DEPTH: Discourse Education through Pre-Training Hierarchically

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Abstract

Language Models (LMs) struggle with linguistic understanding at the discourse level, even though discourse patterns such as coherence, cohesion, and narrative flow are prevalent in their pre-training data. To improve the discourse capabilities of LMs already at the pre-training stage, we introduce DEPTH, an encoder-decoder model that learns latent representations for sentences using a discourse-oriented pre-training objective. DEPTH combines hierarchical sentence representations with two objectives: (1) *Sentence Un-Shuffling*, and (2) *Span-Corruption*. Our approach trains the model to represent both sub-word-level and sentence-level dependencies over a pre-training corpora. When trained either from scratch or continuing from a pre-trained T5 checkpoint, DEPTH learns semantic and discourse-level representations faster than T5, outperforming it in span-corruption loss despite the additional sentence-un-shuffling objective. Evaluations on the GLUE, DiscoEval, and NI benchmarks demonstrate DEPTH's ability to quickly learn diverse downstream tasks, which require syntactic, semantic, and discourse capabilities. Our approach extends the discourse capabilities of T5, while minimally impacting other natural language understanding (NLU) capabilities in the resulting LM. We share ur codebse for reproducibility: https://github.com/zbambergerNLP/depth.git

1 Introduction

Discourse understanding—the ability to understand how sentences and broader textual units form cohesive narratives (Miltsakaki et al., 2004; Prasad et al., 2008; Jernite et al., 2017; Prasad et al., 2018)—is fundamental to effective communication. However, LMs often struggle with this, especially when dealing with long and complex inputs, hindering their performance on tasks like persuasive argumentation (Durmus et al., 2019; Hidey et al., 2017; Chakrabarty et al., 2019), summarization (Zhao et al., 2022), essay scoring (Mim et al., 2021), dialogue systems (Hua et al., 2023), and following instructions (Wei et al., 2022a). Recent evidence from Yu et al. (2024) reinforces this view, demonstrating that human language comprehension occurs at multiple levels and that incorporating discourse-level objectives like next sentence prediction (NSP) can lead to more human-like language representations and improved contextual understanding.

Early attempts to incorporate discourse awareness into pre-training, such as Next Sentence Prediction (NSP) in BERT (Devlin et al., 2019) and Sentence Order Prediction (SOP) in ALBERT (Lan et al., 2020), proved overly simplistic and hindered learning effective discourse representations (Liu et al., 2019; Lan et al., 2020; Raffel et al., 2020). Subsequent encoder models like Sentence-level Language Model (SLM) (Lee et al., 2020), CONPONO (Iter et al., 2020), and Hi-Transformer (Wu et al., 2021) improved discourse capabilities in LMs but lacked generative capabilities.

Unlike the pre-training tasks for encoder LMs, next-token prediction provides decoder LMs like GPT (Radford et al., 2018, 2019; Brown et al., 2020; OpenAI et al., 2023) with powerful generative capabilities. However, without a dedicated and costly alignment phase (Ouyang et al., 2022; Wei et al., 2022a; Bai et al., 2022), these LMs tend to falter in understanding and executing human queries.

Even with a dedicated alignment phase, large decoder-only models generally perform poorly on discourse-oriented benchmarks that measure coherence and cohesion (Chen et al., 2019; Maimon and Tsarfaty, 2023a,b; Wang et al., 2023). Encoder-decoder models such as T5 (Raffel et al., 2020) and BART (Lewis et al., 2020a) consistently outperform much larger ($\approx 400\times$) decoder-only models like GPT-3 (Brown et al., 2020) and GPT-4 (OpenAI et al., 2023) on these tasks. Recent work

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by Katz et al. (2024) indicates that incorporating encoder-decoder attention mechanisms into modern decoder-only models like Llama-3 (Grattafiori et al., 2024), Qwen-2.5 (Qwen et al., 2025), and Mistral (Jiang et al., 2023) also boosts performance, suggesting potential additional benefits from pre-training models with such attention schemes.

To improve the discourse-capabilities of encoder-decoders already at the pre-training stage, we propose DEPTH (**D**iscourse-**E**ducation through **P**re-**T**raining **H**ierarchically), a hierarchical language model that learns representations for both sub-word and sentence-level tokens. DEPTH extends the pre-training objective of SLM from encoder-only models like BERT, to encoder-decoder models like T5. Notably, DEPTH introduces latent, heirarchical representations for sentences (as in Lee et al. (2020); Yang et al. (2021); Yu et al. (2024)) directly into the objective of a *generative* pre-training task. By employing a hierarchical attention mechanism across sub-word and sentence level tokens, DEPTH captures both fine-grained semantic dependencies and broader inter-sentence relationships. When pre-trained from scratch, our DEPTH model obtains meaningful representations for downstream tasks much faster than our baseline T5. Continuously pre-training T5 models with the DEPTH objective improves the discourse capabilities of the resulting models, without sacrificing performance in downstream NLU tasks.

2 Method

Pre-training DEPTH involves simultaneously performing span corruption (Raffel et al., 2020), while also un-shuffling sentences as in Lee et al. (2020). In Section 2.1 we introduce a new tokenizer for DEPTH, which combines T5's tokenizer with the sentence segmentation operation required for sentence un-shuffling. In Section 2.2, we detail how we combined the pre-training objectives of both models into the sequence-to-sequence framework of T5. Next, in Section 2.3, we discuss how we introduce hierarchical representations during pre-training, and how this hierarchy encourages the model to learn discourse representations. Finally, in Section 2.4, we demonstrate how to combine the losses of T5 and SLM into a unified objective that is conducive to traditional teacher-forcing.

2.1 Tokenization

We introduce a tokenization function, t, which transforms an input string, s, into a sequence of tokens, $X = (x_{1,1}, x_{1,2}, \ldots, x_{m,\text{len}(m)})$, in our vocabulary, V. Each token $x_{i,j}$ denotes the j'th token of the i'th sentence, where m is the number of sentences and len(i) is the length of the i'th sentence. V includes special tokens <EOS>, <BOS>, <PAD>, and sentinel tokens V_{sentinel} of the form <special_token_z> as in the original T5 paper.

To facilitate DEPTH's hierarchical structure, we segment sentences using NLTK (Bird and Loper, 2004) and create $k+1$ new tokens[1]:

$$S = \{\texttt{<SENT\_1>}, \ldots, \texttt{<SENT\_k>}, \texttt{<EOSEN>}\}$$
$$V' = V \cup S$$

We augment our tokenizer function t to form t', which maps sequence s to tokens in V'. In each sentence, we prepend a <SENT_i> token and append a <EOSEN> token:

$$X = \{\texttt{<SENT\_a>}, x_{1,1}, x_{1,2}, \ldots, x_{1,\text{len}(1)}, \texttt{<EOSEN>}, \ldots, x_{m,\text{len}(m)}, \texttt{<EOSEN>}, \texttt{<EOS>}\}$$

The integer i in <SENT_i> represents a sentence's index, sampled uniformly at random from $\{1, \ldots, k\}$ without replacement. We truncate sentences beyond the k'th to limit vocabulary size.

Unlike SLM (an encoder-only LM with an auxiliary pointer-decoder), DEPTH is an encoder-decoder that predicts <SENT_i> and <EOSEN> token IDs directly. The <EOSEN> token signals the next token is either <SENT_i> or <EOS>, allowing for dynamic attention masking in the decoder.

Formally, we define a pre-tokenization function $f : s \rightarrow s'$, where s' includes <SENT_i> and <EOSEN> tokens. The tokenized input for DEPTH is produced with $T(s) = t(f(s)) = X$. We use the SentencePiece (Kudo and Richardson, 2018) tokenizer as t, adjusted to support DEPTH's sentence-level pre-training objective.

