# Pretraining Language Models for Diachronic Linguistic Change Discovery

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#### **Abstract**

Large language models (LLMs) have shown potential as tools for scientific discovery. This has engendered growing interest in their use in humanistic disciplines, such as historical linguistics and literary studies. These fields often construct arguments on the basis of delineations like genre, or more inflexibly, time period. Although efforts have been made to restrict inference to specific domains via fine-tuning or model editing, we posit that the only true guarantee is domain-restricted pretraining—typically, a data- and compute-expensive proposition.

We show that efficient pretraining techniques can produce useful models over corpora too large for easy manual inspection but too small for "typical" LLM approaches. We employ a novel date-attribution pipeline in order to obtain a temporally-segmented dataset of five 10-million-word slices. We train two corresponding five-model batteries over these corpus segments, efficient pretraining and Llama3-8B parameter efficiently finetuned.

We find that the pretrained models are faster to train than the finetuned baselines and that they better respect the historical divisions of our corpus. Emphasizing speed and precision over a-historical comprehensiveness enables a number of novel approaches to hypothesis discovery and testing in our target fields. Taking up diachronic linguistics as a testbed, we show that our method enables the detection of a diverse set of phenomena, including en masse lexical change, non-lexical (grammatical and morphological) change, and word sense introduction/obsolescence. We provide a ready-to-use pipeline that allows extension of our approach to other target fields with only minimal adaptation.

#### 1 Introduction

Certain fields of study invest heavily in the epistemological importance of boundaries that demarcate their objects of study into groups. These distinctions range from those as straightforward as the arrow of time (e.g. diachronic change in linguistics) to those derived from traditional means of practice (e.g. specific forms of poetry in literary studies).<sup>1</sup>

Such methodological investments are somewhat at odds with the dominant modern technology for language research, pretraining large language models (LLMs). LLMs are at least in part successful due to their omnivorous nature (Kaplan et al., 2020), they develop general skills by consuming as diverse and as large a corpus as possible (Polo et al., 2024). Our target fields are inherently characterized by both limited data and specific interest—in the case of our particular exemplar field, diachronic linguistics, in language rather than general model capability. Whether desirable or not, LLMs have some limited ability to divide information

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(for example, produce a haiku and not a limerick in a zero-shot setting) (Cheng et al., 2024; Ifergan et al., 2024). However, prompting or other information elicitation techniques offer little immediate evidence that a particular generation or string likelihood evaluation was performed using only knowledge appropriate to the desired period or division. The most convincing solution to this problem is also the most straightforward. To ensure a model's weights contain no "out of domain" information, you must simply train your own model on a restricted corpus of your own choosing.

We show that pretraining under a tight academic budget of data (and compute) proves surprisingly effective when performed using the efficient methods provided by the BabyLM challenge community (Hu et al., 2024). Although those techniques are designed for data efficiency and cognitively-plausible pretraining, we find that BabyLlama-2 (Tastet & Timiryasov, 2024) is also an efficient and effective recipe for academic pretraining.

To leverage this efficiency, we develop a multiple-model approach that shifts the paradigm of diachronic linguistics research by offering access to corpus-level hypotheses concerning lexical change, non-lexical (grammatical and morphological) change, and word sense introduction/obsolescence that were previously obscure or unavailable. Specifically, we train a series of 5 models each with a pretraining dataset of 10 million tokens drawn from consecutive historical periods. We evaluate these pretrained models, as well as larger models finetuned on the same data slices, using standard metrics and evaluation sets. Moreover, as pretraining contrastive LLMs presents a new paradigm, we showcase its potential with a novel word-sense preference evaluation set, qualitative analysis and use case examples. We find that:

- Our models train nearly two times faster than DoRA finetuned models while retaining adequate performance for many tasks
- 2. The finetuned models "leak" information across time periods in a way that our models do not, jeopardizing tasks such as lexical sense-change analysis that require precise boundaries
- 3. When properly utilized, our full battery of models can be used to generate hypotheses about grammatical and lexical change across our corpus
- 4. This technique is likely useful to multiple domains, and can be adopted for automated hypothesis discovery in other fields.

