

Hu et al., 2020 Sinha et al., 2019

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Symbolic Generalization

Motivation

Natural language understanding systems to generalize in a systematic and robust way

- Diagnostic tests - how can we probe these generalization abilities?
 - **Syntactic generalization** (Hu et al., 2020, “SG”) and **logical reasoning** (Sinha et al., 2019, “CLUTRR”)
- Evaluation metrics for language models?

SG: Man shall not live by perplexity alone

Perplexity **is not sufficient** to check for human-like syntactic knowledge:

- It basically measures the probability of seeing some collection of words together
- However some words which are rarely seen together are grammatically correct
- *Colorless green ideas sleep furiously* (Chomsky, 1957)
- Need a **more fine-grained** way to test human-level understanding of syntax

SG: Paradigm

Assess NL models on custom sentences designed using psycholinguistic and syntax literature/methodology

- Compare critical sentence regions NOT full-sentence probabilities.
- Factor out confounds (e.g token lexical frequency, n-gram statistics)

SG: Paradigm

- Cover the scope of syntax phenomena: 16/47 (Carnie et al., 2012)
- Group syntax phenomena into 6 circuits based on processing algorithm

SG: Circuits

1. Agreement
2. Licensing
3. Garden-Path Effects
4. Gross Syntactic Expectation
5. Center Embedding
6. Long-Distance Dependencies

SG: Agreement

- (A) The farmer that the clerks embarrassed
knows_{V_{sg}} many people.
- (B) *The farmer that the clerks embarrassed
know_{V_{pl}} many people.
- (C) The farmers that the clerk embarrassed
know_{V_{pl}} many people.
- (D) *The farmers that the clerk embarrassed
knows_{V_{sg}} many people.

$$P_A(V_{sg}) > P_B(V_{pl}) \wedge P_C(V_{pl}) > P_D(V_{sg})$$

SG: NPI Licensing

- The word “any” is a negative polarity item (NPI)
- The word “no” can license an NPI when it structurally commands it, such as in A

A) **No** managers that respected the guard have had **any** luck

>

B) *The managers {that respected **no** guard} have had **any** luck

(Reflexive Pronoun Licensing was also included in sub-class suites)

SG: NPI Licensing

- (A) No managers that respected the guard have
NPI
had any luck. [+NEG, -DISTRACTOR]
- (B) *The managers that respected no guard have
NPI
had any luck. [-NEG, +DISTRACTOR]
- (C) *The managers that respected the guard have
NPI
had any luck. [-NEG, -DISTRACTOR]
- (D) No managers that respected no guard have
NPI
had any luck. [+NEG, +DISTRACTOR]

$$P_A(\text{NPI}) > P_C(\text{NPI}) \wedge P_D(\text{NPI}) > P_B(\text{NPI}) \wedge \\ P_A(\text{NPI}) > P_B(\text{NPI})$$

Acceptable orderings:

ADBC

ADCB

DABC

DACB

ACDB (?)

Chance: 5/24

SG: NP/Z Garden-Paths

- (A) !As the ship crossed the waters $\overbrace{\text{remained blue}}^{V^*}$
and calm. [TRANS,NO COMMA]
- (B) As the ship crossed, the waters $\overbrace{\text{remained}}^{V^*}$
blue and calm. [TRANS,COMMA]
- (C) As the ship drifted the waters $\overbrace{\text{remained blue}}^{V^*}$
and calm. [INTRANS,NO COMMA]
- (D) As the ship drifted, the waters $\overbrace{\text{remained blue}}^{V^*}$
and calm. [INTRANS,COMMA]

$$S_A(V^*) > S_B(V^*) \wedge S_A(V^*) > S_C(V^*) \wedge \\ S_A(V^*) - S_B(V^*) > S_C(V^*) - S_D(V^*)$$

(Main Verb / Reduced Relative Clause paths were also included in sub-class suites)

SG: Gross Syntactic Expectation

- (A) The minister praised the building .
- (B) *After the minister praised the building .
- (C) ??The minister praised the building, it started to rain.
- (D) After the minister praised the building, it started to rain.