2.2 Corruption

Span-Masking: We apply a corruption process to each batch of tokenized sequences. We sample masked spans using a geometric distribution (as in Joshi et al. (2020) and Raffel et al. (2020)), parameterized with an average span length of λ and a masking probability of p. Spans overlapping with sentence tokens (<EOSEN> or <SENT_i>) are ignored. Masked token spans are replaced with a single sentinel token <special_token_z>, where

[1]We follow Lee et al. (2020), using $k = 20$ sentence tokens.

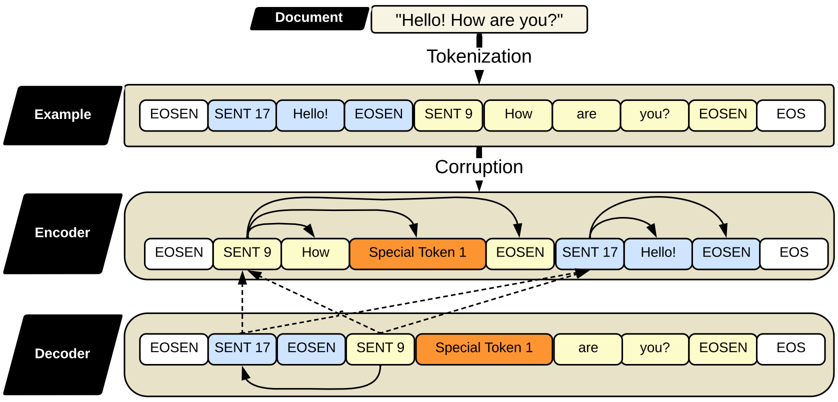


Figure 1: DEPTH tokenization and corruption process. Given an input document, DEPTH introduces sentence tokens (<SENT_i> and <EOSEN>), applies span masking, and shuffles sentences with probability 0.5. Attention patterns are shown with arrows (dotted for cross-attention, solid for self-attention).

(z) is a uniformly sampled integer from $0, \ldots, 99$. The missing token sequences appear after the corresponding sentinel token in the labels. Note that in the original T5 implementation, sentinel tokens appear in the same incrementally decreasing order in each example (`<special_token_99>` followed by `<special_token_98>`, etc...). We randomly sample sentinel token ID's for DEPTH to eliminate hints about sentence positions from the sentinel tokens. For example, with the T5 scheme for span-masking, the presence of `<special_token_99>` indicates that the sentence in which it appears comes first, making sentence un-shuffling too easy.

Sentence Un-Shuffling: Given an input sequence of up to k sentences, we randomly shuffle the order of sentences in the model input[2]. We then task the model with reconstructing the original order of the sentence tokens in the target. We shuffle all examples in a batch with probability $p = 0.5$ (as in SLM). By disrupting the original sentence order, DEPTH encourages learning of (1) the complete meaning of individual sentences, independent of their surrounding context, and (2) representations that encode how sentences relate to each other[3]. We show DEPTH's corruption process in Figure 1.

2.3 Attention masks

Our baseline model (T5) utilizes bidirectional attention in the encoder, auto-regressive attention in the decoder, and full cross attention from the decoder to the encoder. However, T5's formulation does not account for the hierarchical treatment of sentences used by SLM and DEPTH.

[2] We do not shuffle the order of tokens within a sentence

[3] E.g., discourse markers, co-reference, and entailment

We define *non-sentence* tokens, x_{reg}, as tokens $x \in X$ where $x \notin S$. We compose attention masks to impose hierarchy. As part of encoder self-attention, non-sentence tokens can attend to all other tokens in the corrupted input sequence, while `<SENT_i>` tokens can only attend to tokens within their own sentence (including sentinel tokens). As part of decoder self-attention, all tokens have an auto-regressive attention mask, but `<SENT_i>` tokens can only attend to past sentence tokens. Finally, as part of cross attention, non-sentence tokens in the decoder can attend to the entire input in the encoder, while sentence tokens in the decoder can only attend to sentence tokens in the encoder. This scheme is depicted in Figure 1.

This scheme encourages the model to use sentence token representations in the encoder to predict the next sentence token in the decoder via cross-attention. It also ensures that non-sentence tokens in the encoder provide relevant discourse information to their corresponding sentence tokens.

2.4 Loss Formulation

Let $Y = \{y_{1,1}, y_{1,2}, \ldots, y_{m,\text{len}(m)}\}$ be the target sequence, where each token $y_{i,j}$ belongs either to the span-masking task (non-sentence tokens) or to the sentence un-shuffling task (sentence tokens). We denote by $\hat{S}$ the set of all sentence tokens in Y. The model prediction is given by $\hat{Y} = \{\hat{y}_{1,1}, \hat{y}_{1,2}, \ldots, \hat{y}_{m,\text{len}(m)}\}$, where $\hat{y}_{i,j}$ represents the predicted probability distribution over the vocabulary for token $y_{i,j}$. Let the total number of tokens be $N = |Y|$.

The loss for DEPTH, which jointly optimizes the reconstruction (span-masking) and sentence un-shuffling tasks, is defined as the token-averaged cross-entropy:

$$L_{\text{DEPTH}} = -\frac{1}{N}\sum_{i=1}^{m}\sum_{j=1}^{\text{len}(i)} y_{i,j} \cdot \log \hat{y}_{i,j}$$

$$= \underbrace{-\frac{1}{N}\sum_{y_{i,j}\in Y\cap\hat{S}} y_{i,j} \cdot \log \hat{y}_{i,j}}_{\text{Sentence Loss}} \; \underbrace{-\frac{1}{N}\sum_{y_{i,j}\in Y\setminus\hat{S}} y_{i,j} \cdot \log \hat{y}_{i,j}}_{\text{Reconstruction Loss}}$$

In this formulation, the summation runs over all sentences in the input (i.e., up to m sentences, where $1 \leq m \leq k$), and within each sentence over its tokens. This allows us to decompose the model's performance into the contributions from the sentence un-shuffling and the span-masking tasks. We explore additional loss formulations and weighting schemes in Appendix B.1.

3 Experimental setup

The aim of our experiments is to measure the effectiveness of DEPTH against a standard encoder-decoder model. Accordingly, our experiments explore the learning dynamics of DEPTH model relative to a T5-Base (220M parameter) baseline. We pre-train both models on the C4 dataset (Raffel et al., 2020; Dodge et al., 2021) to resemble the manner in which the original T5 was trained (see additional reasoning in Appendix D.2). We chose to use Base-sized models given limited computational resources, and ease of reproducibility (following the example of Lee et al. (2020); Levine et al. (2020); Zhang et al. (2020); Raffel et al. (2020)). We did not use SLM as our baseline since its codebase and checkpoints are not released, and it cannot perform free-form text generation.

We chose to run our experiments without example packing since this is how the SLM model, which inspired DEPTH, was trained. Furthermore, example-packing in T5 enables unrelated examples to impact the model's decisions, thereby harming performance (Krell et al., 2021; Shi et al., 2024). While example-packing is critical for more computationally-efficient training (Ding et al., 2024), we were interested in measuring which model was able to use training examples more effectively. We examine the impacts of avoiding example packing in Appendix A.2.

Consistent with Nawrot (2023), we found that the Adafactor optimizer (Shazeer and Stern, 2018), while more computationally efficient, slightly harmed model performance. We therefore use AdamW (Loshchilov and Hutter, 2019) instead. We use a linearly increasing learning rate during the first $10,000$ steps, and then reduce the learning rate linearly for DEPTH (as in SLM), and with an inverse square learning rate ratio for T5 (as in the original T5 paper). We chose to use a masking probability of $p = 0.3$,[4] and an average span length of $\lambda = 3$. Our mask probability is higher than the advised 0.15 from T5 to accommodate for the fact that sentence-tokens within DEPTH cannot be masked.