## 2 Related work

Multiple works suggest that LLMs could serve linguistic studies in flexible ways not imagined before (Warstadt & Bowman, 2022), such as simulating human subject responses (Wilcox et al., 2020; Trott, 2024; Aher et al., 2022) or modeling language acquisition (Hu et al., 2024; Warstadt et al., 2023). We draw upon this thinking, calling for pretraining as a now feasible and promising way of contrasting corpora and aiding linguist queries, broadly, and specifically in semantic change. Lexical semantic change is an entire field dedicated to finding words that changed in meaning, those often do use an LLM, albeit not a causal LLM (Periti & Montanelli, 2024). As such works use existing LLMs a large part of the field is dedicated to processing and aligning those embeddings (Schlechtweg et al., 2020). We know of no work utilizing LLM automation to aid morphological, grammatical, orthographical and other linguistic changes beyond lexical semantic change. In that sense, our work is distinct from previous works.

# 2.1 Efficient finetuning

Increased finetuning costs have lead to the development of parameter-efficient rank-adaptor finetuning techniques like LoRA (Hu et al., 2022) and DoRA (Liu et al., 2024). As these techniques are the most similar in compute and token demands to our approach we use DoRA finetuning to set our baseline.

## 2.2 Domain-specific language modeling

Previous approaches to domain specific modeling that employ embedding models have typically chosen BERT-like architectures, and have employed finetuning (Hosseini et al., 2021; Qiu & Xu, 2022) and pretraining (Beck & Köllner, 2023; Manjavacas & Fonteyn, 2022). However, beyond being non-causal, these strategies employ large sets of data, limiting their ability to be adapted for smaller domains of interest. One project trains a recent-history-aware (2011 to 2022) model on GPT2, but does so in order to detect knowledge-level analogies rather than provide a methodological lever, and also employs a large dataset (Drinkall et al., 2024).

## 2.3 Evaluating and guaranteeing historically-specific model knowledge

Datasets for evaluating diachronic model knowledge have previously focused on historical performance, both linguistic (Manjavacas & Fonteyn, 2022) and at the level of knowledge (Dhingra et al., 2022; Piryani et al., 2024) , with these latter sets typically being structured in QA form.

# 3 Experiments

## 3.1 Setup

**Training data.** We employ a multistage pipeline to prepare time-bound slices for pretraining. This pipeline integrates three sources to accurately estimate the publication date of each document found in the Project Gutenberg collection. (1) Author information sourced from WikiData, WD (2) Work metadata found in the Project Gutenberg Catalog, PGC (3) Inference performed by LLMs

We first define a historical range that will structure our inquiry, the years 1750-1940, inclusive. We use a fuzzy string matching system, described in Appendix B, to align authors to works.

We acquire final publication dates for each author-associated work collected in the previous fuzzy matching step by prompting an instruction-tuned LLM. In order to evaluate the efficacy of this work-date attribution approach, we selected a variety of open- and closed-source LLMs and calculated performance against a gold-annotated test set consisting of a set of works published from 1550-1850. While the closed-source LLMs perform best, Llama3.3-70B (Grattafiori et al., 2024), quantized to 4 bits using the BitsAndBytes library Belkada et al. (2023) performs well enough to justify its use (see Appendix B for details of the evaluation process). We prompt this model to provide a date of writing for each of the PG works for each author in the set produced by the fuzzy author matching stage.

Finally, we split this corpus into 5 sections using the date information generated by the previous step. We set the boundaries for these slices by negotiating between ideal *a priori* boundaries (say, 50 years or 30 years) and our desire to obtain 10 million training tokens for each split. We further reserve 5 million tokens for testing and 1 million for validation during training. This results in 5 equal subcorpora for the time periods 1750-1820, 1820-1850, 1850-1880, 1880-1910, and 1910-1940.

#### 3.2 Procedure

**Model training.** We employ two training approaches over each split of the historical data: (1) finetuned models adapted from a larger pretrained model, and (2) pretrained models trained solely on the small historical datasets.