$$P_A(\text{END}) > P_B(\text{END}) \wedge P_D(\text{MC}) < P_C(\text{MC})$$

SG: Center Embedding

The paintings that the artist painted deteriorated

>

*The paintings that the artist deteriorated painted

SG: Long Distance Dependencies

The **keys** to the cabinet **are** on the table

>

*The **keys** to the cabinet **is** on the table

SG: Cleft

The **keys** to the cabinet **are** on the table

>

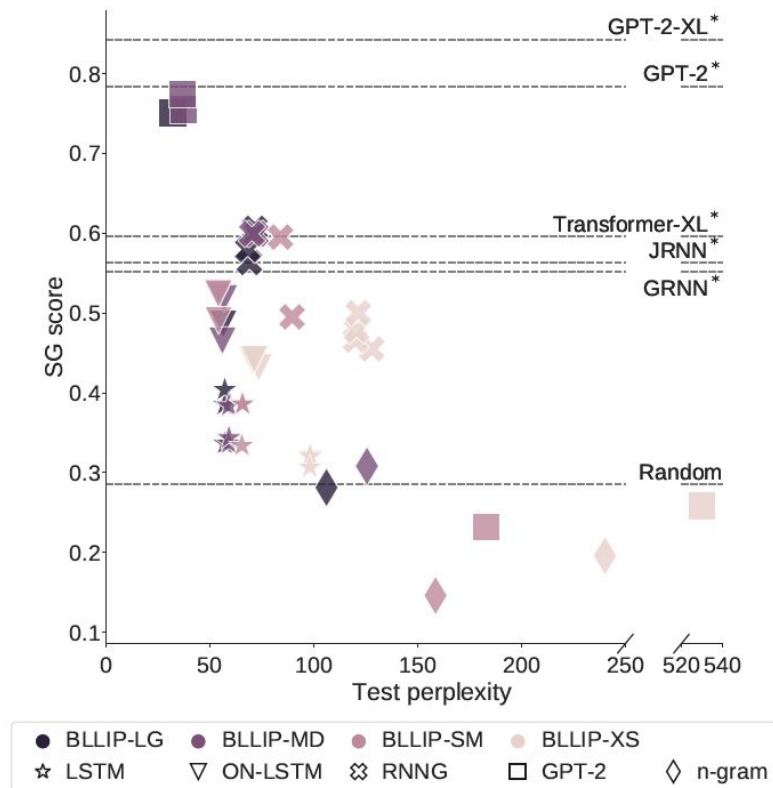
*The **keys** to the cabinet **is** on the table

Syntactic Generalization

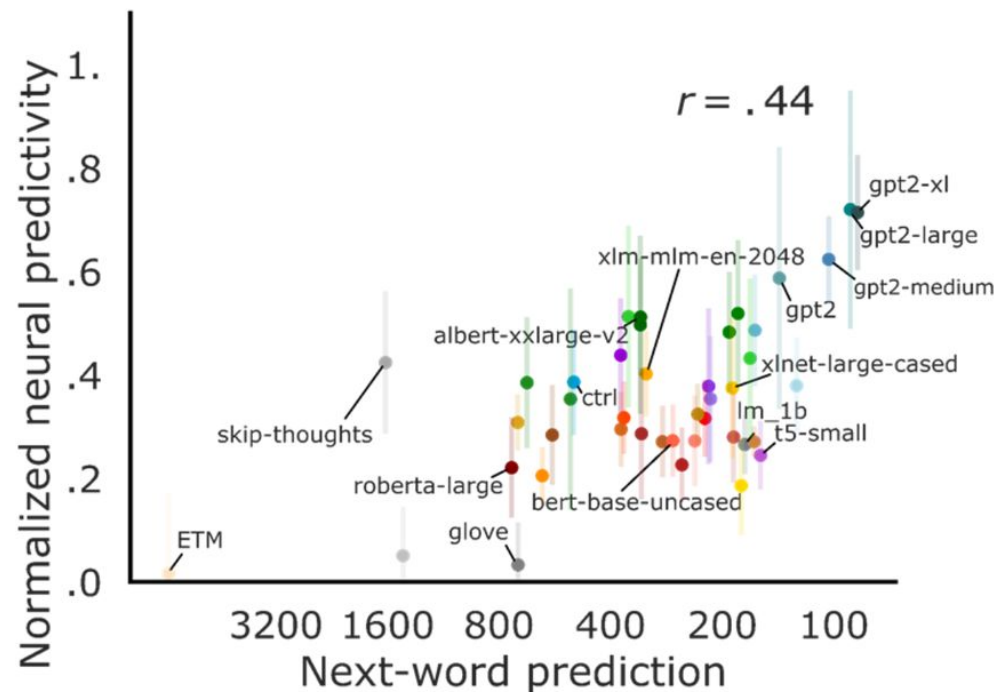
Assess NL models on custom sentences designed using psycholinguistic and syntax literature/methodology