We conduct two types of pre-training experiments:

1. **From Scratch (FS)**: Both T5 and DEPTH models are randomly initialized, and pre-trained on C4 with their respective objectives.

2. **Continuous Pre-Training (CPT)**: Both T5 and DEPTH models are initialized from the T5-Base checkpoint on HuggingFace (Wolf et al., 2019), and continue to pre-train on C4 with their respective objectives.

We note that our CPT experiments build on top of T5 models that have been trained for over 1T tokens, whereas the amount of tokens they see during continuous pre-training is relatively minuscule ($\approx$ 67$\times$ fewer tokens for T5, and $\approx$ 80$\times$ fewer tokens for DEPTH). We compare configurations of similar-sized models in Appendix D.1.

3.1 Fine-tuning experiments

We follow up our pre-training experiments with a collection of downstream tasks. We evaluate our models on natural language inference (MNLI, Williams et al. (2018)), sentiment analysis (SST2, Socher et al. (2013)), and grammar (CoLA, Warstadt et al. (2019)) within the GLUE benchmark (Wang et al., 2018). We also use the DiscoEval suite (Chen et al., 2019) to evaluate models on their understanding of discourse. We use two tasks from DiscoEval: Sentence Permutation (SP) and Discourse Coherence (DC). SP involves identifying the correct position of a removed, while DC involves predicting whether or not a paragraph was coherent. Finally, we measure our model's generative abilities on the Natural Instructions (NI) dataset (Mishra et al., 2022), which measures the ability of LMs to follow instructions, and served as a benchmark for NanoT5 (Nawrot, 2023).

[4] Raffel et al. (2020) reports that this span corruption ratio does not adversely impact downstream performance, although recently Ankner et al. (2024) suggested a dynamic masking rate tends to perform best.

Our experimental framework is inspired by Pythia (Biderman et al., 2023), which evaluates the performance of LMs on downstream tasks from intermediate checkpoints. We run evaluation with checkpoints from both T5 and DEPTH models, gathered at steps $\{2K, 4K, \ldots, 512K, 1M\}$ in order to examine these models' emergent capabilities. The exponential distance between these checkpoints allows us to scale intermediate checkpoint evaluation to much longer training runs.[5]

4 Results

4.1 C4 pre-training

During pre-training, we find that DEPTH consistently achieves a lower validation loss than a comparably trained T5 model. This is true for both FS and CPT. Furthermore, when we isolate the reconstruction loss (the objective used by T5, without sentence tokens), we find that DEPTH outperforms T5 despite balancing an additional pre-training objective (Figure 2 for FS and Figure 3 for CPT). These results are consistent with the findings in SLM, where their model converged faster, and on fewer tokens than models such as BERT and T5.

While we were not able to match the performance of the baseline model of Raffel et al. (2020) (see Appendix A for speculations on why), we have obtained the lowest loss scores among PyTorch implementations of T5 models. Specifically, in our FS setting, we find that our randomly initialized T5 model outperforms the validation loss of NanoT5, achieving 1.65 vs. 1.95 at step 64,000.

Figure 2: From Scratch Pre-Training loss (validation) for both T5 and DEPTH

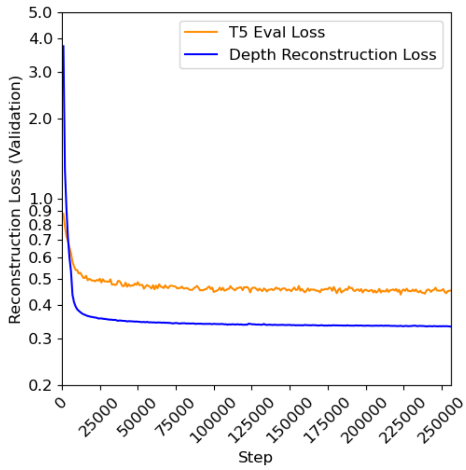


Figure 3: Continuous Pre-Training loss (validation) for both T5 and DEPTH.

4.2 GLUE fine-tuning

We found that over the course of FS pre-training, both models improved on GLUE tasks. However, T5's improvement pattern was slower than DEPTH's (top row of Figure 4). We found it difficult to replicate the results of the original T5 (both on GLUE tasks and the pre-training loss) as discussed in Appendix A. We project that with more substantial training (i.e., 1–3M pre-training steps, and ≥ 2048 examples per batch, as in T5), DEPTH could match or exceed the performance of T5 and SLM on downstream tasks.

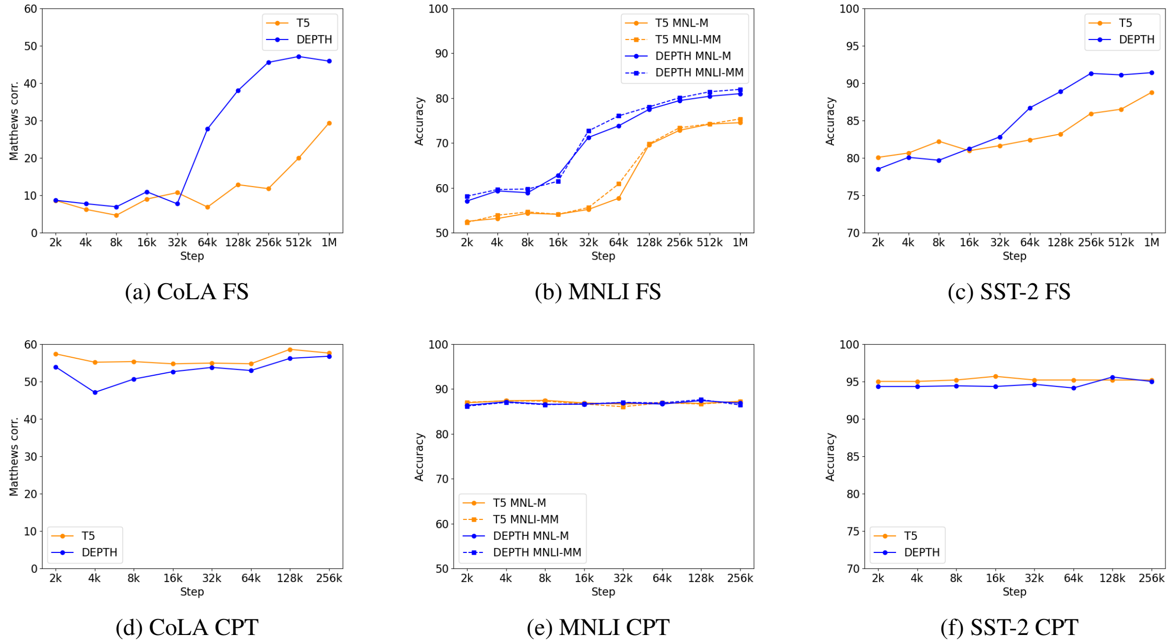
In the CPT setting (Figure 4, bottom row), we found that DEPTH and T5 perform similarly, both improving only slightly beyond the baseline. Fine-tuning DEPTH on early CPT checkpoints performs worse than fine-tuning comparable T5-CPT checkpoints. We speculate that this dip in performance is related to the change in objective from span-masking to span-masking *and* sentence unshuffling. We share our full results on GLUE in Appendix F.

4.3 DiscoEval fine-tuning

We find that in the FS setting DEPTH consistently outperforms T5 across DC tasks, indicating its robustness in understanding discourse [6] (Figure 5, top row). This suggests DEPTH's pre-training objective is particularly beneficial for tasks that require a deep understanding of narrative structures (both in conversations as in DC-Chat, and more formal and informative texts as in DC-Wiki). We note that between steps 32k and 64k, DEPTH ex-

[5] Evaluating intermediate checkpoint performance every 10,000 steps (as was done in Pythia) on datasets as large as MNLI is unfeasible with our limited computational resources.