We train the finetuned models using DoRA adapters on top of a Llama3 8B backbone. We train our experiment pretrained models using the BabyLlama-2 recipe, which employs a distillation approach. Ultimately, pretraining the BabyLlama-2 models was quicker and more efficient than the DoRA finetuning process. More details regarding the training procedures can be found in Appendix A.

#### 3.3 Evaluation

We evaluate the trained BabyLlama-2 models ("pretrained"), DoRA models ("finetuned"), and two baseline LLMs (The pretrained versions of BabyLlama-2 and Llama3-8B) using a modified version of the BabyLM evaluation pipeline, perplexity, and a novel cloze evaluation set.

Text	Sense Year
"They had a bunch of crazy ideas that would never work"	1599
"I tried to call the operator but the phone was <b>dead</b> "	1882
"You know how it is. I'm not into ironing. It's not my thing"	1936
"Let's go where there's some life. Whatta ya say? Hey baby, I'm <b>down</b> "	1952

Table 1: Cloze task examples and the year when the word sense first appeared

**Perplexity.** To verify the strength of our temporal boundaries and ensure that we capture time-specific linguistic information, we calculate perplexity for each model on a test set drawn from its own timeslice as well as ones drawn from each other timeslice. We also use perplexity as a measure of general fluency.

BabyLM Evaluation Pipeline: BLiMP. The BabyLM evaluation pipeline provided by Choshen et al. (2024) is a version of EleutherAI's lm-evaluation-harness (Gao et al., 2023), modified to support the evaluation of models trained over a token-limited corpus, in our case the overlap in-vocabulary for all of the time slices. Specifically, this set consists of samples where every word appears twice in the model training sets ("maximally filtered"). The pipeline supports evaluation over BLiMP, GLUE (Wang et al., 2018) and EWoK (Ivanova et al., 2024) of which we solely utilize BLiMP (Warstadt et al., 2020). Concretely, BLiMP tests the model's ability to understand different linguistic phenomena, which we aggregate to measure linguistic model performance. We also closely analyze the results of specific BLIMP phenomena to explore BLiMP's capacity to uncover historically-specific linguistic preferences learned by our models in §4.2.

Novel word sense cloze evaluation set We construct this dataset using the Oxford English Dictionary (OED), which catalogs most English words and their respective word senses. For each word sense the OED provides the year of its first registered usage, as well as a list of curated example sentences illustrating the word sense in context. To generate a usable cloze task for next-token prediction models without the ability to follow instructions, the masked words need to be located at the end of the sentences. We select sentences where the word in question appears within the last 10% of characters. For practicality, we further restrict the dataset to words the OED doesn't consider exceptionally rare, specifically ones appearing once every thousand to a million words (Table 12 in the appendix). During evaluation, the dataset is filtered akin to the BLiMP task, such that sentences with uncommon words, which have less than two occurrences in any training set, are filtered out.

Evaluation is performed by generating the top k one-word responses. This is achieved using a custom LogitsProcessor, which redistributes the probability mass of tokens initiating a new word to the EOS token. In combination with probability-based beam search (length penalty set to zero) this method efficiently approximates the top-k responses. We were unable to find a similar approach in the literature. Example tasks are shown in Table 1. More details on sense distribution and evaluation details can be found in Appendix C.

## 3.4 Analysis

For the exploratory analysis, we contrast the log perplexity of the different models. This is done by first min-max normalizing the perplexities over a sentence. Despite the models having different baseline perplexities, their normalized log perplexity follows a similar trajectory, with the exception of words particularly characteristic (domain-specific) for a model's dataset. This phenomenon is shown in Table 2, where a significant shift can be seen for "station", which lowers in perplexity as the railway system is widely adopted during

Model	Sentence
1750 to 1820	with whom he talked in the station at fort wayne interested him
1820 to 1850	with whom he talked in the station at fort wayne interested him
1850 to 1880	with whom he talked in the station at fort wayne interested him
1880 to 1910	with whom he talked in the station at fort wayne interested him
1910 to 1940	with whom he talked in the station at fort wayne interested him

Table 2: Normalized perplexities for different models, lighter red signifies higher surprisal.

