Exploring Graph Representations of Logical Forms for Language Modeling

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https://coli-saar.github.io/gfolds

What is a language model over logical forms (LFLM)?

- **Logical Form:** A sentence in a formal language *L*, such that *L* carries a predicate-argument structure that can be used to represent (aspects of) truth-conditional linguistic meaning.
  - e.g. FOL, (D)MRS (Copestake et al., 2005; Copestake, 2009), AMR (Banarescu et al., 2013), etc.

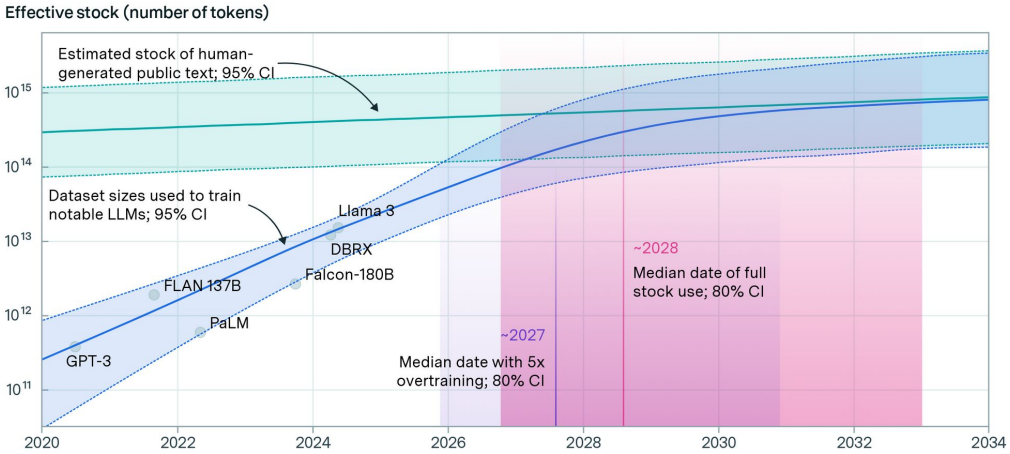
- **Language Model over Logical Forms (LFLM):** a language model that takes as input (sequences of) logical form representations of natural language.

Why LFLMs?

We are running out of training data

- Larger and larger LLMs require more and more training data:
  - GPT-2 (Radford et al., 2018): 1.5 billion parameters
  - GPT-3 (Brown et al., 2020): 175 billion parameters
  - GPT-4 (OpenAI, 2023): >1 trillion parameters (estimated)

- Villalobos et al. (2024): high-quality English training data will be exhausted sometime between 2026 and 2032



https://epoch.ai/blog/will-we-run-out-of-data-limits-of-llm-scaling-based-on-human-generated-data

Why logical forms?

1. **Linguistically-informed LMs can improve over textual models**, without using additional training data (e.g. Xu et al. 2021; Zhou et al., 2020; Zhang et al., 2020; etc.)

2. **Semantics is better than syntax:** semantically-informed LMs outperform syntactically-informed LMs (Wu et al., 2021; Prange et al. 2022)
    - I argue this is due to a syntactic/morphological de-noising effect:

"John saw Mary" ⇒ *see*(*j*, *m*)
"Mary was seen by John" ⇒ *see*(*j*, *m*)

"goose" ⇒ $goose_{\text{NUM:SG}}$
"geese" ⇒ $goose_{\text{NUM:PL}}$

The Linguistic Knowledge Catalysis Hypothesis (LKCH):

> *The (aspects of) linguistic knowledge incorporated into LFLMs greatly accelerates their learning of elementary linguistic phenomena, in turn accelerating the learning of more complex patterns.*

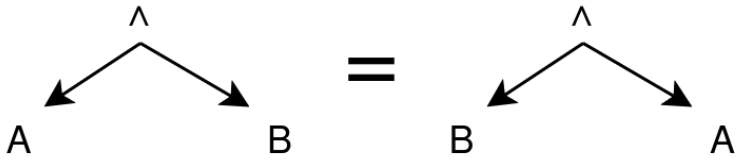
Contributions

- Experimental support for the LKCH
- Proof-of-concept of the downstream applicability of LFLMs
- Evidence supporting the scalability of LFLMs

Graph-based Formal-Logical Distributional Semantics (GFoLDS)

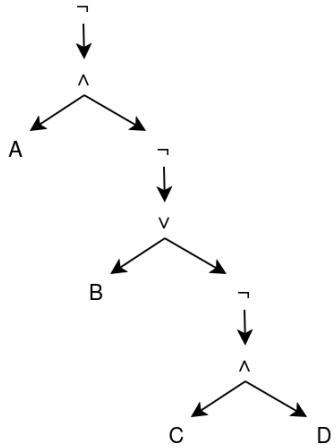
Why graphs?

- Graph representations permit permutation-invariance: the nodes in a graph are not ordered:



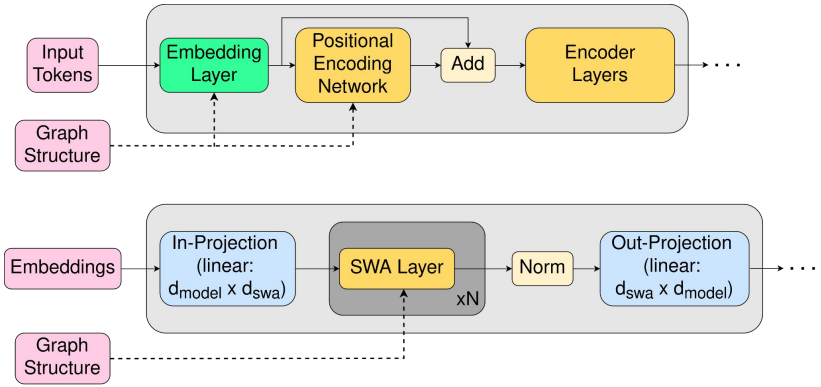
- Graphs facilitate the encoding of hierarchical structures:

$$\neg(A \wedge \neg(B \vee \neg(C \wedge D))) \quad \textit{vs.}$$



Instantiating an LFLM: GFoLDS

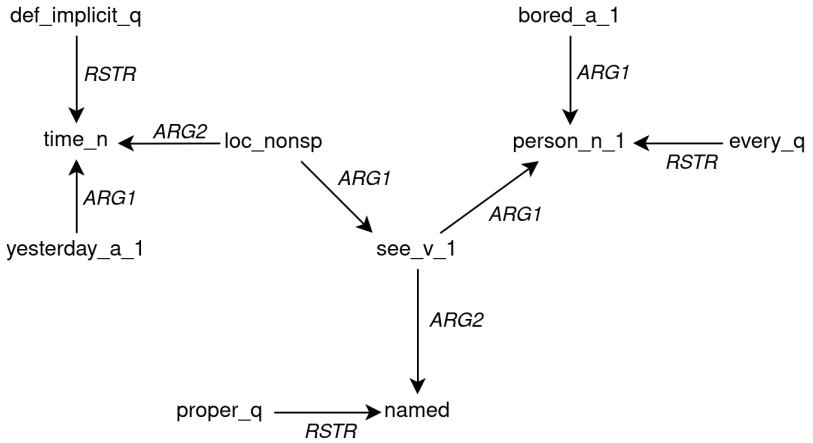
- I introduce the Graph-based Formal-Logical Distributional Semantics (GFoLDS) model, a pretrained graph transformer (Wu et al., 2021) over DMRS-derived representations