[6] In particular, sentence-level discourse relations, as discussed in Jernite et al. (2017)



(a) CoLA FS (b) MNLI FS (c) SST-2 FS

(d) CoLA CPT (e) MNLI CPT (f) SST-2 CPT

Figure 4: GLUE results for FS and CPT models. Top row: From Scratch (FS), Bottom row: From Pretrained (CPT).

perienced a large positive boost in performance on DC-Wiki, perhaps indicative of an emergence (Wei et al., 2022b) of discourse understanding during this phase of pre-training. For T5, we found that the model struggled to learn the SP-Arxiv task, achieving random-guess accuracy late in pre-training. However, in SP-Wiki and SP-Rocstory, T5 improves in performances between steps 64k and 128k, perhaps indicating an emergent ability occurring within this timeframe. We report our full results on DiscoEval in Appendix G.

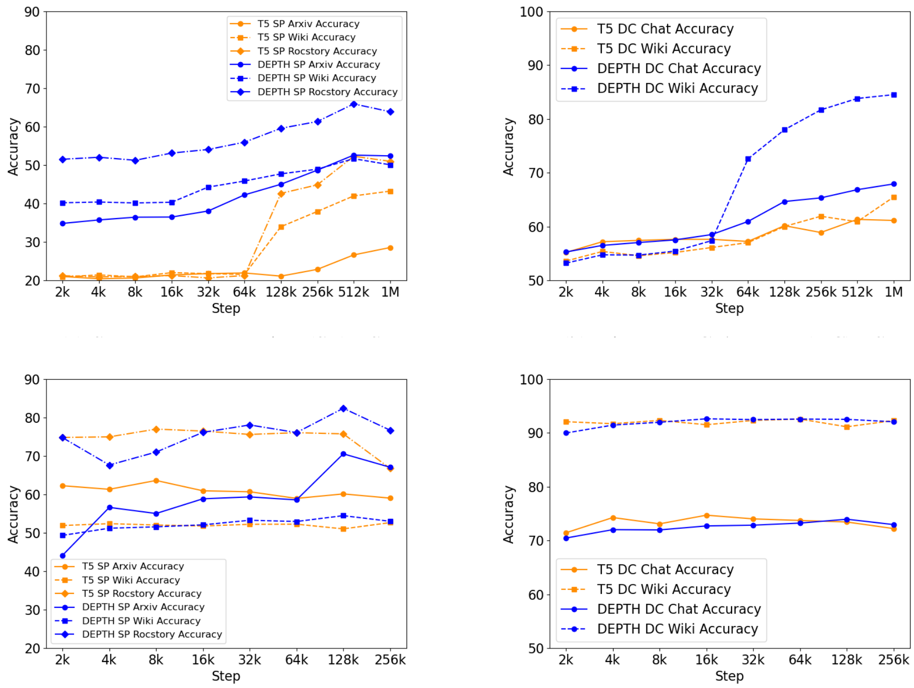
While DEPTH outperformed other models in DC tasks, it failed to reach a high performance level on SP tasks (under-performing relative to SLM, as seen in Table 1). This problem stems already from the pre-training stage, where DEPTH's sentence un-shuffling accuracy is relatively low ($\leq 5\%$ accuracy on shuffled sentence tokens; see Appendix B for additional details). This highlights the complexity of sentence un-shuffling relative to older discourse objectives like NSP and SOP. Surprisingly, while this task was challenging for DEPTH, SLM reported strong performance on sentence un-shuffling. SLM used a dedicated pointer-generator network that consists of a shallow DNN. This module "points" to one of at most k sentences as it iterates over a target sequence consisting of **only** sentence tokens. Also, SLM's non-sentence tokens cannot observe sentence-level tokens as part of the reconstruction loss, avoiding a potential "distraction" in their task.

Model	**SP**	**DC**
RoBERTa-Base	38.7	58.4
BERT-Base	53.1	58.9
BERT-Large	53.8	59.6
CONPONO	60.7	72.9
SLM (1M)	72.4	75.4
SLM (3M)	**73.4**	76.1
T5-Base	58.1	80.5
T5-FS	40.91	63.31
T5-CPT	59.48	<u>82.27</u>
DEPTH-FS	55.45	76.22
DEPTH-CPT	<u>65.59</u>	**82.49**

Table 1: Comparison of various models on the SP and DC tasks within DiscoEval. All models aside from T5 and DEPTH and encoder-only models trained with discourse-oriented objectives.

4.4 NI fine-tuning

In the FS setting (Figure 6a), we observe that DEPTH outperforms T5 in the NI benchmark, with a notable leap in performance between steps 16k and 32k. T5, by comparison, only improves significantly after step 64k, and obtains worse performance than DEPTH by the end of training. However, in the CPT setting (Figure 6b), DEPTH's pre-training appears to hinder downstream perfor-



(c) Sentence Permutation (SP) CPT

(d) Discourse Coherence (DC) CPT

Figure 5: DiscoEval results for DEPTH and T5 models. Top row: From Scratch (FS), Bottom row: From Pretrained (CPT).

mance compared to T5, possibly due to the domain shift from T5's pre-training task to DEPTH's pre-training task, which involves learning from shuffled inputs. We present a more complete analysis of these results in Appendix H.

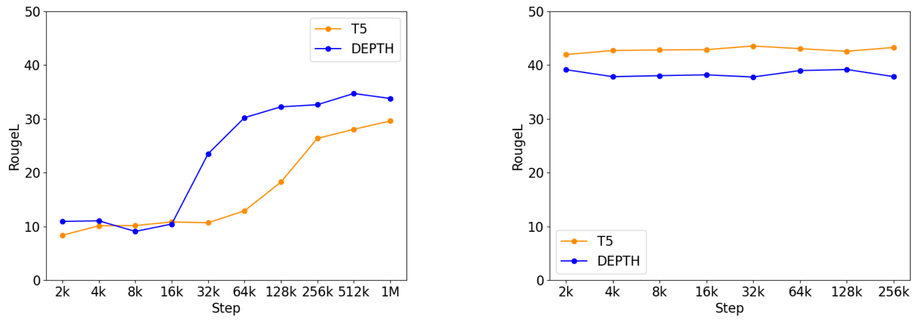
4.5 Error Analysis

We performed error analysis on the DiscoEval benchmark to better understand the nature of discourse errors that DEPTH and T5 made. For the SP task, we show in Table 3 that DEPTH made more reasonable mistakes than T5. For example, in SP-Arxiv FS, 23% of DEPTH's mistakes were reasonable, relative to 7% by T5). We define "reasonable" mistakes as incorrect predictions that would have still resulted in a coherent sentence ordering. Both models struggled with pronoun resolution, which frequently led to incorrect predictions (accounting for 10-30% of all predictions we observed). T5-FS, in particular, often failed to recognize when a removed sentence should come first, a mistake largely resolved in T5-CPT. We note that some examples correctly predicted by FS models were incorrectly predicted by CPT models, and vice versa.

In the DC task, we noted a significant number of incorrectly formatted predictions (e.g., "cooherent" rather than "coherent"), especially in the DC-Chat subset. Each of these incorrectly formatted predictions, when adjusted to a correctly formatted prediction, were incorrect (e.g., an example that the model predicted "cooherent" is labeled "incoherent"). We show in Table 4, that DEPTH-FS was incorrect in DC-Chat examples that humans might find ambiguous (i.e., replacing a random sentence leaves the resulting passage coherent), reinforcing its strength in handling more complex discourse structures. We discuss this further in Appendix E.