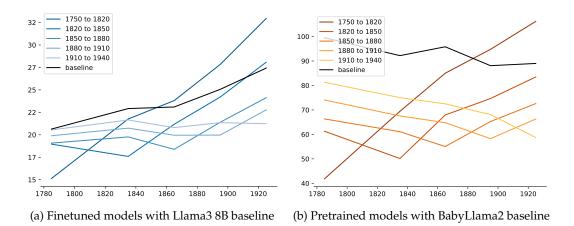


Figure 1: Cross-time perplexities

1840s and 50s. We use this perplexity data to generate candidates for word sense change, motivated by the notion that words whose later sense has not yet emerged should have a higher perplexity for earlier models.

## 4 Results and discussion

## 4.1 Perplexity

The baseline and finetuned models are fluent, but lack historical specificity. The baseline models show slight time-period preferences but are logically a-historical (Figure 1). The DoRA-adapted models have overall low perplexity Models trained on earlier time slices show a strong preference for data from their respective time slice, whereas those trained on later slices do not show such a prominent specialization.

The pretrained models are less fluent, but are specialized to their historical period. The BabyLlama-2 models uniformly produce their lowest perplexities when measured against their period's corresponding test set. Cross-evaluation of the models against the other reserved test sets (Figure 1) yields encouraging signs that the linguistic information captured by the pretrained models follows an appropriate historical arc, and that there is little to no information from any of the untargeted time slices. Perplexity is low at the relevant period and increases linearly both when testing older and newer texts.

#### 4.2 BLiMP

The pretrained models perform reasonably despite underperforming the baseline models. The two unmodified baseline models earn aggregate scores of 0.74 (BabyLlama2) and 0.82 (Llama3-8B) on our most filtered version of the BLiMP dataset. This is expected in both cases, as our model was trained over a different mix of 10,000,000 tokens (in the case of the former) and far fewer tokens (in the case of the later). Nonetheless, our model slices approach the general competence of baseline BabyLlama2.

Model	1750-1820	1820-50	1850-80	1880-1910	1910-40
pretrained finetuned	0.67	0.68	0.69	0.72	0.72
	0.80	0.81	0.83	0.84	0.84

Table 3: Aggregate maximally filtered BLiMP accuracy across all timeslices.

Model	1750-1820	1820-50	1850-80	1880-1910	1910-40
pretrained		0.00	0.33	0.82	0.91
finetuned	0.92	0.96	0.98	1.00	0.99

Table 4: Accuracy for maximally filtered BLiMP "only NPI licenser present" task across all timeslices. Our pretrained models begin to prefer "only" to "even" in later slices.

The finetuned models consistently outperform the pretrained models (Table 3). This is to be expected given that these models have access to a much larger sample of linguistic information. However, beyond verifying that the models are usable models of language, we care about the contrastive differences between them. We note an increase in BLIMP competency over time. Interestingly, this is not a sign of incompetence, but rather a newly found ability to distinguish general linguistic change.

The pretrained models capture historically specific grammatical change in a way the finetuned models do not. Table 4 collects the timeslice-relative performance of each modeling strategy on the BLiMP "only NPI licenser present" task. For comparison, baseline BabyLlama2 and Llama3-8B score 0.76 and 0.90 on this task, respectively.

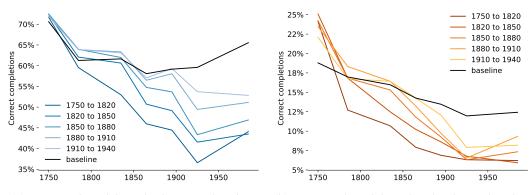
Negative polarity items (NPIs) are words that indicate a negative sentence (Penka & Zeijlstra, 2010). This specific BLiMP phenomenon evaluates whether a given model prefers the typically negatively polar construction "only...ever" to the typically positively polar "even...ever," as in the example taken from the filtered BLiMP test set found below:

Only Nina ever falls asleep. \*Even Nina ever falls asleep.