- Test for stability by including syntactically irrelevant but semantically plausible syntactic content before the critical region
 - E.g:
 - The keys to the cabinet on the left are on the table
 - *The keys to the cabinet on the left is on the table
- Compare model class to dataset size

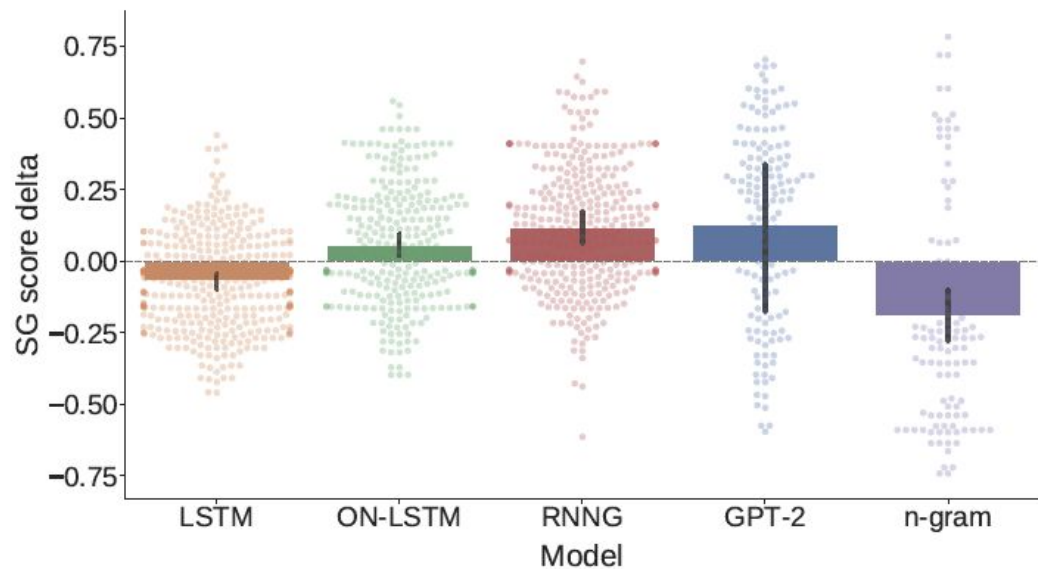
SG: Perplexity and SG Score



(SG:) Perplexity and Brain-Score

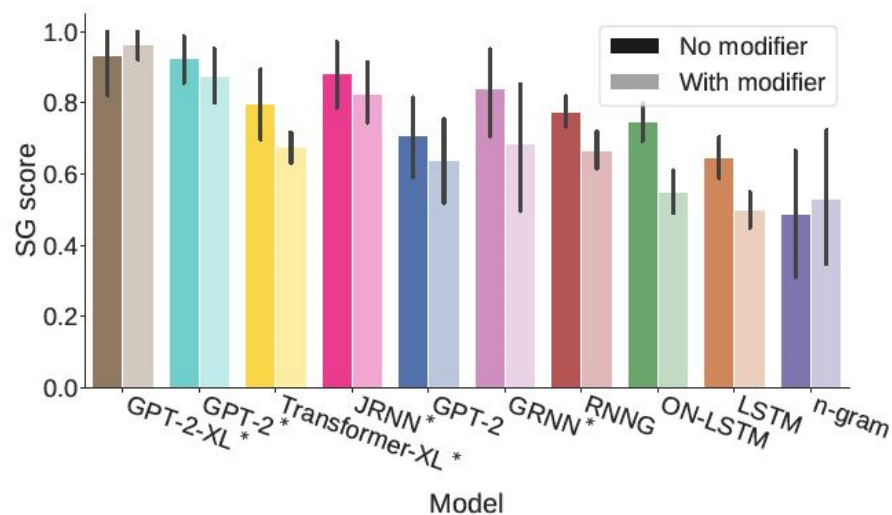


SG: The Influence of Model Architecture

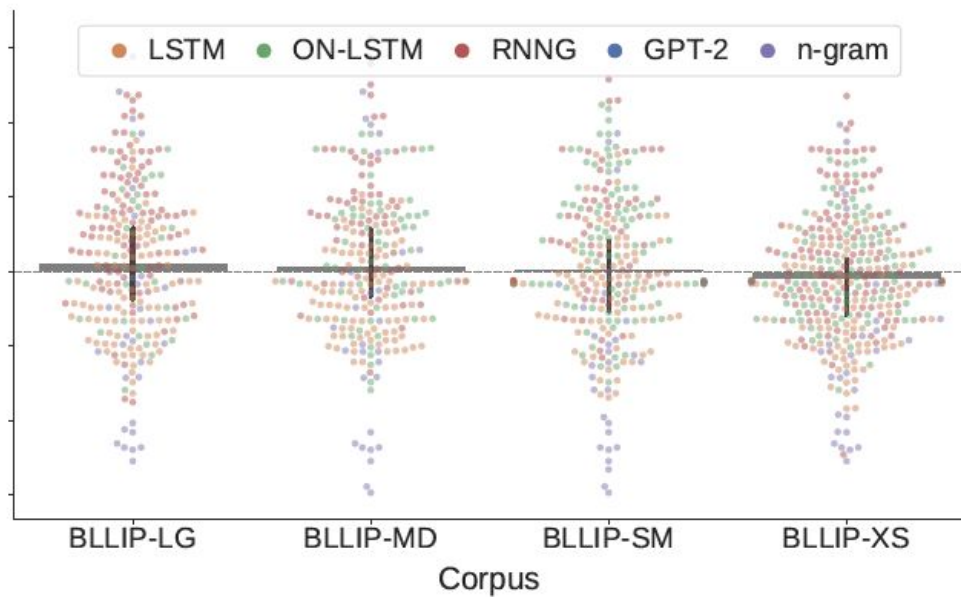


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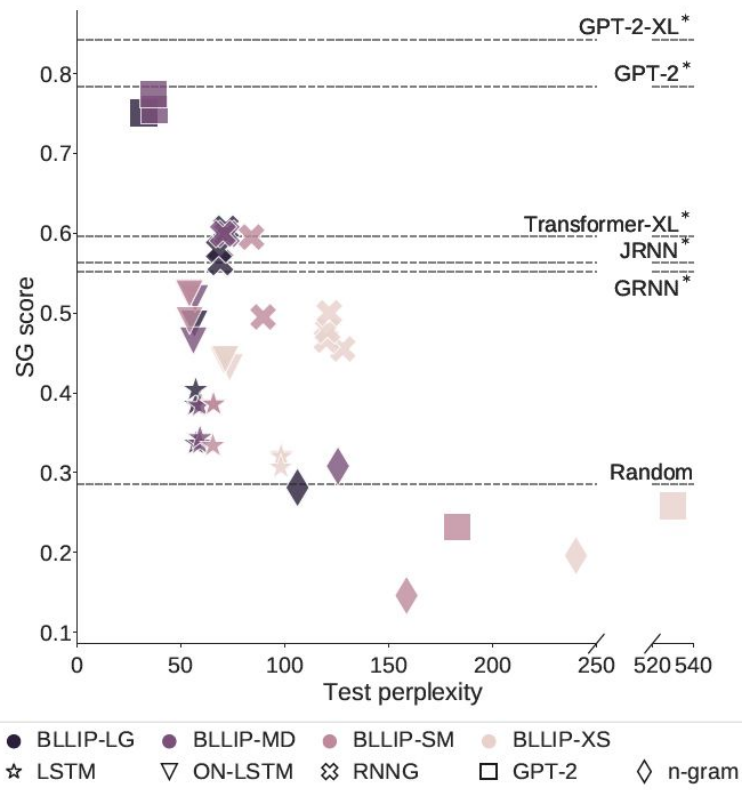