5 Related work

The potential of encoder-decoder architectures in today's NLP landscape cannot be overstated. These architectures dominate context-heavy tasks ranging from translation (Üstün et al., 2024; Xue et al., 2021; Tay et al., 2022) to summarization (Zhang et al., 2020; Guo et al., 2022; Tay et al., 2022), and even following instructions across diverse domains (Aribandi et al., 2022; Wei et al., 2022a; Chung et al., 2024). Like their decoder-only counterparts, encoder-decoders are able to accommodate long inputs (Guo et al., 2022), and scale effectively effectively as a function of model size and training data (Sutawika et al., 2024). Ormazabal et al. (2024) released a series of encoder-decoder models, where their dense 21B parameter model outperformed all models of its size in the lmsys



(a) Natural Instructions (NI) FS

(b) Natural Instructions (NI) CPT

Figure 6: NI results for DEPTH and T5 models.

benchmark (Zheng et al., 2023).[7] Encoder-deocder models are also strong multi-modal learners (Ormazabal et al., 2024; Wu et al., 2023; Dosovitskiy et al., 2021; Zhai et al., 2022). When scaled sufficiently, encoder-decoders like Reca-Core may be competitive with state of the art models like GPT-4 (OpenAI et al., 2023), Gemini (Team et al., 2023), and Claude-3.

While specialized encoder-decoder models such as PEGASUS (Zhang et al., 2020), DialogVED (Chen et al., 2022), and a multi-party dialogue pre-training model (Li et al., 2023) demonstrate the value of discourse-oriented tasks for encoder-decoder models, they have limited utility for broader tasks. Long-T5 (Guo et al., 2022) and UL2 (Tay et al., 2022) improved the ability of encoder-decoders to handle long contexts, but did not explicitly tackle discourse understanding. Flan-T5 (Wei et al., 2022a) and Ex-T5 (Aribandi et al., 2022) demonstrated the applicability of encoder-decoders across a variety of tasks, including ones that are heavily discourse dependent. However, these models depend on a vast yet costly annotated dataset to learn human preferences. Finally, BART (Lewis et al., 2020a) is an encoder-decoder which leverages sentence shuffling during pre-training, but does not train dedicated hierarchical representations for sentences (essentially behaving like a DEPTH model without sentence-tokens, and without attention-mask induced hierarchy).

6 Limitations

Given our lack of computational resources (Appendix C), we were not able to pre-train our models with a batch size that would allow an aggressive learning rate like that used in Raffel et al. (2020)'s T5 (see Appendix A for additional details). We also pre-trained on substantially fewer tokens than T5. As a result, our model converges to a worse loss during pre-training, and performs worse on downstream tasks. We also lacked computational resources to compute confidence intervals or statistical significance for our downstream experiments.[8]

Encoder-decoder LMs have fewer tools available for computationally efficient pre-training. For example, FlashAttention (Dao et al., 2022; Dao, 2023), which provides a massive training speedup, is not available for encoder-decoder models. It is therefore difficult to create scalable pre-training experiments with new encoder-decoder architectures and objectives.

7 Conclusions and future work

DEPTH's new pre-training objective and hierarchical representations complement efforts to scale model size, parallelize architectures, and acquire high quality data for pre-training. Despite training over fewer tokens, DEPTH significantly outperformed T5 both during pre-training and during fine-tuning. DEPTH's remarkably efficient learning and downstream performance on discourse oriented tasks underscore the importance of discourse-oriented pre-training.

Looking forward, the application of DEPTH to RAG (Lewis et al., 2020b), especially over sentence "chunks", presents an exciting avenue for future research. Additionally, extending DEPTH's pre-training objectives to encompass higher-level discourse units—such as paragraphs, chapters, and

[7]This Reka model is competitve with mixtral 8x22b (Jiang et al., 2024) (which was trained with significantly more parameters using a mixture-of-experts architecture).

[8]Running a single downstream experiment on MNLI takes 5-7.5 hours. We run $\approx$ 120 experiments for each of 10 benchmarks, and do not have the capacity to repeat experiments $\geq 5\times$ to obtain statistical significance.

whole documents—offers further flexibility emerging hierarchical RAG systems (Chen et al., 2024). Moreover, conducting further experiments with larger DEPTH models is helpful for understanding the scalability of discourse-focused training objectives. Such investigations could reveal whether the promising capabilities observed in DEPTH are amplified with increased model capacity. Finally, sentence-level pre-training tasks such as next-sentence prediction (as in Krishna et al. (2022) and Zhang et al. (2020)) may prove powerful alternatives to sentence un-shuffling.

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A Challenges in replicating T5

A.1 Our speculations

We recognize that both DEPTH and T5 CPT models quickly reach a significantly lower reconstruction loss than their FS counterparts. While the original T5's reached a final training loss of ≈ 0.75 (with 512k steps of batch size 128 with packing) (Raffel et al., 2020), our training loss reached ≈ 0.8 (after 800k steps of batch size 200 without packing). We propose the following ideas to explain this gap:

1. The baseline model from which CPT models are initialized is trained on 1T tokens. This is $\approx 20\times$ greater than the amount of tokens we used to train FS models.

2. Our examples never consist of the later text in long documents. By truncating text after 512 tokens, our FS models might miss out on valuable text to train on.

3. Our training examples consists of $\approx 2\times$ fewer tokens (on average) than examples the original T5 was trained on. Furthermore, there is much greater variance in example lengths in our pre-training experiments. These factors may impact our models' learning dynamics (e.g., learning effective positional representations given the presence of irregular padding patterns).

4. The T5 baseline plot was reported using a masking probability of 0.15, which is $2\times$ lower than the one we used. Our higher masking probability makes the reconstruction task more challenging.

5. T5 models using the T5x framework use aggressively high learning rates, which can lead to a different, and perhaps more effective training dynamics than the ones we found in our FS experiments. Using such high learning rates in our settings caused our models to diverge.

A.2 Example packing

Given our choice of avoiding example-packing, we found that we were not able to pre-train T5 with the same hyper-parameters used in (Raffel et al., 2020). Specifically, we found that with a batch size of 128 and a learning rate of $1e^{-2}$, our model consistently diverged. This issue persisted with a learning rate of $1e^{-3}$. To stabilize our loss given the absence of packing, we used a lower maximum learning rate ($1e^{-4}$), which is in line with those used to pre-train BERT, SLM, and PMI. On the other hand, we see that given the same training parameters (i.e., learning rate and batch size), pre-training with packing can converge at a high learning rate (see Figure 7).

We speculate that packing acts in a similar way to increasing the batch size during training. The model is exposed to loss on a greater amount of tokens in each optimization step, and is therefore able to generalize even with a larger learning rate.

One possible side effect of avoiding example-packing is the truncation of long examples (examples are not dynamically chunked, so every token past the context limit of 512 is ignored). We empirically find that while T5 suffers greatly from no packing, DEPTH is able to train effectively despite these limitations.

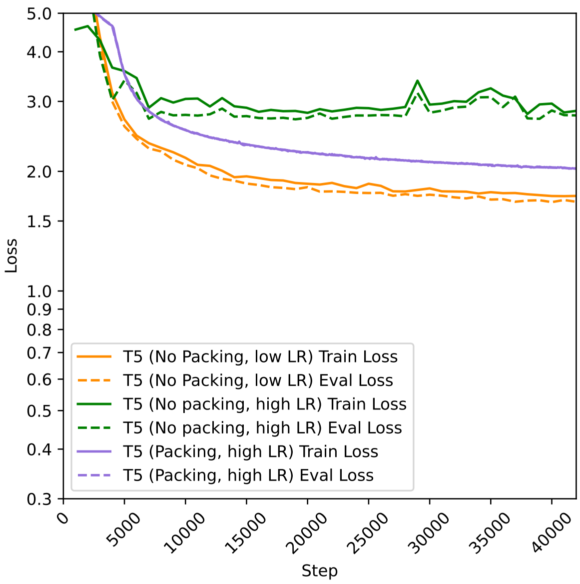

Figure 7: Exploration of packing and learning rates when pre-training T5 models. "High LR" corresponds to a learning rate of $1e^{-2}$, while "Low LR" corresponds to a learning rate of $1e^{-4}$.