The underlying conditions that license the use of an NPI are complex, and continue to be the subject of research. However, scholars generally agree that licensing conditions vary between languages and across diachronic periods of single tongues (Herburger, 2023; Labelle & Espinal, 2014; Penka & Zeijlstra, 2010; Zeijlstra, 2016). Our models capture this diachronic sensitivity. While the finetuned DoRA models demonstrate preference for "only…ever" to "even…ever" across all timeslices, the pretrained BabyLlama2 models only start to prefer the former construction in the later corpus sub-periods. More precisely, the earlier models seem to prefer associating "even" with a specifically negative polarity. Examining the earliest and latest training corpora reveals plentiful attributions of general "only…ever" (235 and 228 respectively) and "even…ever" constructions (137 and 113 respectively).

The latest corpus slice contains far more unambiguously negative-context uses of "only...ever" (e.g. "only girl that ever", "only time he ever") than the earliest slice. Here, "only" is employed more broadly, for example as a form of "just" (e.g. "only thus much: if you have ever had any cause to believe him impressed with your idea").

Per the pretrained models, this change in preference increases monotonically over time with a final sharp discontinuous rise. The finetuned models offer no such insight, likely due to the linguistic priors they retain from their historically-agnostic pretraining phase. Catastrophic forgetting does not completely obliterate these priors, endangering the historical specificity of their predictions. The token count and sourcing limitations of the corpus slices might render extending the diachronic conclusions offered by our models to the whole of English fraught. However, even if this insight is corpus-specific, the baseline models do not register any such change at all. By offering the capacity to discover diachronic narratives, and



- (a) Finetuned models with Llama3 8B baseline
- (b) Pretrained models with BabyLlama2 baseline

Figure 2: Model performance on the top 100 completion cloze task

compare trends across corpora, our modeling approach opens up avenues to further study that the finetuned models silently pass over.

The pretrained models capture time period-specific changes in lexical meaning in a way the finetuned models do not. While the finetuned models generally "succeed" more in completing a given cloze sentence across the entirety of the corpus, they achieve this in part by integrating inappropriate timeslice information (Figure 2), rendering them less useful for contrasting corpora and studying change. This is shown in Figure 3, where the "Leakage" or recall over future senses is measured. The finetuned models consistently outperform over future senses. More in Appendix D.

Performing error analysis over each slice of both the pretrained and finetuned models confirms that finetuned models from early timeslices perform inappropriately well on future cloze tasks, while the pre-

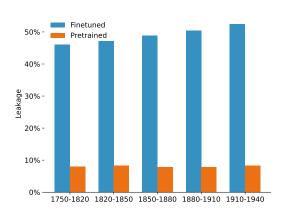


Figure 3: Probability of Leakage, over pretrained and finetuned models.

trained models do not. Table 5 presents two examples of this phenomenon for models trained on the 1750-1820 timeslice. The first example, "pound" is ranked as most likely by the finetuned model and unlikely by the pretrained model. Given the intended time period specialization, there is no way that this particular car-centric sense should even be obliquely available in the training data, making this a pure historical error, where the finetuned version relies on its prior linguistic information to make a determination.

The second example, centering on "silver" as an elliptical for "silver medal" is correctly completed by the finetuned model, but also ranked as reasonably likely by pretrained version. However, this example includes a collocation of "gold," that could steer a model from any of our time slices towards a higher probability of "silver." We find that this trend continues throughout the time slices. While the pretrained models are at times inappropriately performant, it is only on this particular subset of cloze tasks that makes a correct answer likely by other means. In contrast, the finetuned model consistently performs out of its bounds on both this set of examples as well as those similar to the first sample that are more obviously out of bounds.

The pretrained models enable novel hypotheses about lexical changes across our corpus. In addition to these two types of errors, manual inspection reveals a third, more exciting form. Table 6 contains an example of this error type, drawn from a cloze task that centers

Sentence	Definition	Year	Pretrain	Finetune
	A place in which vehicles impounded by the police or other authorities are kept	1970	101	0
Hill which won three gold and a <b>silver</b> .	Elliptical for silver medal n.	1960	7	0

Table 5: Two examples for time slice 1750-1820 with their rank per model.