Top-level architecture of the GFoLDS model (top) and positional encoding network (bottom)

Pretraining

- I pretrained GFoLDS for four epochs on 17.5 million randomly-selected sentences (~84% parsable) from English Wikipedia[1]
  - ~6.5x smaller than BERT's (Devlin et al. 2019) pretraining dataset
- Pretraining objective: masked node modeling (MNM)



[1]https://huggingface.co/datasets/wikimedia/wikipedia/viewer/20231101.en

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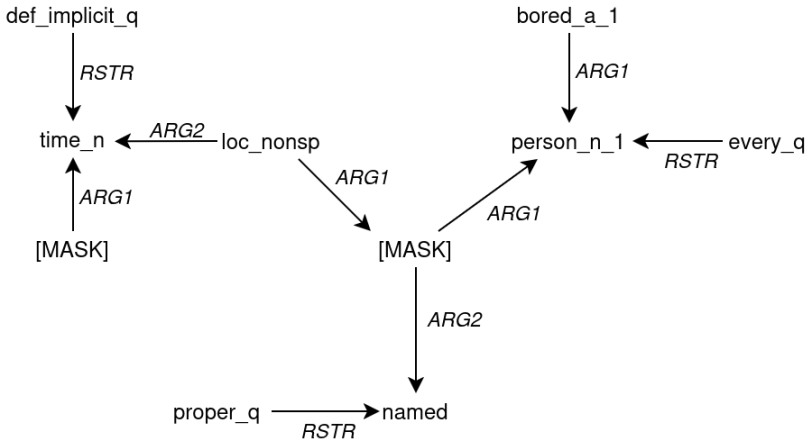

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Experiments

Experiment 1: Evaluating the LKCH

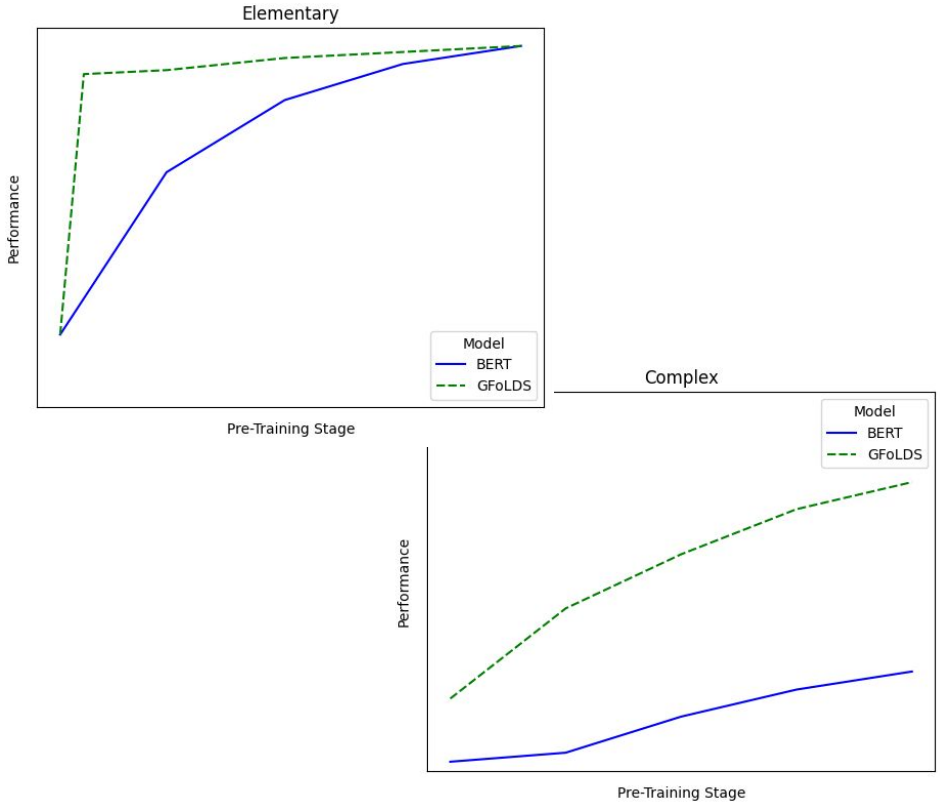
- Evaluated GFoLDS and BERT comparison models at 80 intervals throughout pretraining

- Elementary tasks:
  - POS prediction
  - Quantifier agreement prediction
- Complex task: RELPRON (Rimell et al. 2016)
  - *“a device that astronomers use is a ___”*
    (TARGET = *telescope*)

The Linguistic Knowledge Catalysis Hypothesis (LKCH):

> *The (aspects of) linguistic knowledge incorporated into LFLMs greatly accelerates their learning of elementary linguistic phenomena, in turn accelerating the learning of more complex patterns.*

Prediction



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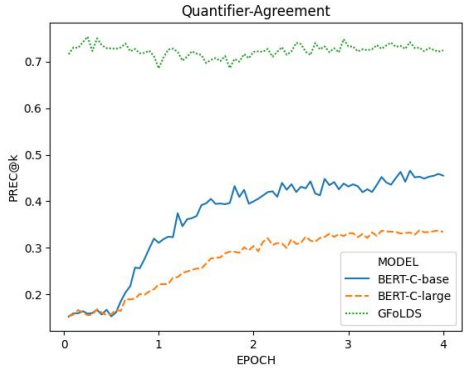
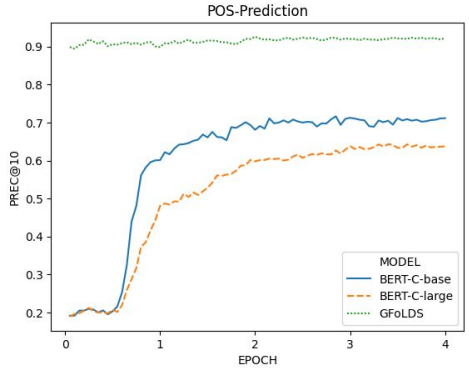
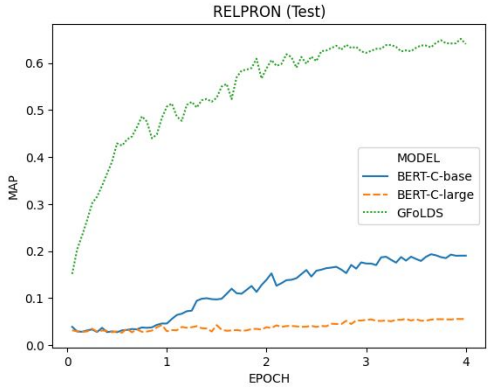
Results

Elementary:





Complex (RELPRON):



Contributions

✅ Experimental support for the LKCH

- Proof-of-concept of the downstream applicability of LFLMs

- Evidence supporting the scalability of LFLMs

Experiment 2: Downstream Tasks

1. RELPRON test set

Term/Hypernym	Properties	Corresponding Templates
telescope/ device	*astronomers use*	"A device that astronomers use is a [redacted]"
	detects planets	"A device that detects planets is a [redacted]"
assignment/ document	*student writes*	"A document that a student writes is an [redacted]"
	receives a grade	"A document that receives a grade is an [redacted]"
ruin/ building	*archaeologist discovers*	"A building that an archaeologist discovers is a [redacted]"
	jungle covers	"A building that the jungle covers is a [redacted]"

2. SNLI (Bowman et al., 2015)

Premise	Hypothesis	Label
It is raining	The ground is wet	*Entailment*
The man is lying down	The man is standing	*Contradiction*
It is December	It is five o'clock	*Neutral*

