

How abstract is linguistic generalization in LLMs?

Evidence from Argument Structure

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- **Question:** Do language models have a linguistically-principled understanding of the language they've learned?
 - What do humans know when they know a language?
 - How can we test for similar behavior in LLMs by teaching them new words?
- **Conclusion:** LLMs's knowledge of language differs from humans' in a way that leads to "failures" of the functional generalizations which humans can readily make use of

What does it mean to know language?

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TO

I sprayed the _____ on the _____

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TO

I sprayed the paint on the _____

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TO

I sprayed the paint on the wall

What does it mean to know language?

T1

I sprayed the *paint*
on the *wall*

T0

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- I sprayed the *wall* with the *paint*
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Main Q: Where does LLM generalization fit on this chart?

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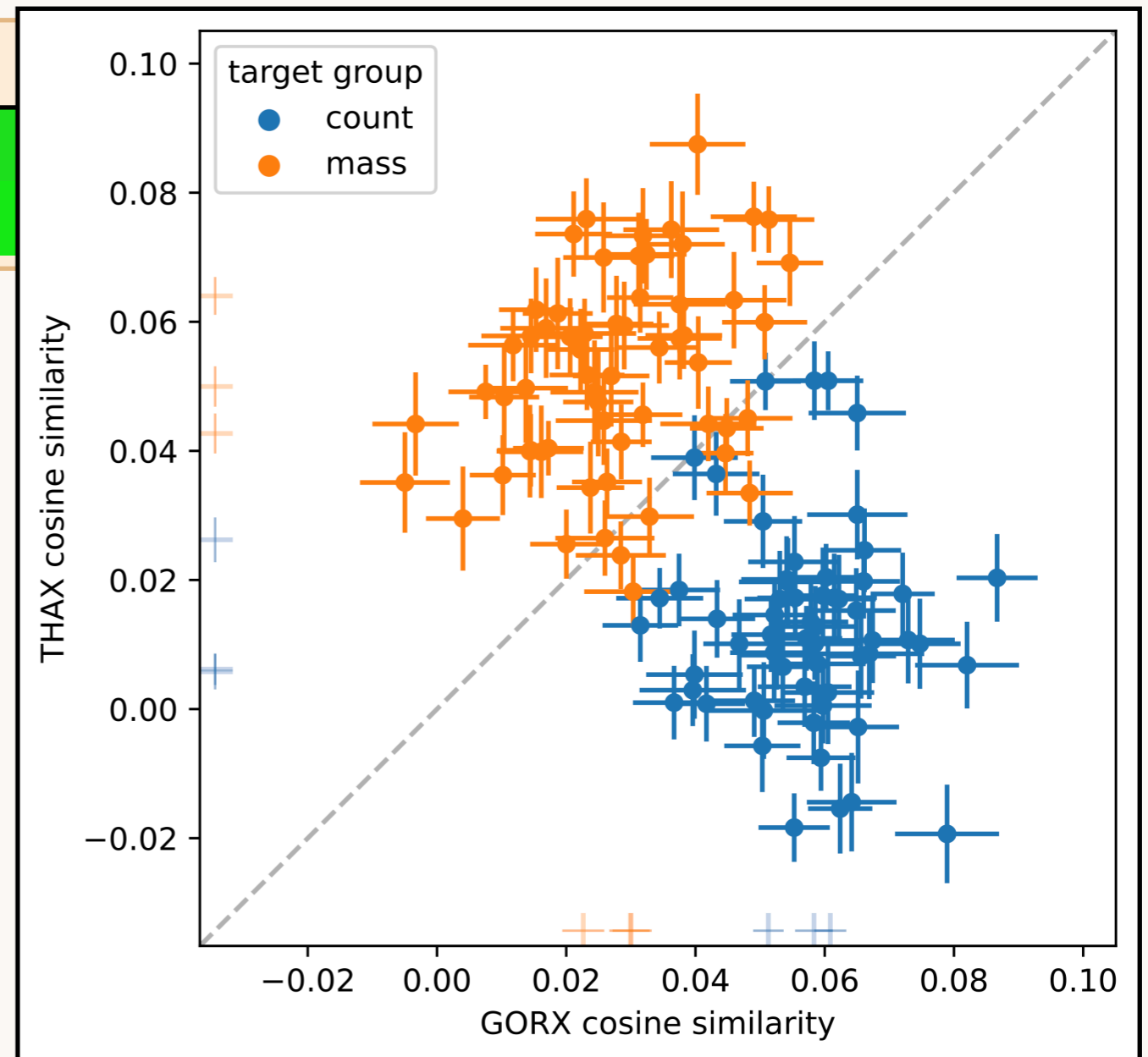
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- What about T2 generalization?

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		SO	OS	SO	OS
RoBERTa	79.2	66.7	53.6	44.8	39.5
BERT	86.1	75.5	54.2	54.4	55.7
DistilBERT	88.9	74.8	49.4	51.9	39.9
MultiBERT 00	80.6	63.9	50.8	48.7	40.8
MultiBERT 05	84.7	80.4	49.8	51.0	21.4
MultiBERT 10	82.6	70.1	55.2	44.1	42.7
MultiBERT 15	76.4	68.8	49.7	53.3	43.6
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The **[subj]** *blorked* the **[obj]**

Which **[obj]** has the **[subj]** *blorked*

Which **[subj]** was the **[obj]** *blorked* by

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	BERT	RoBERTa	DistilBERT
<i>same order</i>	93%	83%	88%
<i>reversed order</i>	86%	79%	78%
Δ	7 pts	4 pts	10 pts

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 - No existing embedding which matches these values
 - Unable to make generalizations on the basis of structure alone, independent from a known similar context

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Questions?

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