Sentence	Definition	Sense Year
They have nowhere to go. This is—how do the Americans say it?—the end of the <b>line</b> .	V. A direction or course of movement. the end of the line (transferred and figurative). Cf. the end of the road at end n	1948

Table 6: The new sense of "line" is accepted by the finteuned (rank #1) and pretrained (#14).

on the phrase "end of the line." Both pretrained and finetuned rank the correct completion within the top 20 completions. However, the pretrained model's ranking differs from the error types examined above. While we cannot rule out that the finetuned model is achieving accuracy due to its future knowledge, we can do so for the pretrained counterpart (for example, a collocation search of the training data reveals that this exact construction is never used). Additionally, unlike the second type of error ("gold...silver") nothing in the context makes "line" a likely conclusion. Thus, the surprising performance of the pretrained model is best explained as a **prefiguration of a construction to come.** The way "line" is used in the 1750-1820 slice of the corpus predicts its ability to be used in this particular construction in the future. Examining the training corpus reveals numerous uses of line in hereditary (i.e. "end of one's line") writing (i.e. "the line ended") and military (i.e. "the British line") contexts, all uses logically associated with the action of "ending." Some uses, especially in writing, seem sufficient to support this construction. In a sense, they "pave the way" for "end of the line," a detail captured by the pretrained, but not by the finetuned models.

Reintroducing the axis of time in the form of the full cross-time battery of models further enhances our method's ability to **detect subtle changes in use**. Table 7 shows the rank of the correct word "cholera" for each of the models when completing the context sentence:

The potatoes failed, the pigs were affected with a disease which the people called **cholera** 

This sense of "cholera" is attributed to 1837, and concerns a specific hog disease originally grouped with the human malady due to its surface-level similarities. Only the earliest pretrained model considers "cholera" acceptable in this context, while the finetuned models rank it highly across all time-slices. Collocation of "cholera" in the earliest slice reveals that the nature of the disease had not yet solidified in discourse. Manual inspection shows that multiple forms of cholera, "morbus" and "infantus", both ailments unrelated to the modern understanding of the disease, share lexical space with phenomenological descriptions of their symptomatic similarity ("fever", "diarrhea" etc.). By the next two time slices, the term begins to coalesce around the common 19th century understanding of cholera as a specific, communicable human disease capable of producing mass illness events, as demonstrated by collocations like "epidemic" and "plague." The pretrained models capture this moment of conceptual solidification, while the DoRA baselines offer no such insight. To sum, these findings on changes we know happened hint at potential uses even beyond linguistic change, such as historical studies of social and knowledge change.

	1750-1820	1820-1850	1850-1880	1880-1910	1910-1940
Pretrained	41	NaN	NaN	NaN	NaN
Finetuned	18	19	11	14	11

Table 7: Rank of "cholera" completion. Llama3-8B ranks it 8, BabyLlama-2 ranks it 57. NaN indicates it is outside the top k.

## 4.3 Diachronic analysis

The efficiency and historical certainty of our modeling approach enable numerous novel ways to analyze linguistic change. For example, contrasting the information provided by each timeslice model allows more flexible automated hypotheses generation than the cloze approach utilized above.

**Discovering sense trajectories of interest.** Word senses can be said to have trajectories across our corpus slice periods, as judged by their acceptability by the pretrained model trained on a given slice. For example, one would expect earlier models to be perplexed by the word "car", in the sense of an automobile, and expect the later models would accept it. To track how this sort of shift occurs, we set the 1910-1940 model's normalized per-word perplexity scores as a baseline, and retrieve all usages where the perplexity difference decreased continually with time. For tractability, we subset this group to those with the largest change in acceptability between the first and last models.