3. MegaVeridicality V2.1 (White et al., 2018)

Sentence	Label
A particular person didn't mean to do a particular thing	1
Someone didn't tell a particular person to do a particular thing	0
John wasn't upset that a particular thing happened	1
John didn't find that a particular thing happened	0
A particular person was thrilled to do a particular thing	1
A particular person yearned to have a particular thing	0

4. McRae et al. (2005)

Feature	Value
a-utensil	0.634 (19/30)
found-in-kitchens	0.600 (18/30)
used-with-forks	0.534 (16/30)
a-cutlery	0.500 (15/30)
is-dangerous	0.467 (14/30)
a-weapon	0.367 (11/30)

McRae et al. (2005) feature norms for the concept *knife*

Experiment 2: Results

	GFoLDS	Comparison BERT Models		Actual BERT Models	
		Large	Base	Large	Base
RELPRON (MAP)	0.651	0.056 (+0.595)	0.193 (+0.458)	0.769 (-0.118)	0.690 (-0.039)
SNLI (Acc)	81.0%	62.0% (+19.0%)	79.9% (+1.1%)	91.1% (-10.1%)	90.7% (-9.7%)
MegaVeridicality (Acc)	81.3%	76.2% (+5.1%)	78.1% (+3.2%)	85.6% (-4.3%)	84.2% (-2.9%)
McRae et al. (ρ)	0.205	0.134 (+0.071)	0.167 (+0.038)	0.241 (-0.036)	0.247 (-0.042)

	GFoLDS	Comparison BERT Models		Actual BERT Models	
		Large	Base	Large	Base
Parameters (Millions)	174	335 (-161)	110 (+64)	335 (-161)	110 (+64)
Pretraining Data: Base/Actual (Millions of Words)	508/472	508/508 (-0/-81)		3300/3300 (-2792/-2828)	
Pretraining Epochs	4	4 (-0)		∼40 (-36)	

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Experiment 3: Scalability

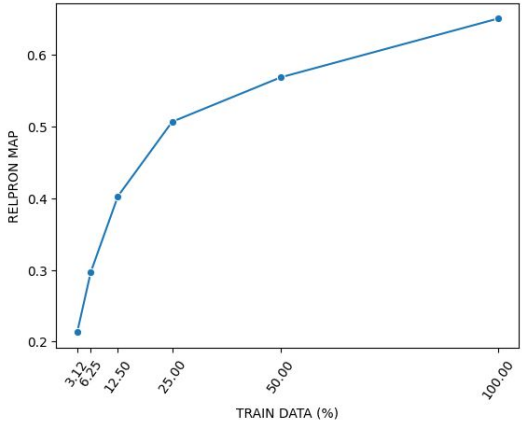
- Applied the Chinchilla Scaling Laws (CSLs; Hoffmann et al., 2022, Muennighoff et al., 2024) to GFoLDS to establish its scalability

- Pretrained five additional GFoLDS models on 50%, 25%, 12.5%, 6.25%, and 3.125% of the original pretraining data

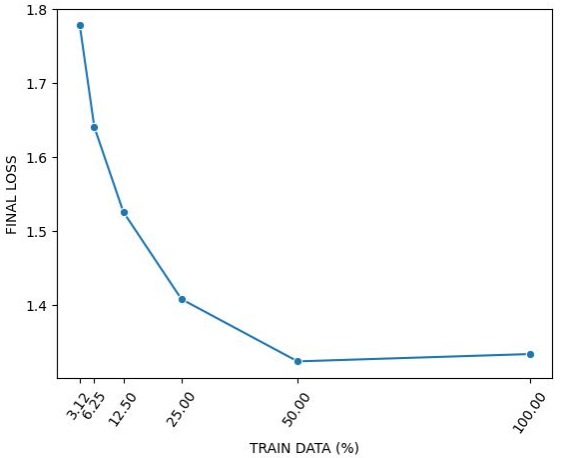
- Measured final pretraining loss and performance on a downstream task (RELPRON)

Experiment 3: Results

- Continued performance increases on the RELPRON dataset: GFoLDS is likely to scale with dataset size



- Final loss plateau: GFoLDS is *underparameterized* (too small) even for half of its pretraining dataset
  - For comparison: CSLs predict that LMs of the same size become underparameterized with a dataset **20x** larger



Contributions

✅ Experimental support for the LKCH

✅ Proof-of-concept of the downstream applicability of LFLMs

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Appendix

Preprocessing

- Due to difficulties with tokenization, I removed CARGs and out-of-vocabulary items from the DMRS input graphs:

"*John went to the park in the spring of 2017*"

⇓

"[NAMED] *went to the park in* [SEASON] *of* [YEAR]"

Preprocessing

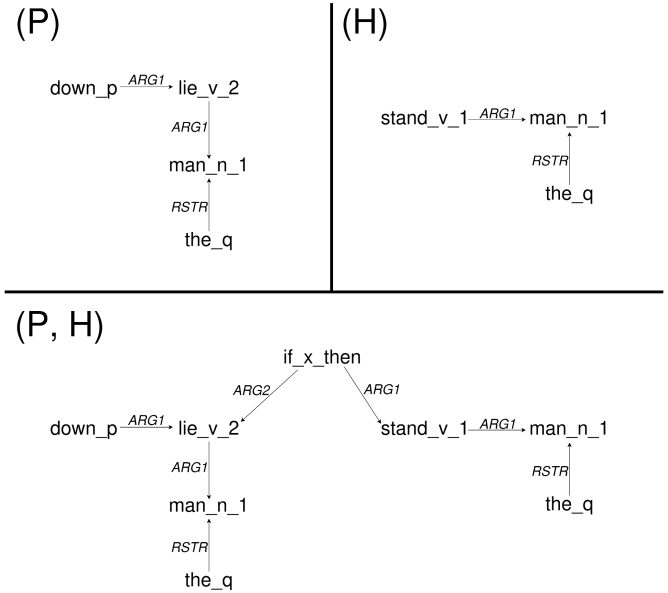
- Removed *focus_d* and *parg_d*

- Replaced edge labels:

Original Label	Interpretation/Role	Replacement
ARG1	First-place argument	—
ARG2	Second-place argument	—
ARG3	Third-place argument	—
ARG4	Fourth-place argument	—
MOD	Indicates a shared handle between two predicates	—
RSTR	Restriction of a quantifier	—
ARG	Argument of the "*unknown*" predicate	*MOD*
L-INDEX	Left-hand conjunct of two coordinated variables	*INDEX*
R-INDEX	Right-hand conjunct of two coordinated variables	*INDEX*
L-HNDL	Left-hand conjunct of two coordinated handles	*HNDL*
R-HNDL	Right-hand conjunct of two coordinated handles	*HNDL*

SNLI preprocessing

- Problem: GFoLDS can only take one input sentence at a time
  - Solution: turn each (premise, hypothesis) pair into a single sentence