B DEPTH loss decomposition

When we decompose DEPTH's losses in the FS setting, we find that sentence loss is consistently lower than reconstruction loss, but plateus early on into training. The overall loss is dominated by the reconstruction loss, reflected by overlapping lines in Figure 8. In the CPT setting (Figure 9), we find that both of DEPTH's losses plateu sooner, and that the sentence loss is approximately equal (though with higher fluctuations) to the reconstruction loss.

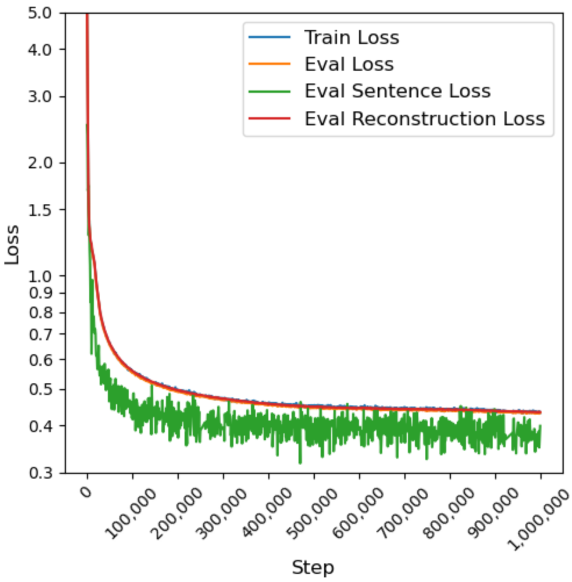

Figure 8: Decomposition of from-scratch pre
losses (validation) for DEPTH.

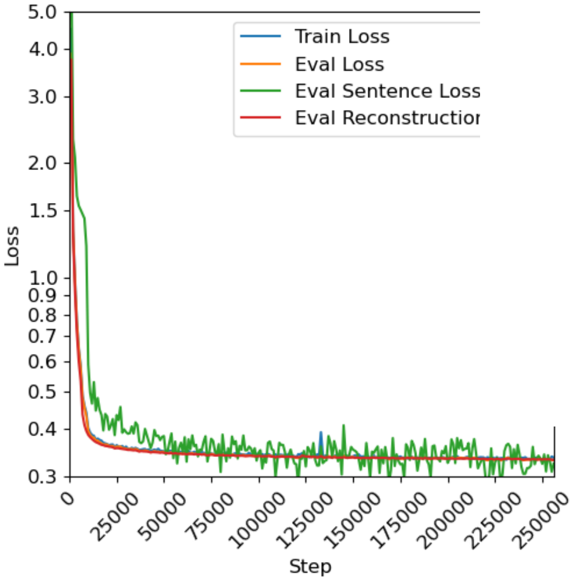

Figure 9: Decomposition of continuous pre-training losses (validation) for DEPTH

We note that DEPTH's loss over sentence tokens in the FC setting, is close to that which the DEPTH-CPT achieved (both in the range of 0.3-0.4, where the more examples are shuffled, the higher the sentence loss). In practice, given comperable ratios of shuffling sentences, CPT DEPTH outperforms FS DEPTH in predicting the next sentence accurately during pre-training ($\approx 1\% - 3\%$ higher given a fixed shuffling ratio). We speculate that the better representations for non-sentence tokens in the CPT setting is the reason for this performance boost.

B.1 Weight of sentence loss

We explored the impact of increasing the weight of the sentence loss during DEPTH pre-training. Our "Baseline" run is the DEPTH model we reported on in the main body of the paper. In our "Sentence Weight 1x" run, our loss is composed of the average loss over sentence tokens plus the average loss over non-sentence tokens (as opposed to the average loss over all tokens). This formulation places increased weight on sentence tokens, since there are significantly fewer sentence tokens than non-sentence tokens. In the "Sentence Weight 5x" run, we weighed the sentence loss $5\times$ more than reconstruction loss.

We found that increasing the weight of this loss had minimal impact on the model's accuracy in predicting sentence tokens, and adversely harmed the model's loss (see Figure 10).

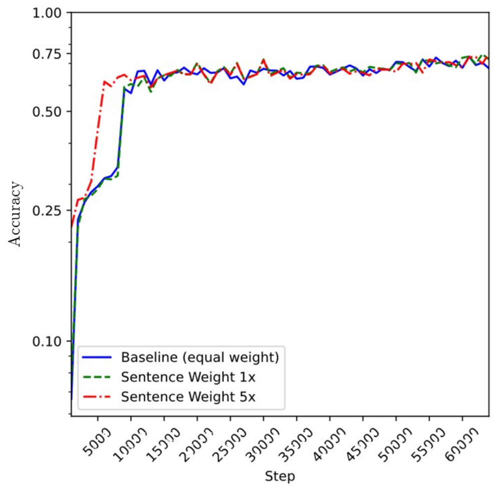

Figure 10: We explore the impact of weighing sentence loss more than reconstruction loss, and find that it has minimal impact beyond early stages of pre-training.

C Computational resources

We utilize 4 A40 GPUs, and 64 CPUs for training. We use a batch size of 200, since it helps us achieve much better GPU memory utilization. We leverage 16 CPUs for each GPU in order to increase the data loading time to accommodate for DEPTH's more-complex corruption method, and to allow effective optimizer offloading with DeepSpeed Zero2 (Rajbhandari et al., 2020).

D Pre-training considerations

D.1 Pre-training scale

In Table 2 below we show the relative magnitude of DEPTH's pre-training. Specifically, we compare the number of observed tokens and optimization steps of our T5 and DEPTH models to comparably sized models (such as SLM, BERT, and RoBERTa). We highlight that the models we independently pre-trained (bottom 4 rows of the table) observed far fewer tokens than comparable LMs.

D.2 Pre-training data

The rationale behind selecting C4 extends beyond its sheer volume and diversity. Given DEPTH's architectural roots in the T5 model, which was originally pre-trained on C4, leveraging the same dataset facilitates a direct comparison of the enhancements our model introduces. This baseline compatibility is crucial for isolating the effects of our architectural and methodological innovations on the model's performance. Furthermore, C4 is a subset of both Dolma (Soldaini et al., 2024) and RedPajama (Computer, 2023). These datasets were used to train the most capable fully-open-source LMs (with released data) to date: OLMO (Groeneveld et al., 2024) and LLama (Touvron et al., 2023) respectively. This suggests that C4 is an effective component in pre-training effective LMs, and offers multiple additional datasets components that would be new to our model for future training. Finally, Muennighoff et al. (2023) suggest that pre-training over the same data up to 4× still improves model performance, while (Raffel et al., 2020)'s model has not completed even one full iteration over the C4 dataset. This hints at the viability of continuing to pre-train T5 on the same dataset it was already pre-trained on.

E Error Analysis

We select randomly select 30 examples from each task in DiscoEval, and manually inspect the nature of our models' errors. For example, in the SP task, we were interested in observing if a model tended to misunderstand clues from pronouns or transitions. For both DC and SP, we were also counted the number of examples where a human might find the LLM's answer reasonable (given the human-perceived coherence of the example).

