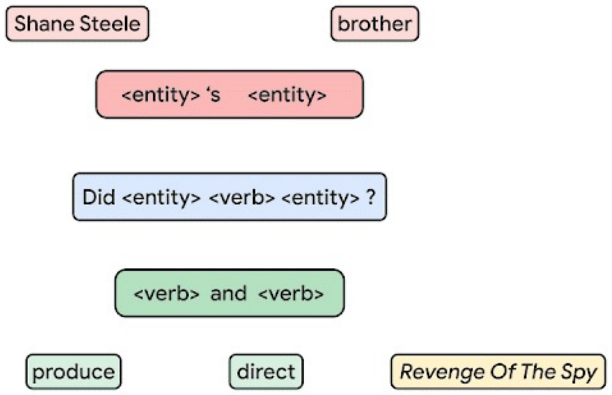

From Keysers et al, 2020

Compositionality is a critical component of complex language

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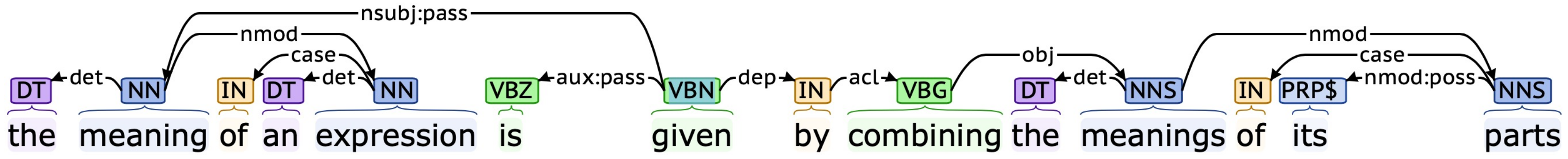
Compositionality: the meaning of an expression is given by combining the meanings of its parts (Montague 1970, Frege 1884)



Benchmarking Compositional Generalization

Compositional Freebase Questions (CFQ): successor to the SCAN dataset to evaluate real-world performance of question answering models

Freebase™

Who directed and produced Goldfinger and Inception?

$$\exists x.\ \mathrm{direct}(x, \mathrm{Goldfinger}) \wedge \mathrm{produce}(x, \mathrm{Goldfinger})$$
$$\wedge \mathrm{direct}(x, \mathrm{Inception}) \wedge \mathrm{produce}(x, \mathrm{Inception})$$

Maximum Compound Divergence splits (MCD1, MCD2, MCD3) test **generalization to unseen compositions** at test-time

"Measuring Compositional Generalization: A Comprehensive Method on Realistic Data", Keysers et al 2020

Grounded Graph Decoding improves compositional generalization

Challenge 1: Challenging to retain syntax structure from complex inputs → **Grounding via Attention**

Challenge 2: SPARQL output domain is group and permutation invariant → **Conjunctive graph decoding**

Results: SOTA results (+36% MCD1 accuracy) with smaller models and no pre-training

Method	# Params.	Accuracy per-split MCD1	MCD2	MCD3
LSTM w/ attention (Keysers et al., 2020)		$28.9 \pm 1.8\%$	$5.0 \pm 0.8\%$	$10.8 \pm 0.6\%$
Transformer (Keysers et al., 2020)		$34.9 \pm 1.1\%$	$8.2 \pm 0.3\%$	$10.6 \pm 1.1\%$
Universal Transformer (Keysers et al., 2020)		$37.4 \pm 2.2\%$	$8.1 \pm 1.6\%$	$11.3 \pm 0.3\%$
Evolved Transformer (Keysers et al., 2020)		$42.4 \pm 1.0\%$	$9.3 \pm 0.8\%$	$10.8 \pm 0.2\%$
T5-base (Furrer et al., 2020)	220M	$57.6 \pm 1.4\%$	$19.5 \pm 1.0\%$	$16.6 \pm 1.5\%$
T5-large (Furrer et al., 2020)	770M	$63.3 \pm 0.6\%$	$22.2 \pm 1.5\%$	$18.8 \pm 2.6\%$
T5-11B (Furrer et al., 2020)	11000M	$61.4 \pm 4.8\%$	$30.1 \pm 2.2\%$	$31.2 \pm 5.7\%$
T5-11B (modified) (Furrer et al., 2020)	11000M	$61.6 \pm 12.4\%$	$31.3 \pm 12.8\%$	$33.3 \pm 2.3\%$
Grounded Graph Decoding	0.3M	$\mathbf{97.9 \pm 0.2\%}$	$\mathbf{47.1 \pm 10.4\%}$	$\mathbf{50.8 \pm 17.2\%}$

⬅️ Pre-training
+19.2% MCD1

⬅️ Ours
+36% MCD1 vs. T5

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https://github.com/ucbrise/graphdecoder

- **Compositional generalization** enables expressing complex concepts from simple constructs
- **Large + pretrained** models perform poorly at compositional generalization
- We introduce (a) **grounding** and (b) **graph decoding** to mitigate common compositional failures.
- We improve MCD1 accuracy on the CFQ dataset by **36%**.