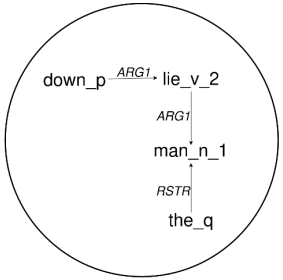


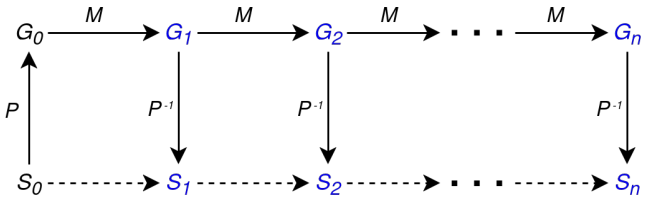
Future directions: multi-sentence model

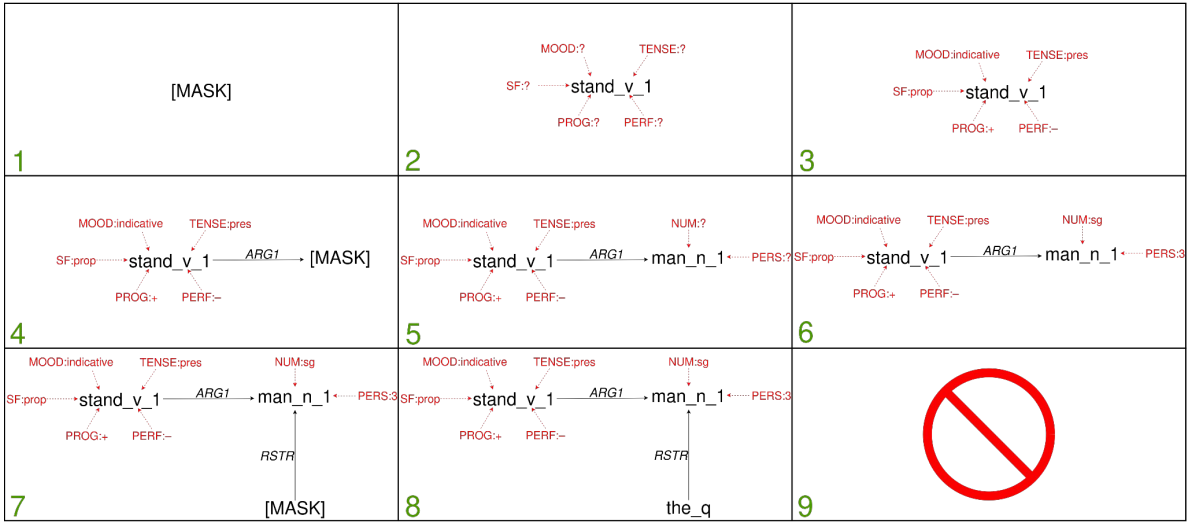
$$\vec{e_i} = E(n_i, G) = \mathcal{E}_T(n_i) + Norm\left(\sum_{\phi \in F(n_i, G)} \mathcal{E}_F(\phi)\right) \tag{7.7a}$$

$$\vec{e_{k,i}} = E(n_{k,i}, G_k) = \mathcal{E}_T(n_{k,i}) + Norm\left(\sum_{\phi \in F(n_{k,i}, G_k)} \mathcal{E}_F(\phi)\right) + \mathcal{E}_S(k) \tag{7.7b}$$

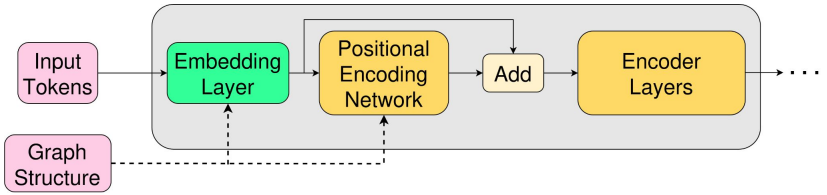
Future directions: graph-to-graph generative model

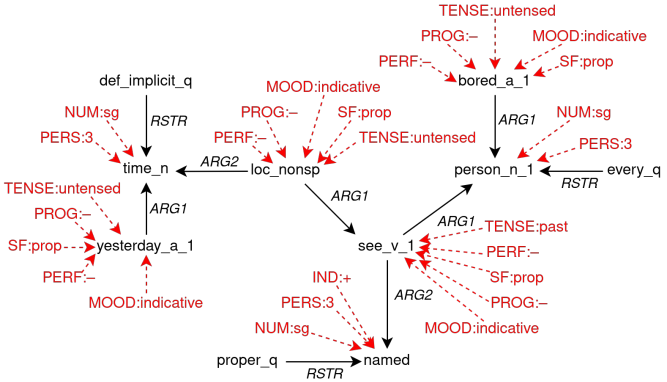






GFoLDS Architecture

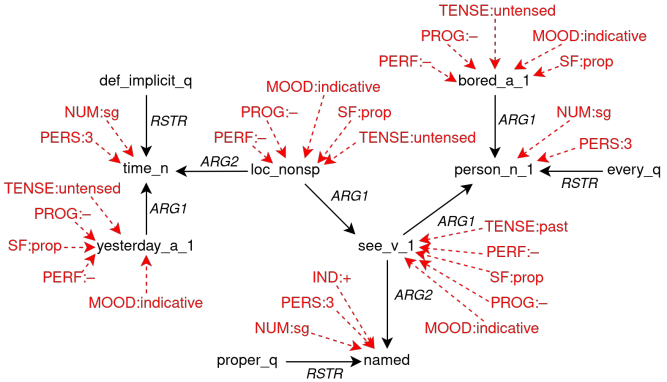


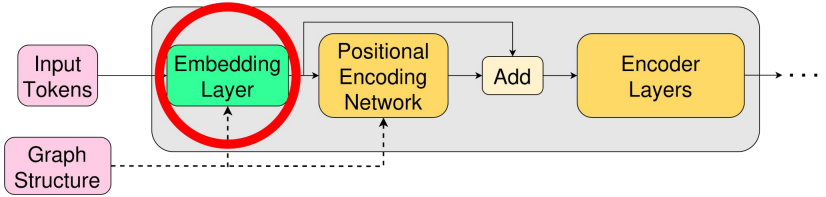


"*Every bored person saw Mary yesterday*"

- GFoLDS is a **Graph Transformer** (Wu et al., 2021): a graph neural network (GNN) coupled with a transformer encoder

GFoLDS Architecture





$$\vec{e_i} = \mathcal{E}_T(n_i) + Norm\left(\sum_{\phi \in F(n_i)} \mathcal{E}_F(\phi)\right)$$

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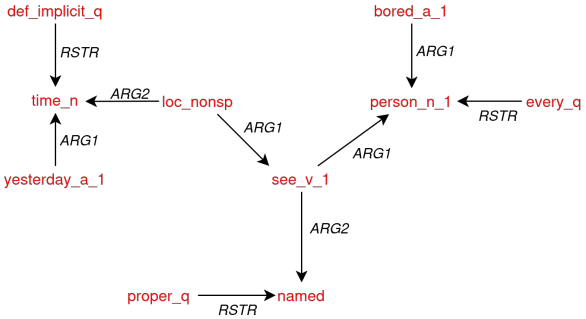

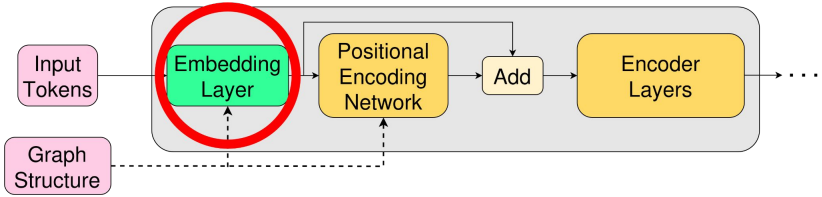

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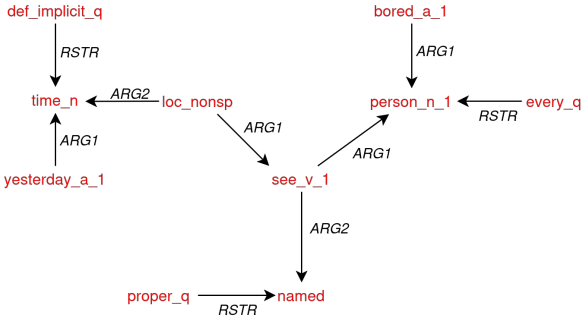