E.1 Sentence Position

Consistent with the macro-level results from our DiscoEval fine-tuning experiments, DEPTH generally performs better in FS than T5. However, in the CPT setting, while DEPTH shows better reasoning in some cases, T5-CPT outperforms it, particularly on simpler tasks like SP-Wiki and SP-Rocstory, likely benefiting from more consistent pretraining. DEPTH's greater number of reasonable mistakes indicates its strength in engaging with complex discourse structures, but pronoun resolution and transition errors remain areas for further improvement.

Given the 30 examples we've sampled, we categorize the types of errors our models tend to make. An error type is a reason by which a person might be able to infer the correct label. If the model predicts incorrectly given an "obvious" hint (e.g. introducing an entity that is referenced via a pronoun), then we categorize the error type based on that hint. In Table 3 we show the counts of error types that each model made on each subset of SP.

E.2 Discourse Coherence

We found that in the Discourse Coherence (DC) subset, both models were strictly incorrect by predicting poorly formatted outputs. Each of the poorly formatted predictions was incorrect (e.g., if the model predicted "cooherent" instead of "coherent", the correct label was "incoherent"). We analyze the ratio of these types of predictions on DC in Table 4. Further, we find that in DC-Chat, both models tend to make errors that a human might find reasonable. This implies that the augmentation on the input example (i.e., replacing one if the sentences in the paragraph with another one) did not adversely impact the example's coherence. Strangely, we found that FS models predicted more correct outputs than their CPT counterparts. This may be the result of selecting a too small a sample-size of examples to analyze.

F GLUE results

In this section we show the full results from our downstream experiments on GLUE tasks. Table 5 is reflected in the top row (FS) of Figure 4, while Table 6 is reflected in the bottom row (CPT) of figure 4. Consistent with our hypothesis, we found that both DEPTH and T5 improve across downstream tasks as a function of the pre-training steps they've

Model	Tokens	Steps	Batch Size	# Params	Learning Rate
SLM-1M	$125B$	$1M$	256	$\approx 110M$	$1.5e^{-4}$
SLM-3M	$375B$	$3M$	256	$\approx 110M$	$1.5e^{-4}$
BERT-Base	$137B$	$1M$	256	$\approx 110M$	$1e^{-4}$
BERT-Large	$137B$	$1M$	256	$\approx 340M$	$1e^{-4}$
RoBERTa-Base	$2.2T$	$500k$	8000	$\approx 110M$	$1e^{-4}$
CONPONO (*)	-	$256k$	256	$\approx 110M$	$1e^{-4}$
T5-Base	$1T$	$1M$	2048	$\approx 220M$	$1e^{-2}$
T5-FS	$58.6B$	$1M$	200	$\approx 220M$	$1e^{-4}$
T5-CPT (*)	$15B$	$256k$	200	$\approx 220M$	$1e^{-4}$
DEPTH-FS	$48.9B$	$1M$	200	$\approx 220M$	$1e^{-4}$
DEPTH-CPT (*)	$12.5B$	$256k$	200	$\approx 220M$	$1e^{-4}$

Table 2: Hyper-parameters of comparable models to DEPTH. We show published hyper-parameters in the top rows of the table, and the models we train ourselves in the bottom of the table. We mark all models initialized from publically released pre-training models with (*). Note that CONPONO did not report the number of tokens it pre-trained on, so we exclude that value from the table above.

Dataset	Model	0	1	2	3	4
SP-Wiki CPT	T5	0.57	0.07	0.23	0.13	0.07
	DEPTH	0.57	0.03	0.23	0.2	0.03
SP-Wiki FS	T5	0.57	0.07	0.23	0.13	0.07
	DEPTH	0.57	0.03	0.23	0.2	0.03
SP-Arxiv CPT	T5	0.63	0.07	0.2	0.1	0
	DEPTH	0.57	0.13	0.2	0.1	0
SP-Arxiv FS	T5	0.37	0.23	0.3	0.07	0.03
	DEPTH	0.43	0.1	0.3	0.23	0
SP-Rocstory CPT	T5	0.77	0.07	0.1	0.07	0
	DEPTH	0.57	0.13	0.2	0.1	0
SP-Rocstory FS	T5	0.47	0.2	0.27	0.07	0
	DEPTH	0.6	0.2	0.13	0.07	0

Table 3: Approximate ratio of prediction types for SP-Wiki, SP-Arxiv, and SP-Rocstory across T5 and DEPTH models in FS and CPT settings. There are 30 total examples. Each prediction over these examples is categorized into one of 5 prediction types: 0 - Correct prediction, 1 - Incorrect (hint from transitions), 2 - Incorrect (hint from pronoun), 3 - Incorrect (reasonable error), 4 - Incorrect (hint from punctuation).

taken. While DEPTH outperforms T5 across all tasks is the FS setting, it did not reach the scores of Raffel et al. (2020)'s T5 model. In the CPT setting, T5 and DEPTH perform quite comparably. In fact, in the penultimate checkpoint (128k) we found that DEPTH outperformed T5 on all tasks except for CoLA.

G DiscoEval results

In this section we show the full results from our downstream experiments on discourse tasks from

Dataset	**Model**	**0**	**1**	**2**
DC-Wiki-FS	T5	0.87	0.32	0.00
	DEPTH	0.87	0.13	0.00
DC-Wiki-CPT	T5	0.80	0.08	0.00
	DEPTH	0.83	0.08	0.00
DC-Chat-FS	T5	0.60	0.42	0.17
	DEPTH	0.63	0.35	0.23
DC-Chat-CPT	T5	0.83	0.30	0.10
	DEPTH	0.77	0.29	0.07

Table 4: Prediction types for models and dataset splits. 0: Correct predictions (Type 0), 1: Poorly formatted predictions (Type 1), 2: Reasonable errors (Type 2).

the DiscoEval benchmark. In Table 7, we show the full results of our models in the FS setting, while in Table 8 we show the full results of our models in the CPT setting. These tables reflect the top and bottom row of Figure 5 respectively.

In the FS setting, we found that DEPTH's wins over T5 are even more pronounced in DiscoEval than they were in GLUE. Specifically, T5 struggles to learn discourse tasks (especially SP) during early stages of pre-training. On the other hand, DEPTH was highly effective in discourse tasks already from early pre-training checkpoints. In the CPT setting, we found that DEPTH still outperformed T5, despite the fact that the original checkpoint was pre-trained substantially with a different objective.

Model	CoLA	SST-2	MNLI	
			Matched	*Mismatched*
T5-Base @ 0 (Test)	12.3	80.62	68.02	68.0
T5-Base @ 1M (Test)	53.84	92.68	84.24	84.57
T5-Base @ 1M (Val)	53.98	94.73	87.28	87.1
T5 @ 2k	8.62	80.08	52.54	52.3
DEPTH @ 2k	8.67	78.52	57.07	58.14
T5 @ 4k	6.23	80.66	53.16	53.89
DEPTH @ 4k	7.75	80.08	59.31	59.62
T5 @ 8k	4.66	82.23	54.33	54.62
DEPTH @ 8k	6.93	79.69	58.92	59.73
T5 @ 16k	8.99	80.96	54.1	54.1
DEPTH @ 16k	10.94	81.25	62.79	61.46
T5 @ 32k	10.72	81.64	55.18	55.6
DEPTH @ 32k	7.73	82.81	71.23	72.7
T5 @ 64k	6.86	82.42	57.68	60.88
DEPTH @ 64k	27.78	86.72	73.84	76.05
T5 @ 128k	12.85	83.2	69.61	69.82
DEPTH @ 128k	38.01	88.87	77.5	78.06
T5 @ 256k	11.78	85.94	72.82	73.39
DEPTH @ 256k	45.57	91.31	79.45	80.07
T5 @ 512k	19.96	86.52	74.22	74.26
DEPTH @ 512k	47.14	91.11	80.42	81.43
T5 @ 1M	29.35	88.77	74.53	75.37
DEPTH @ 1M	45.91	91.41	81.0	81.96

Table 5: GLUE benchmark results for From Scratch (FS). Note that the first two rows are reported by Raffel et al., 2019, while all later rows are the best reported results on the validation set across 3 attempted learning rates.