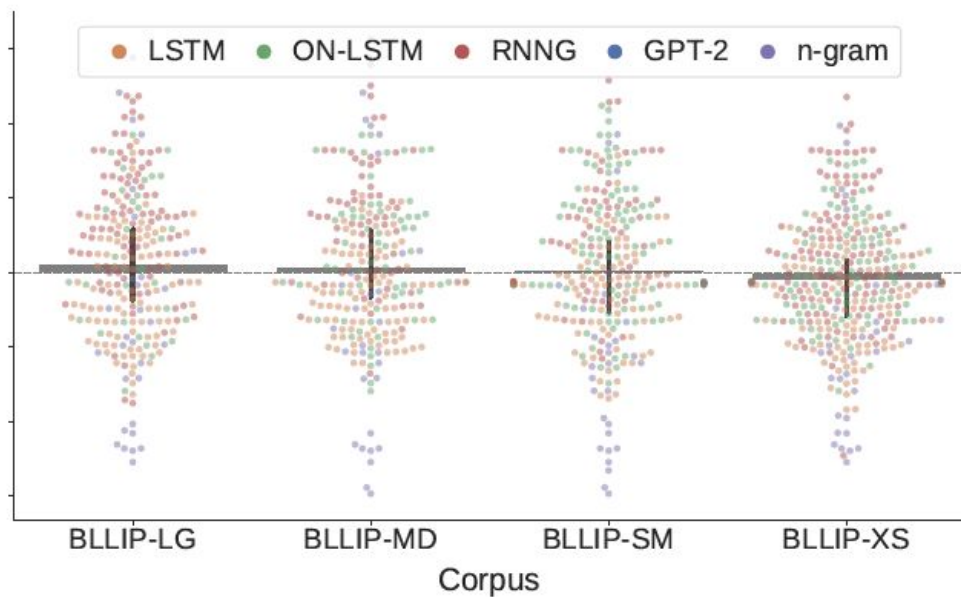
- Architectures as priors to the linguistic representation that can be developed
- Robustness depends on model architecture



SG: The Influence of Dataset Size



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SG: The Influence of Dataset Size

- Increasing amount of training data yields diminishing returns:
 - *“(...) require over 10 billion tokens to achieve human-like performance, and most would require trillions of tokens to achieve perfect accuracy – an impractically large amount of training data, especially for these relatively simple syntactic phenomena.”*
(van Schijndel et al., 2019)
- Limited data efficiency
- Structured architectures or explicit syntactic supervision
- Humans? 11-27 million total words of input per year? (Hart & Risley, 1995; Brysbaert et al., 2016)

CLUTRR: Motivation and Paradigm

- **C**ompositional **L**anguage **U**nderstanding and **T**ext-based **R**elational **R**easoning
- Kinship inductive reasoning
- Unseen combinations of logical rules
- Model robustness

Kristin and her **son Justin** went to visit her **mother Carol** on a nice Sunday afternoon. They went out for a movie together and had a good time.



Q: How is **Carol** related to **Justin** ?