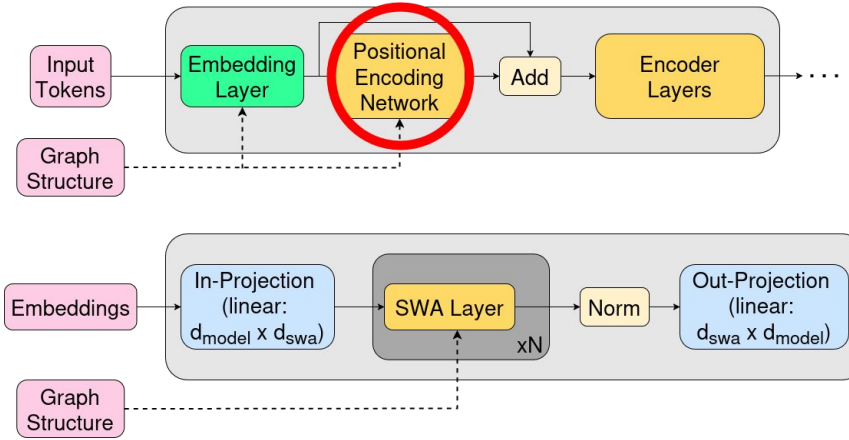

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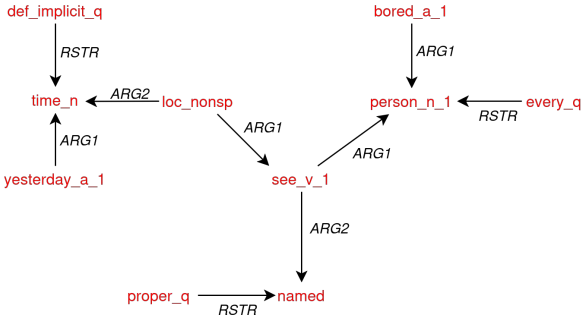

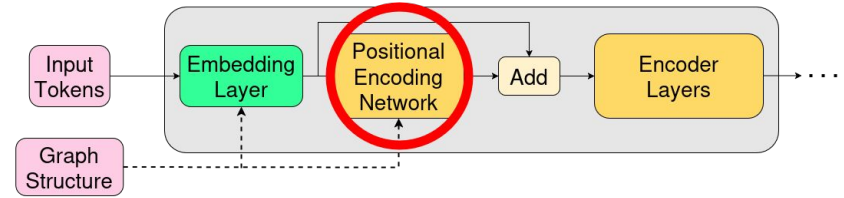

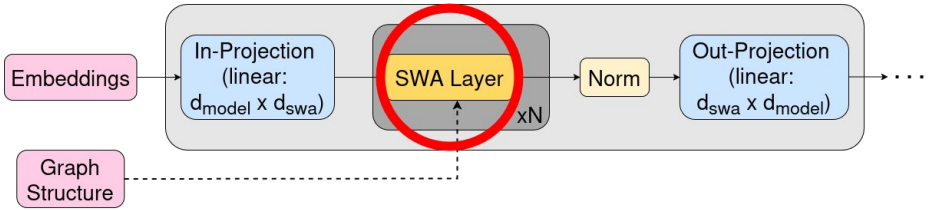

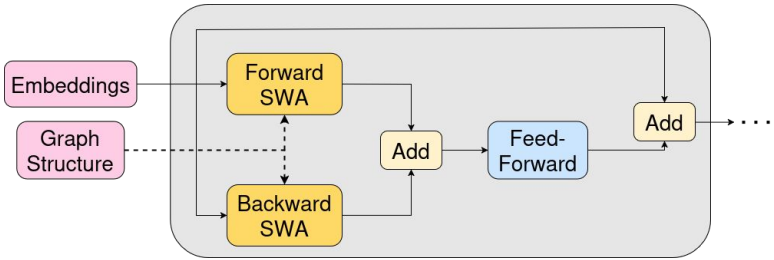

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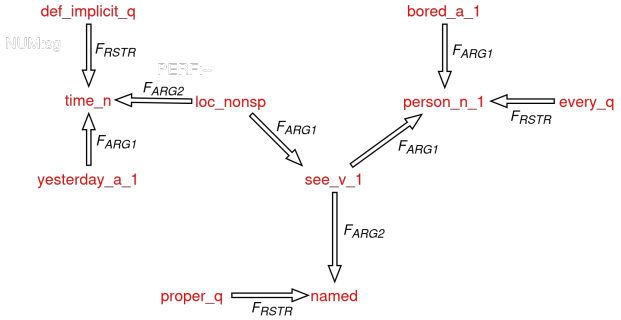
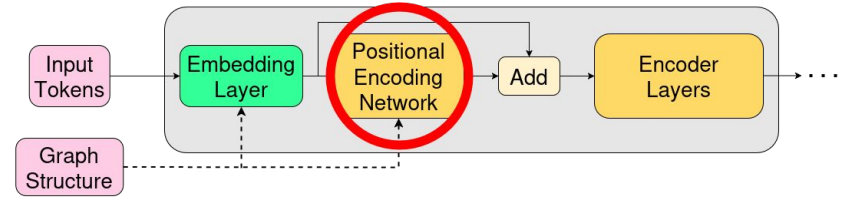
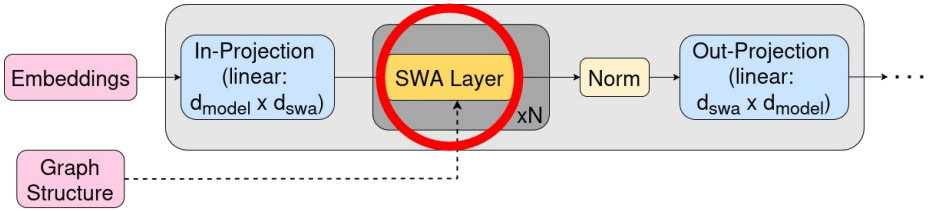
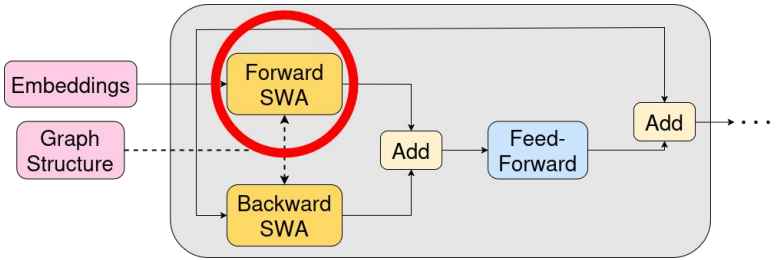