This approach captures distinctions in usage over time, and separates synchronically distinct senses of words. Figure 4 depicts the trajectories for the word "station." (See the full data used in this analysis in the supplementary materials.) Two senses of the word emerge after applying our filtering approach. The first sense is associated with a railroad station, and the second with a stopover or encampment site. While both of these senses becomes more acceptable as time goes on, they follow distinct trajectories. The rail-related sense becomes precipitously more acceptable in the 1820-1850 timeslice, no doubt due to the adoption of rail technology during that period. In contrast, the camp/stopover sense begins its trajectory from a place of relative acceptability, and then proceeds to become smoothly even more acceptable as time passes.

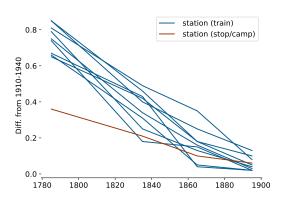


Figure 4: Natural appearances of "station" with a descending probability trajectory and manually labelled for sense.

These observations lead to any number of hypotheses about the interaction between these senses that could be pursued by further means over larger corpora. For example, this information allows the question of whether the already-acceptable usage of "station" as camp or stop grew more acceptable due to the influence of the emerging rail-related sense. We offer some further analytical directions in Appendix E.

#### 5 Conclusion and future work

Our modeling approach leverages efficient pretraining in order to offer a novel, boundary-guaranteed, form of linguistic hypothesis discovery across comparative corpora. While we believe this approach has massive potential for the specific use case examined above, diachronic change, we also believe that it is extensible, and can be leveraged in a similar way across different corpus divisions and fields. Further work could verify these beliefs by testing our approach's ability to detect linguistic shifts across synchronic boundaries.

Additionally, increasing the size of the training corpora could lead to increased model knowledge, allowing for the discovery of knowledge-level hypotheses relevant to disciplines like literary studies and history.

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# A Additional model and training details

DoRa adapters of rank 16 were chosen for efficiency purposes. We adopt the hyperparamers used in the original paper (Table 8).

We finetune using next-token prediction loss on the data slices. We train the models for three epochs, with one training run taking around eight hours on a single A100 GPU, which emits 0.11KG  $CO_2$  an hour (Lacoste et al., 2019). We choose the best model checkpoints based on evaluation loss. Notably, models trained on data after 1850 reached optimal performance after a single epoch, while those trained over earlier periods continued to show improvement during the second epoch.

We train the pretrained models using the BabyLlama2 training recipe. We adopt the same Llama-345M model (Table 10) and training hyperparameters (Table 9) as the original paper.

BabyLlama2 uses a distillation strategy where the logits of two trainer models are used to train a student model. Notably, the teacher and student models are of the same size. We

Hyperparameters (DoRA)	LLaMA3-8B
Rank r	16
α	32
Dropout	0.05
Optimizer	AdamW
LŔ	$1 \times 10^{-4}$
LR Scheduler	Linear
Batch size	16
Warmup Steps	100
Epochs	3
Ŵhere	Q, K, V, Up, Down

Table 8: Hyperparameter configurations of DoRA for LLaMA3-8B.

Hyperparameter	Value
Learning rate	$7 \cdot 10^{-4}$
Number of epochs	8
Batch size	128
Weight decay	5
Distillation <i>α</i>	0.5

Table 9: Training and distillation hyperparameters of BabyLlama-2

initialize a Byte-Pair-Encoding tokenizer for each time slice and train two teacher models over the training data for eight epochs. We select the model with the best validation score (consistently epoch four during our runs). Training a teacher model took around 32 minutes on a single A100 GPU. From the two teachers, we then distill a student model using the distillation loss after Hinton et al. (2015), with  $L = \alpha L_{CE} + (1 - \alpha)L_{KL}$  This loss is made up in equal parts of the normal next token prediction loss and the loss over the soft trainer logits. We train the student over eight epochs; the last epoch consistently having the lowest evaluation loss. Training the student model took 3 hours and 20 minutes on an A100.

# B Attribution pipeline details

We extract from WD all entities with an occupation of "author" or "writer" that also have birth dates that fall within this range. We further constrain this subset by filtering it to only include authors WD indicates were known to write in English.

