Progressive Learning in LLMs Using Structured Grammar Books

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Context

Introduction

The development of Large Language Models (LLMs) has significantly advanced natural language processing, enabling machines to perform tasks such as translation, summarization, and question-answering with remarkable proficiency.

Traditional LLM training approaches often rely on vast, unstructured datasets, necessitating substantial computational resources and time. However, recent research suggests that a more structured and efficient learning paradigm—one that mirrors human language acquisition—can enhance model performance while reducing training complexity.

In this paper, we propose a progressive training framework for LLMs that emulates human language acquisition through the pre-training of a sequence of grammar books and incorporating morphological word embeddings. This approach aims to improve model competence and efficiency by optimizing training methodologies through linguistic tagging and curriculum-based training

Related Work

Less is More

- **Minimum Description Length (MDL):** Optimal models balance complexity and generalization (Rissanen, 1978).
- **Data Efficiency:** Selective use of high-quality, diverse data improves generalization and reduces overfitting (Sorscher et al., 2022).
- **Domain-Specific Models:** Smaller, fine-tuned models (e.g., BioBERT, legal LLMs) often outperform large general-purpose ones in specialized tasks.
- **Efficient Architectures:** Techniques like pruning, compression, and parameter sharing (e.g., DistilBERT, ALBERT, DeepSeek) reduce model size without sacrificing performance.

Curriculum Learning

- **Human-Like Learning:** Traditional LLMs process each sequence in isolation, unlike human learners who build from simple sounds to complex sentences, yielding deeper contextual understanding
- **Curriculum Learning Framework:** Bengio et al. (2009) formalized "start small" training—ordering data from easy to hard—later extended by Narvekar et al. (2020) in reinforcement learning and surveyed broadly by Wang et al. (2020)
- **Sample Efficiency:** Warstadt (2023) showed that pretraining on developmentally plausible, child-like corpora achieves strong performance with far fewer data and compute resources
- **Adaptive Pacing Gains:** Introducing complex linguistic phenomena only after mastering simpler structures can halve the number of training epochs needed for comparable results
- **Enhanced Transferability:** Curriculum-trained models demonstrate stronger performance when transferred to diverse downstream tasks beyond their original training objectives
- **Stability and Robustness:** Models trained via curriculum learning exhibit lower variance across training runs and greater resilience to domain shifts

Methodology

Components

Datatset Preparation

1. Constructed from the **New Concept English textbook series** (Volumes 1–4)
2. Digitized and preprocessed one volume using **Tesseract** (OCR)
   - Correction of OCR errors like ligature fixes, punctuation standardization
   - Consistent formatting of dialogue, currency, and number formats
   - Structuring lessons with metadata tags with **Stanza**
3. **Trec** dataset for classification task

18067 sentences extracted

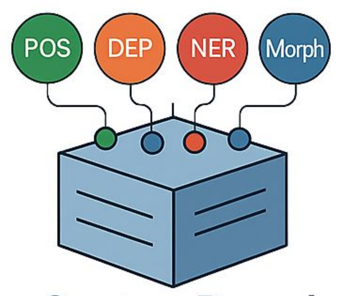
Syntactic Feature Extraction

- Part-of-Speech tags,
- Dependency relations,
- Named Entity Recognition tags, and
- Morphological features (tense, number).

(POS, DEP, NER, Morph)

1704 combinations

('NOUN','root','O','Number=Sing')
('VERB','parataxis','O','Mood=Imp|VerbForm=Fin')



Training Strategy

1. **Training from Scratch (No Weights)**
   - All models were **trained from scratch** with **randomly initialized weights**.
   - This setup removes any influence from pretrained models, isolating the effect of the grammar curriculum.
2. **Curriculum Pre-training**

Progressive training over **345 structured lessons** from advancing from simple to complex grammar

- Each lesson contains **20–70 sentences**
- Lessons are trained **in a loop**, reinforcing earlier structures while introducing new ones.
- Focus: build **syntactic competence** from scratch using pedagogically aligned, grammatically consistent content.

3. **Fine-Tuning on TREC**

Adaptation to the **TREC question classification** task with six coarse-grained labels :

DESC, ENTY, ABBR, HUM, LOC,NUM

- Fine-tunes pretrained models to map input questions to correct classes.