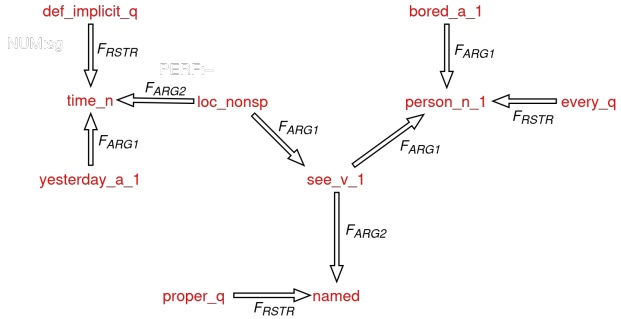


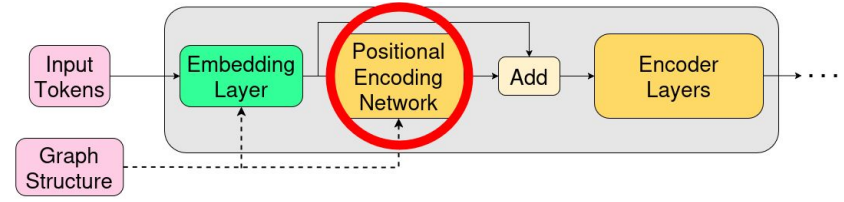


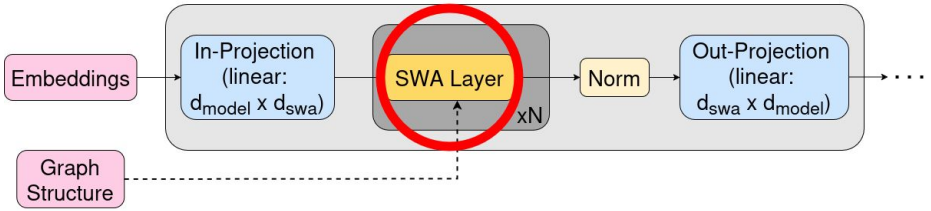


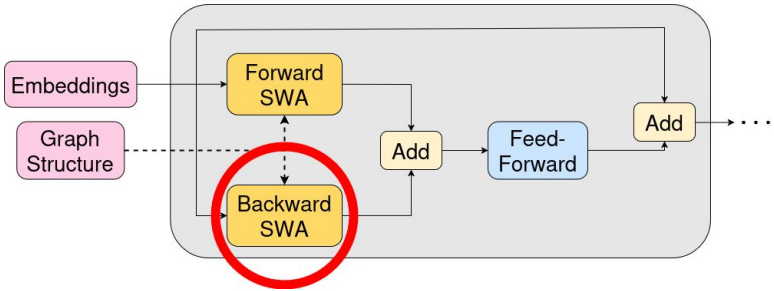
$$\vec{f}_i = Norm\left(\sum_{n_k \xrightarrow{\ell} n_i \in G} W_\ell^{(f)} \vec{h}_k\right)$$

GFoLDS Architecture



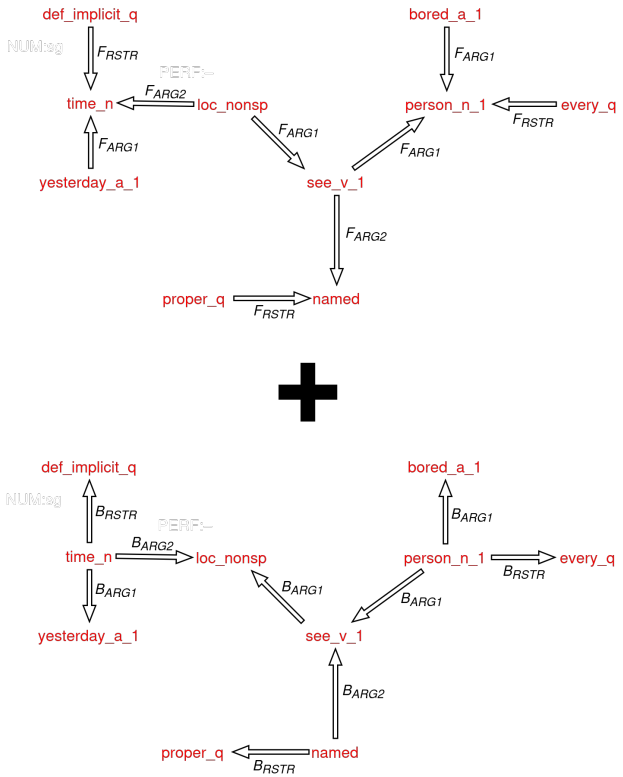


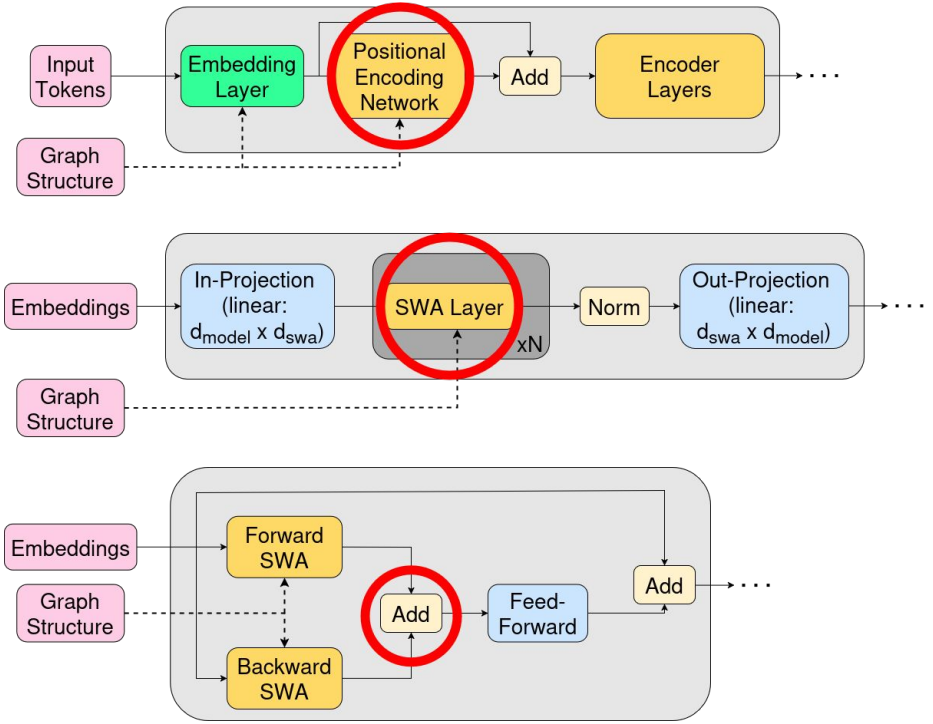




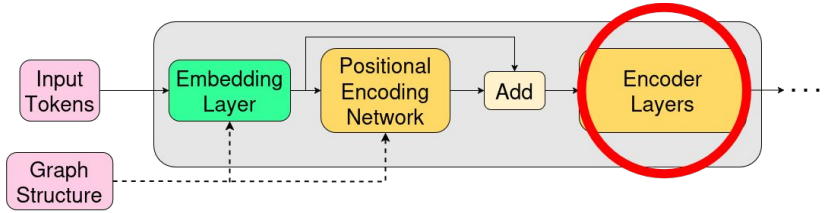
$$\vec{b_i} = Norm\left(\sum_{n_i \xrightarrow{\ell} n_k \in E} W_\ell^{(b)} \vec{x_k}\right)$$