H NI results

In the from-scratch setting (Figure 6a and Table 9), we observe that DEPTH outperforms T5 in the NI benchmark, with a notable leap in performance between steps 16k and 32k. This indicates that DEPTH's pre-training objective is more effective at learning representations that are beneficial for the NI task. However, at steps 2k, 8k, and 16k, DEPTH underperforms compared to T5, suggesting that the benefits of DEPTH's pre-training objective may not be immediately apparent in the early stages of training.

However, in the continuously pre-trained setting (Figure 6b and Table 10), we find that DEPTH's pre-training harms downstream performance compared to T5. Additionally, we observe that CPT models are less sensitive to learning rate and can train effectively across a wider range of learning rates, with the exception of DEPTH in the early stages of CPT, where it is adapting to a task that differs from its initial pre-training. This robustness to learning rate is a positive property that the FS models did not exhibit, likely due to limitations in training scale (e.g., small batch size, avoiding packing, and training on fewer tokens overall). Furthermore, early in the CPT process, DEPTH's performance is somewhat unstable, possibly due to the domain shift from T5's pre-training task to DEPTH's pre-training task. Interestingly, lower learning rates perform worse for DEPTH after CPT, suggesting that the model needs to adjust its representations more substantially to adapt to the downstream task.

Model	**CoLA**	**SST-2**	**MNLI**	
			Matched	*Mismatched*
T5-Base @ 1M (Test)	53.84	92.68	84.24	84.57
T5-Base @ 1M (Val)	53.98	94.73	87.28	87.1
T5 @ 2k	57.41	95.02	86.93	87.06
DEPTH @ 2k	53.93	94.34	86.38	86.2
T5 @ 4k	55.18	95.02	87.4	87.34
DEPTH @ 4k	47.11	94.34	87.14	87.01
T5 @ 8k	55.35	95.21	87.47	87.31
DEPTH @ 8k	50.67	94.43	86.62	86.52
T5 @ 16k	54.75	95.7	86.91	86.67
DEPTH @ 16k	52.65	94.34	86.62	86.67
T5 @ 32k	54.95	95.21	86.64	86.06
DEPTH @ 32k	53.79	94.63	86.95	87.02
T5 @ 64k	54.77	95.21	86.96	86.93
DEPTH @ 64k	52.95	94.14	86.65	86.91
T5 @ 128k	58.62	95.21	86.79	86.67
DEPTH @ 128k	56.21	95.61	87.42	87.64
T5 @ 256k	57.62	95.21	87.27	87.22
DEPTH @ 256k	56.78	95.02	86.86	86.45

Table 6: GLUE benchmark results for Continuous Pre-Training (CPT). As in the FS setting, we report our results on the validation set after a hyper-parameter sweep over 3 learning rates.

Model		**SP**		**DC**	
	Arxiv	*Wiki*	*Rocstory*	*Chat*	*Wiki*
Baseline T5 @ 1M	52.76	51.07	70.58	68.99	92.09
T5 @ 2k	21.0	20.9	21.2	55.18	53.59
DEPTH @ 2k	34.81	40.19	51.51	55.27	53.2
T5 @ 4k	20.4	21.4	20.9	57.18	55.37
DEPTH @ 4k	35.72	40.38	52.03	56.49	54.74
T5 @ 8k	20.6	20.9	21.0	57.42	54.57
DEPTH @ 8k	36.43	40.14	51.25	57.03	54.69
T5 @ 16k	21.4	22.0	21.24	57.62	55.18
DEPTH @ 16k	36.47	40.33	53.13	57.52	55.44
T5 @ 32k	21.75	21.75	20.63	57.62	56.1
DEPTH @ 32k	38.04	44.26	54.05	58.5	57.37
T5 @ 64k	21.92	21.53	21.24	57.23	57.01
DEPTH @ 64k	42.24	45.85	55.96	60.94	72.58
T5 @ 128k	21.09	33.96	42.63	60.16	60.01
DEPTH @ 128k	45.0	47.71	59.57	64.65	78.0
T5 @ 256k	22.85	37.92	44.85	58.89	61.91
DEPTH @ 256k	48.68	48.93	61.33	65.33	81.69
T5 @ 512k	26.61	41.97	52.29	61.33	60.89
DEPTH @ 512k	52.59	51.66	65.92	66.85	83.81
T5 @ 1M	28.54	43.22	50.98	61.13	65.48
DEPTH @ 1M	52.39	50.07	63.89	67.92	84.52

Table 7: DiscoEval Downstream Full Training (FS) Results

Model		SP		DC	
	Arxiv	**Wiki**	**Rocstory**	**Wiki**	**Chat**
T5 @ 2k	62.26	51.9	74.83	92.09	71.44
DEPTH @ 2k	44.14	49.34	74.78	89.99	70.46
T5 @ 4k	61.33	52.39	74.98	91.72	74.27
DEPTH @ 4k	56.62	51.2	67.65	91.46	72.02
T5 @ 8k	63.63	52.03	77.0	92.33	73.1
DEPTH @ 8k	55.03	51.56	71.02	91.99	71.97
T5 @ 16k	60.94	51.78	76.49	91.53	74.71
DEPTH @ 16k	58.86	52.08	76.15	92.63	72.71
T5 @ 32k	60.69	52.22	75.61	92.33	74.02
DEPTH @ 32k	59.35	53.27	78.08	92.48	72.85
T5 @ 64k	58.96	52.25	76.07	92.58	73.73
DEPTH @ 64k	58.57	52.95	76.1	92.58	73.24
T5 @ 128k	60.13	51.03	75.76	91.14	73.44
DEPTH @ 128k	70.56	54.77	82.42	92.53	73.96
T5 @ 256k	59.03	52.66	66.77	92.31	72.22
DEPTH @ 256k	67.07	53.0	76.71	92.07	72.9

Table 8: DiscoEval Downstream Continuous Pre-Training (CPT) Results

Model	Step	RougeL
Baseline T5	1M	42.48
T5	2k	8.36
DEPTH	2k	10.92
T5	4k	10.11
DEPTH	4k	11.03
T5	8k	10.15
DEPTH	8k	9.06
T5	16k	10.82
DEPTH	16k	10.43
T5	32k	10.68
DEPTH	32k	23.51
T5	64k	12.89
DEPTH	64k	30.23
T5	128k	18.24
DEPTH	128k	32.24
T5	256k	26.36
DEPTH	256k	32.63
T5	512k	28.05
DEPTH	512k	34.72
T5	1M	29.6
DEPTH	1M	33.8

Table 9: NI benchmark results for From Scratch (FS) pre-training. The first row reports the performance of the baseline T5 model, while all later rows show the best reported results on the validation set across 3 attempted learning rates.

Model	Step	NI RougeL
T5	2k	41.96
DEPTH	2k	39.15
T5	4k	42.72
DEPTH	4k	37.85
T5	8k	42.83
DEPTH	8k	38.04
T5	16k	42.88
DEPTH	16k	38.19
T5	32k	43.56
DEPTH	32k	37.79
T5	64k	43.06
DEPTH	64k	38.99
T5	128k	42.58
DEPTH	128k	39.19
T5	256k	43.29
DEPTH	256k	37.86

Table 10: NI benchmark results for Continuous Pre-Training (CPT). All rows show the best reported results on the validation set across 3 attempted learning rates.