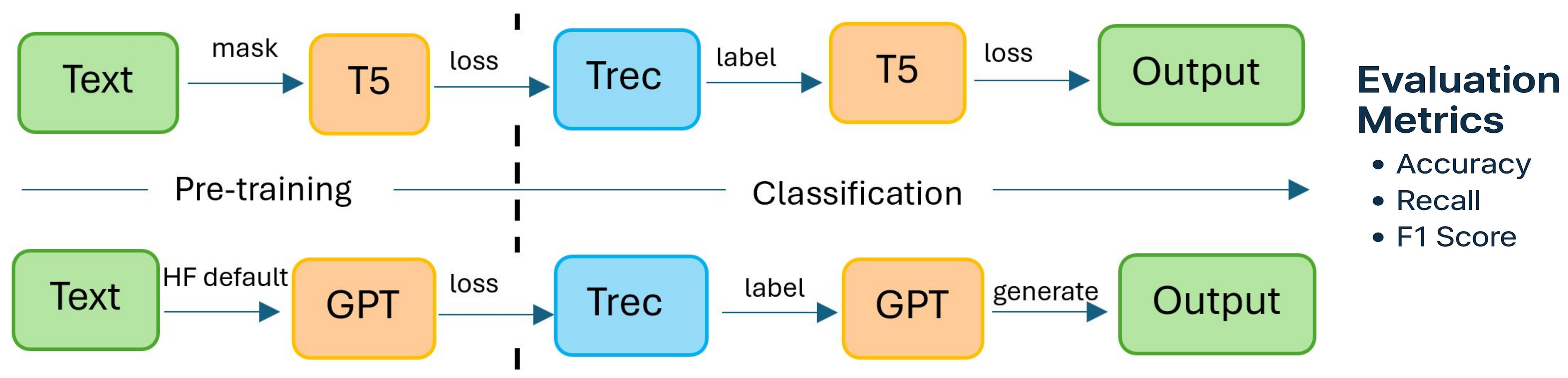
Model Selection: GPT-2 and T5-base

Model	Params (M)	Hidden Size	Layers	Heads
GPT-2	~117	768	12	12
T5-base	~220	768	12	12

Embedding Structure

Model	Original Embedding	With Syntax Embedding
GPT-2	Token + Position	Projected [Token // Syntax] + Position
T5-base	Token only	Projected [Token // Syntax]