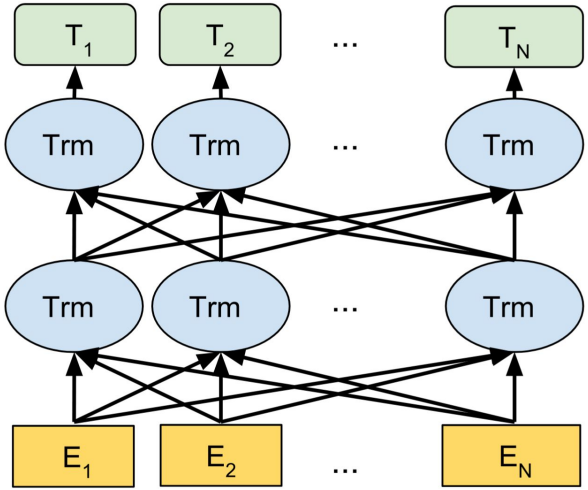
GFoLDS Architecture



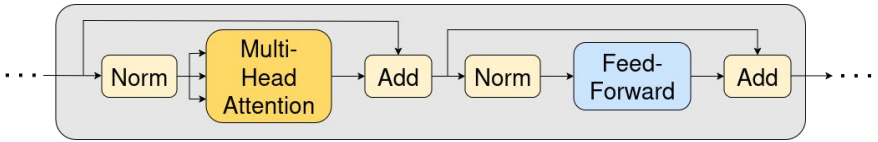


GFoLDS Architecture

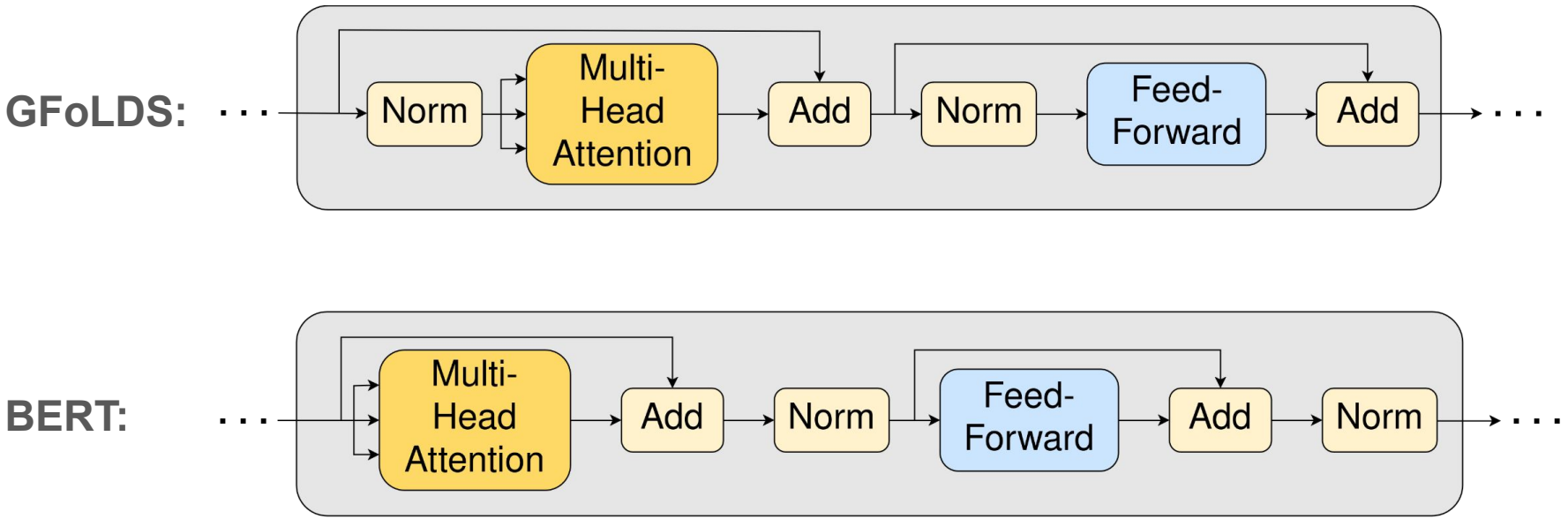




(Devlin et al., 2019)



GFoLDS vs. BERT Encoder Layers



https://github.com/google-research/tuning_playbook?tab=readme-ov-file#how-can-optimization-failures-be-debugged-and-mitigated

Limitations and Weaknesses

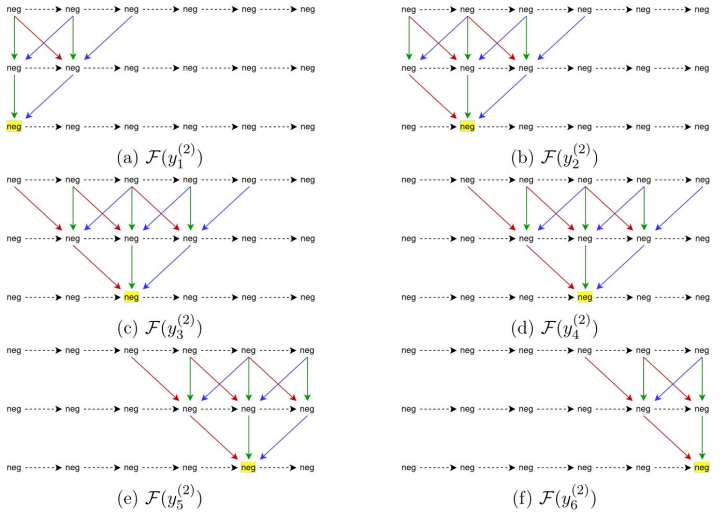
- A serious limitation in GFoLDS' architecture: it can't count repeated sequences of the same token (node label)
  - Caused by local node aggregation of its GNN
  - Prevents learning double-negation cancellation
  - Limits ability to detect node sentence membership in SNLI

Theorem 2. *Given a GFoLDS model (as defined in Chapter 4) M with n SWA layers and an input graph G, let $M(G)_i$ denote the embedding that M assigns to the i^{th} node x_i of G. Suppose that G contains a path $p = x_1 \xrightarrow{\ell} \ldots \xrightarrow{\ell} x_k$ of length k such that all nodes (and all edges) in p have the same label (respectively), and that for all $1 < i < k$, x_i has no incoming or outgoing edges not in p. Then:*

i. for all $1 \leq i \leq n$, and all $1 \leq j \leq k$ such that $i \neq j$: $M(G)_i \neq M(G)_j$

ii. for all $k - n \leq i \leq k$, and all $1 \leq j \leq k$ such that $i \neq j$: $M(G)_i \neq M(G)_j$

iii. for all $n < i, j < k - n$: $M(G)_i = M(G)_j$



Limitations and Weaknesses

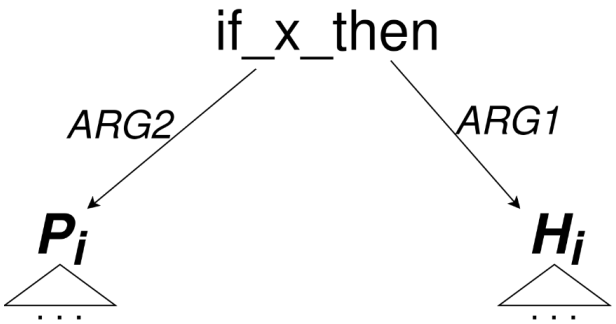
Premise	Template	Hypothesis	Label
A young boy dressed in plaid about to take a picture.	(P, H)	A young boy is about to take a picture.	Entailment
	$(P, (T_{NT})^1 H)$	It is not true that a young boy is about to take a picture.	Contradiction
	$(P, (T_{NT})^2 H)$	It is not true that it is not true that a young boy is about to take a picture.	Entailment
	$(P, (T_{NT})^3 H)$	It is not true that it is not true that it is not true that a young boy is about to take a picture.	Contradiction
A race between friends at the park.	(P, H)	The park is deserted.	Contradiction
	$(P, (T_{NT})^1 H)$	It is not true that the park is deserted.	Entailment
	$(P, (T_{NT})^2 H)$	It is not true that it is not true that the park is deserted.	Contradiction
	$(P, (T_{NT})^3 H)$	It is not true that it is not true that it is not true that the park is deserted.	Entailment
People kneeling on the ground.	(P, H)	People are praying.	Neutral
	$(P, (T_{NT})^1 H)$	It is not true that people are praying.	Neutral