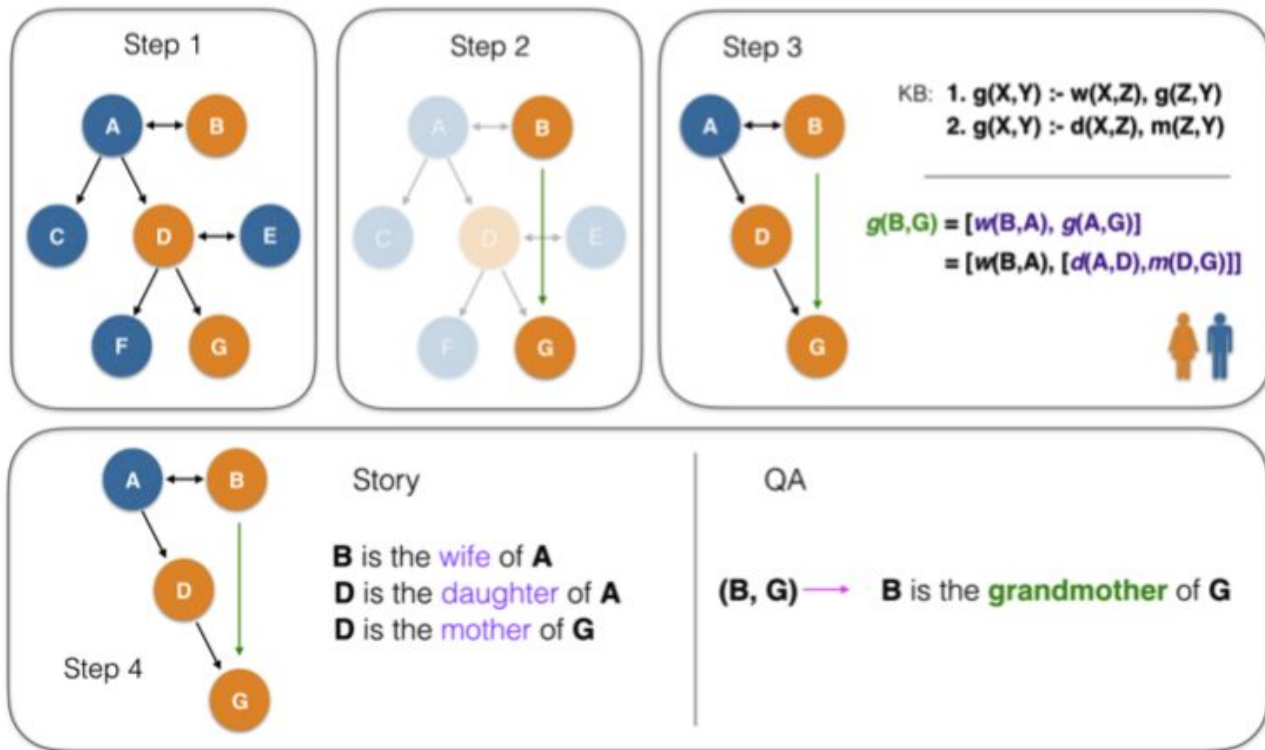
A: Carol is the **grandmother** of Justin



CLUTRR: Motivation and Paradigm

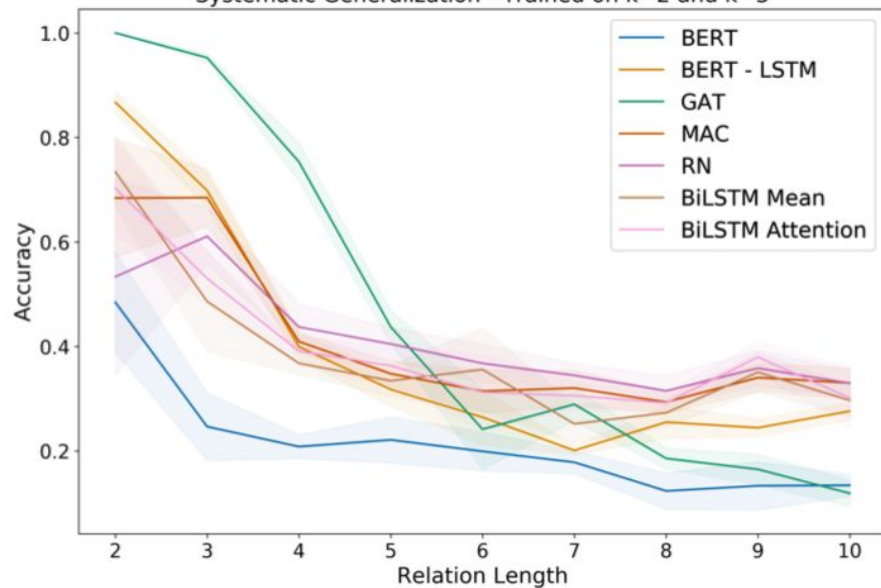
- Productivity
 - `mother(mother(mother(Justin)))` ~ great grandmother of Justin
- Systematicity
 - Only certain sets allowed with symmetries: `son(Justin, Kristin)` ~ `mother(Kristin, Justin)`
- Compositionality
 - `son(Justin, Kristin)` consists of components
- Memory (compression)
- Children are not exposed to systematic dataset