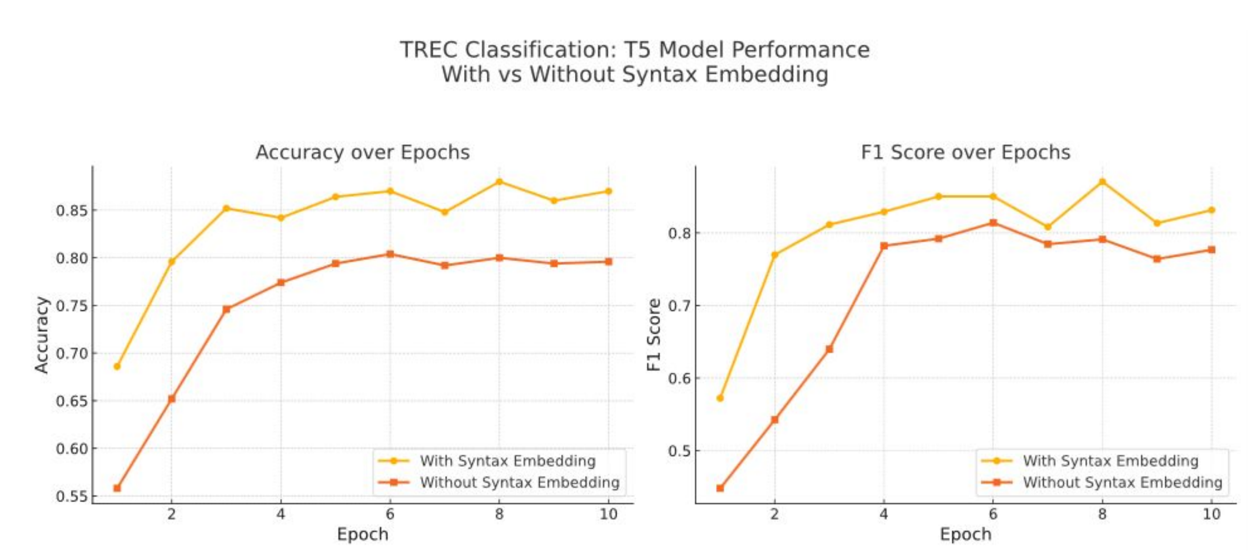
GPT-2 and T5-base Pipelines



Results & Discussion

Model	Accuracy	Recall	F1-score	Pretraining Time	Classification Duration	
					Training	Inference
GPT-2 (Pre-trained)	0.954	0.940	0.922	30 d	387.89 s	32.87 s
T5 (Pre-trained)	0.976	0.8476	0.8387	2.5 d	236.37 s	1.96 s
GPT-2 RAW + GRM + EMBs	0.636	0.201	0.223	1.25 h	288 s	
T5 RAW + GRM + EMBs	0.870	0.846	0.850	3 h	114 s	
Optimal RAW(GPT-2, T5) + GRM	*Details in Section 4.3*					

Table 3: Design of the Evaluation Models



GPT-2

- **SyntaxGPT** (trained on grammar curriculum) achieved **63% accuracy** on TREC, compared to 95.4% for randomly initialized GPT-2 trained directly on TREC.
- During curriculum training, SyntaxGPT showed **elevated eval losses** (5–7), far above typical classification ranges (1.5–2.5).

T5

- Accuracy improved from 68.6% to **88%** by epoch 8, and F1 reached 0.87, reflecting successful curriculum-based learning.
- **Validation loss decreased** steadily from 0.826 to ~0.6, indicating progressive mastery of linguistic structures.

Performance Comparison: TREC Classification

- T5 outperforms GPT-2 when trained from scratch with grammar embeddings and is more efficient

Syntax Embedding Ablation (T5)

- Models with **syntax embeddings outperformed baselines** in both accuracy and F1 on the TREC classification task.
- Syntax-enhanced models **converged more rapidly** and showed smoother improvement during training.
- Explicit syntax enabled the model to **capture deeper grammatical and semantic cues** beyond surface token patterns.

Limitations and Future Works

Limitations

- **Curriculum Complexity Saturation:** Gains plateau as curriculum complexity increases, suggesting diminishing returns from advanced grammar inputs without more semantic diversity
- **Limited Domain and Objective Scope:** Pretraining on structured textbook sentences restricts model exposure to real-world variability, hindering open-domain generalization
- **Data Scale Constraints:** A curriculum dataset of only a few thousand examples limits the learning of robust, transferable representations compared to large-scale corpora
- **Model Architecture Sensitivity:** Decoder-only GPT-2 struggles with limited, structured data, whereas encoder-decoder T5 shows greater resilience to small-scale pretraining

Future Works

- **Expand Linguistic Complexity:** Integrate advanced syntactic structures, semantic nuances, and discourse coherence into the curriculum
- **Incorporate Morphological Enrichment:** Leverage Wiktionary to introduce detailed word-form, inflection, and derivation information
- **Conduct Ablation Studies:** Systematically isolate the impact of grammar embeddings, curriculum stages, and input augmentation strategies
- **Optimize Training Parameters:** Fine-tune learning-rate schedules, optimizer settings, batch sizes, and curriculum granularity to enhance convergence
- **Apply to GEC Tasks:** Extend the progressive curriculum framework to grammatical error correction for deeper linguistic competence acquisition

Conclusion & References

Conclusion

In summary, syntax-augmented progressive pre training provides effective inductive biases that both accelerate convergence and improve classification accuracy of encoder–decoder models in low-resource scenarios. Our ablation experiments of T5-base confirm that integrating syntactic embeddings yields consistent gains, faster training dynamics and higher accuracy and F1 scores, compared to models trained without grammar information. While decoder-only architectures like GPT-2 remain more dependent on large-scale data, our results highlight the complementary role of structured linguistic cues alongside traditional pretraining. This framework offers a promising avenue for developing more data-efficient NLP systems that leverage explicit syntax.

References

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