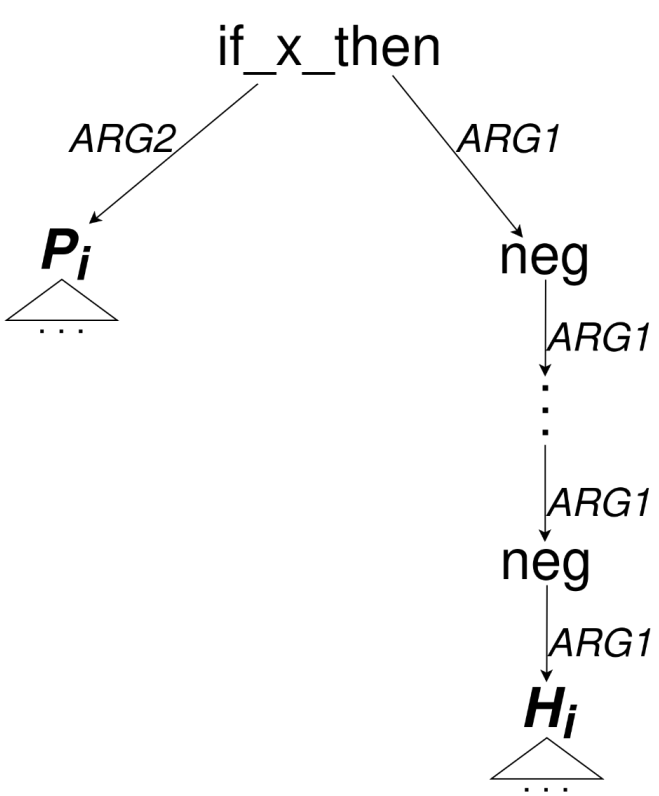
Table 2.1: Examples of depth-n negated challenge data points $(P, (T_{NT})^n H)$ generated from SNLI (some examples have been slightly modified for presentability).

Model	Depth-m test	No inoc.	Depth-1 inoc.	Depth-$\leq$2 inoc.	Depth-$\leq$3 inoc.
$BART_M$	2	0.71	0.32	—	—
$BART_M$	3	0.36	0.93	0.31	—
$BART_M$	4	0.82	0.36	0.94	0.31
$BART_M$	5	0.33	0.88	0.31	0.94
$BART_M$	6	0.86	0.41	0.94	0.31
$RoBERTa_M$	2	0.77	0.36	—	—
$RoBERTa_M$	3	0.34	0.89	0.33	—
$RoBERTa_M$	4	0.85	0.33	0.97	0.32
$RoBERTa_M$	5	0.32	0.88	0.33	0.95
$RoBERTa_M$	6	0.89	0.34	0.97	0.33
$DeBERTa_S$	2	0.56	0.62	—	—
$DeBERTa_S$	3	0.4	0.61	0.32	—
$DeBERTa_S$	4	0.84	0.64	0.96	0.5
$DeBERTa_S$	5	0.3	0.51	0.32	0.96
$DeBERTa_S$	6	0.88	0.77	0.96	0.36
$RoBERTa_S$	2	0.74	0.32	—	—
$RoBERTa_S$	3	0.4	0.89	0.3	—
$RoBERTa_S$	4	0.84	0.35	0.94	0.39
$RoBERTa_S$	5	0.34	0.88	0.3	0.74
$RoBERTa_S$	6	0.83	0.33	0.93	0.53
$BART_{SMFA}$	2	0.77	0.37	—	—
$BART_{SMFA}$	3	0.33	0.91	0.31	—
$BART_{SMFA}$	4	0.84	0.34	0.94	0.29
$BART_{SMFA}$	5	0.3	0.85	0.31	0.92
$BART_{SMFA}$	6	0.86	0.41	0.94	0.28
$RoBERTa_{SMFA}$	2	0.79	0.35	—	—
$RoBERTa_{SMFA}$	3	0.32	0.93	0.32	—
$RoBERTa_{SMFA}$	4	0.83	0.31	0.95	0.32
$RoBERTa_{SMFA}$	5	0.32	0.94	0.32	0.94
$RoBERTa_{SMFA}$	6	0.84	0.32	0.95	0.32
Mean	2	0.72	0.39	—	—
Mean	3	0.36	0.86	0.32	—
Mean	4	0.84	0.39	0.95	0.35
Mean	5	0.32	0.82	0.32	0.91
Mean	6	0.86	0.43	0.95	0.35

Table 2.3: Accuracy for all models on depth-(m>n) external negation (D^m_{NT}) after depth-$\leq n$ inoculation ($n \in \{1, 2, 3\}$) on $D^{\leq n}$. For the sake of convenience, mean accuracy across the models is reported at the bottom of the table; most individual model accuracies do not substantially deviate from these mean values.

Limitations and Weaknesses





Limitations and Weaknesses

Sequence Length	1-SWA	2-SWA	3-SWA	4-SWA
1	✓	✓	✓	✓
2	✓	✓	✓	✓
3	✓	✓	✓	✓
4	X	✓	✓	✓
5	X	✓	✓	✓
6	X	X	✓	✓
7	X	X	✓	✓
8	X	X	X	✓
9	X	X	X	✓
10	X	X	X	✓
11	X	X	X	✓
12	X	X	X	X

Table 6.5: Results of the mod-2 counting experiment for four GFoLDS models with n SWA layers ($1 \leq n \leq 4$). A ✓ symbol at row r indicates that the model was able to correctly classify each $p_{neg}^{(k)}$ sequence as odd or even within 100 training epochs, for all $1 \leq k \leq r$.

Depth	S_1 Accuracy	S_2 Accuracy	Total Accuracy
Overall	87.0%	72.3%	82.1%
1	80.3%	82.4%	81.3%
2	86.3%	89.0%	87.6%
3	83.9%	66.8%	76.5%
4	88.5%	72.5%	83.6%
5	89.3%	61.9%	82.8%
6	89.6%	50.5%	82.6%
7	89.2%	45.3%	83.3%
8	88.5%	46.3%	84.3%
9	87.4%	45.4%	84.1%
10	88.2%	42.1%	85.3%
11	88.5%	43.4%	86.5%
12	87.1%	26.9%	84.6%
13	88.0%	0.0%	85.9%
14	87.4%	0.0%	85.4%
15	77.1%	—	77.1%
16	62.5%	—	62.5%
17	58.8%	—	58.8%
18	66.7%	—	66.7%
19	33.3%	—	33.3%

Table 6.6: GFoLDS' test set accuracy on the S_1/S_2 classification task, by node depth (undirected distance from the *if_x_then* node). *Total accuracy* denotes the accuracy for all S_1 and S_2 nodes at the depth in question. The — symbol in the S_2 column for depths 15-19 indicates that there were no S_2 nodes in the test set at those depths.

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