CLUTRR: Dataset Generation & Paradigm

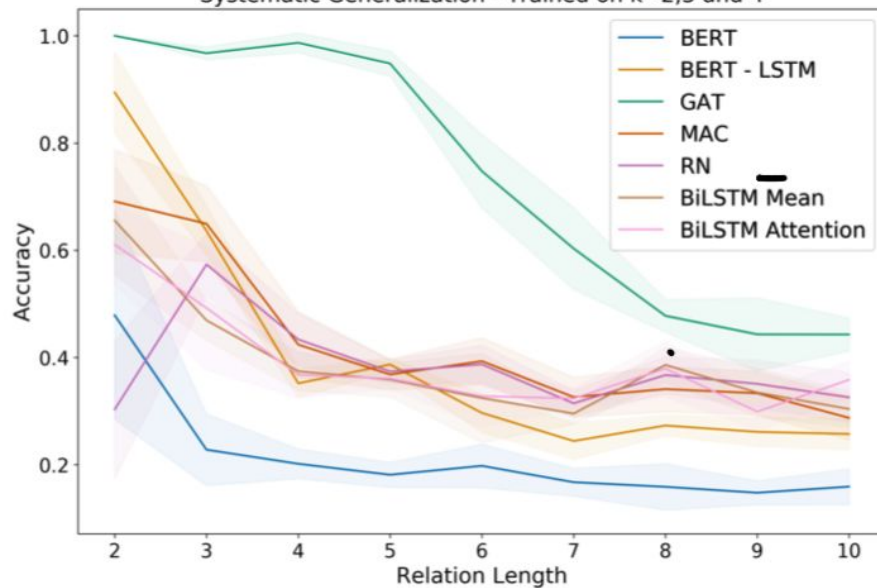


CLUTRR: Experiment Results

Systematic Generalization - Trained on k=2 and k=3



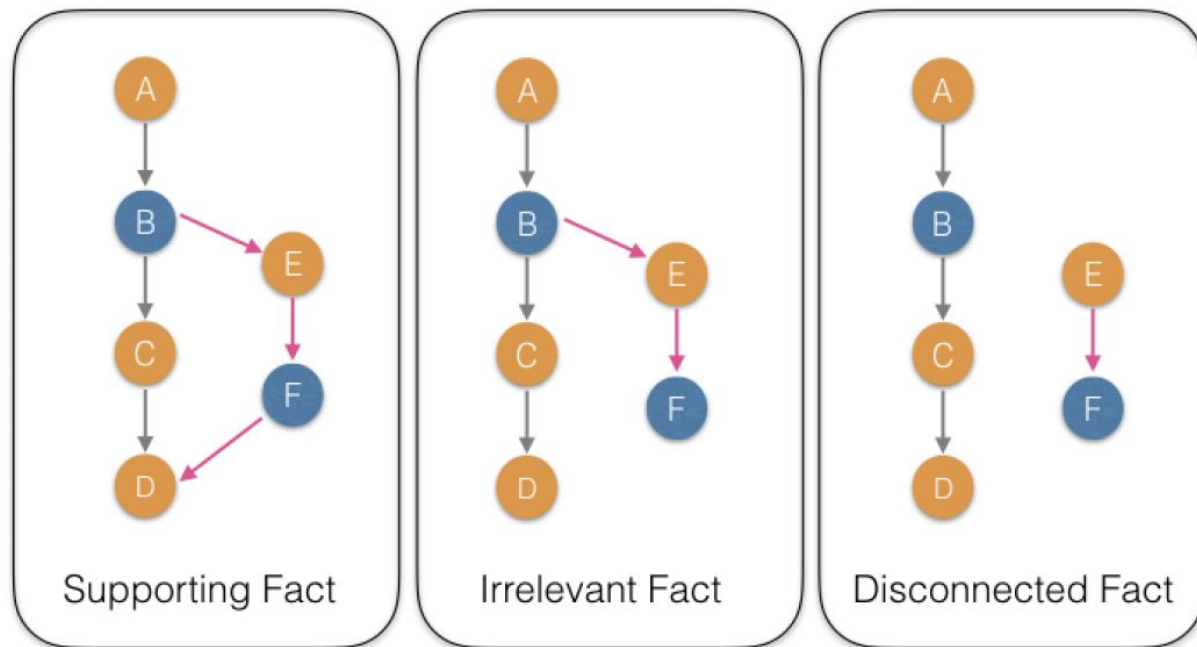
Systematic Generalization - Trained on k=2,3 and 4



CLUTRR: Experiment Results

| Models | | Unstructured models (no graph) | | | | | | Structured model (with graph) |
|--------------|--------------|--------------------------------|------------------------|-----------------|------------------------|-----------------|-----------------|-------------------------------|
| Training | Testing | BiLSTM - Attention | BiLSTM - Mean | RN | MAC | BERT | BERT-LSTM | GAT |
| Clean | Clean | 0.58 \pm 0.05 | 0.53 \pm 0.05 | 0.49 \pm 0.06 | 0.63 \pm 0.08 | 0.37 \pm 0.06 | 0.67 \pm 0.03 | 1.0 \pm 0.0 |
| | Supporting | 0.76 \pm 0.02 | 0.64 \pm 0.22 | 0.58 \pm 0.06 | 0.71 \pm 0.07 | 0.28 \pm 0.1 | 0.66 \pm 0.06 | 0.24 \pm 0.2 |
| | Irrelevant | 0.7 \pm 0.15 | 0.76 \pm 0.02 | 0.59 \pm 0.06 | 0.69 \pm 0.05 | 0.24 \pm 0.08 | 0.55 \pm 0.03 | 0.51 \pm 0.15 |
| | Disconnected | 0.49 \pm 0.05 | 0.45 \pm 0.05 | 0.5 \pm 0.06 | 0.59 \pm 0.05 | 0.24 \pm 0.08 | 0.5 \pm 0.06 | 0.8 \pm 0.17 |
| Supporting | Supporting | 0.67 \pm 0.06 | 0.66 \pm 0.07 | 0.68 \pm 0.05 | 0.65 \pm 0.04 | 0.32 \pm 0.09 | 0.57 \pm 0.04 | 0.98 \pm 0.01 |
| Irrelevant | Irrelevant | 0.51 \pm 0.06 | 0.52 \pm 0.06 | 0.5 \pm 0.04 | 0.56 \pm 0.04 | 0.25 \pm 0.06 | 0.53 \pm 0.06 | 0.93 \pm 0.01 |
| Disconnected | Disconnected | 0.57 \pm 0.07 | 0.57 \pm 0.06 | 0.45 \pm 0.11 | 0.4 \pm 0.1 | 0.17 \pm 0.05 | 0.47 \pm 0.06 | 0.96 \pm 0.01 |
| Average | | 0.61 \pm 0.08 | 0.59 \pm 0.08 | 0.54 \pm 0.07 | 0.61 \pm 0.06 | 0.30 \pm 0.07 | 0.56 \pm 0.05 | 0.77 \pm 0.09 |

CLUTRR: Model Robustness



CLUTRR: Model Robustness

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Future work & Perspectives

- Sub-word tokenization
- Common-sense reasoning
- Abstractions as probabilistic
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References

Brysbaert, M., Stevens, M., Mander, P., & Keuleers, E. (2016). How Many Words Do We Know? Practical Estimates of Vocabulary Size Dependent on Word Definition, the Degree of Language Input and the Participant's Age. *Frontiers in psychology*, 7, 1116.

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