We then fuzzily match this set of authors to those in PGC. The first pass uses Levenshtein distance matching with a predefined threshold in combination with any extractable birth and death information to match PGC authors to the list sourced from WD. The optional second pass uses only fuzzy string matching with a stricter predefined threshold, and matches any remaining PGC authors to an author from WD. This second pass allows for the inclusion of authors without WD-provided date information, compensating for the further loss in certainty with tighter regulation of name similarity. The result of this stage is a mapping between WD authors and PGC authors with an associated list of their works found in PG.

To validate open source and propriety LLM performance on work-date attribution we manually annotated a sample (n=1054) of known-author works with their date of writing using publication information sourced from internet repositories like the HathiTrust collection (This material is available in the supplement). We then used one open weight model (Llama3.3-70B quantized to 4 bits) and two proprietary models (GPT-4, GPT-40) to zero-shot attribute the dates of works using the following prompt:

When was the work {} by {} written? Answer just with the year.

Hyperparameter	Value
Vocabulary size	16,000
Number of layers	32
Number of heads	15
Number of KV heads	5
Embedding dimension	960
Hidden dimension	2560
Total parameters	345M

Table 10: BabyLlama-2 Model Architecture.

Where the first {} was replaced with the work title and the second {} by the work author. We then evaluated performance with a tolerance of +/- 1 year to account for the historically common practice of assigning publication date to copyright year. Noting systematic error in the results provided by the best performing model at this stage (GPT-4o) we collected the set of erroneously attributed texts produced by this model and undertook another round of hand annotation on this set, spending additional effort to source historical materials (publishing industry trade journals, library records) that could disambiguate questionable attributions or provide evidence of earlier publications not in the digitized record. We then re-evaluated the models with tolerances of +/- 1 and 10 years, allowing a match to either date attribution to be acceptable. Additionally, we evaluated the models after disqualifying scores with extreme difference (+/- 50 years) from their ground score, to assess the impact of having a more certain source of information (say, author birth and death dates) that pre-restricts correct answers to a tighter range. Table 11 shows that while the closed-source models perform the best under these conditions, the open source model performs well enough to serve as a first point of departure.

	+/-1	+/-10	DQ +/-1	DQ +/-10
Llama3.3-70B			0.70	0.88
GPT-4	0.74	0.07	0.87	0.99
GPT-40	0.82	0.84	0.96	0.94

Table 11: Performance on work date attribution per LLM. +/- indicates year delta tolerance threshold, DQ indicates that extreme variations from the ground scores (+/-50) were not considered

Notably, this approach is flexible – broader diachronic slices justify tolerating more variance.

## C Cloze evaluation set details

The cloze evaluation set contains 50.4 thousand examples. Of which 14.6 thousand examples remain after filtering, a large portion is of old english origin as can be seen in Figure 5. Evaluation was performed over the top 100 word completion task. If the word appeared within the top 100 words (case insensitive) the completion was considered successful. For evaluation the senses were grouped by time slice. In Figures 2 and 6, each model was evaluated over each time slice. In the leakage reports (Figures 3 and 7) the model performance was contrasted between the senses created before and after the models respective training cutoff.

## D Additional model performance information

We include an overview of mean reciprocal rank over time, for a more detailed insight into model performance (Figure 6). As well as a figure showing model leakage dived by model recall (Figure 7). Here, it can be clearly seen that the finetuned models performance on

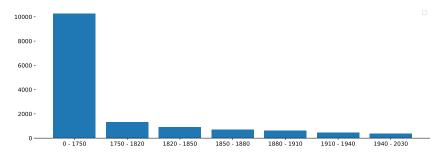


Figure 5: Count of cloze tasks for per time slice for the set filtered for our data (14.6 thousand examples).

Band	Freq./mil.	% in OED
8	>1,000	0.02%
7	100 - 1,000	0.18%
6	10 - 100	1%
5	1 - 10	4%
4	0.1 - 1	11%
3	0.01 - 0.1	20%
2	< 0.01	45%
1	_	18%

Table 12: Word Frequency Bands and their respective counts per a million words and the percentage of non-obsolete OED entries

future time slices is unprecedented also when correcting for the relatively weak performance of the pretrained models.

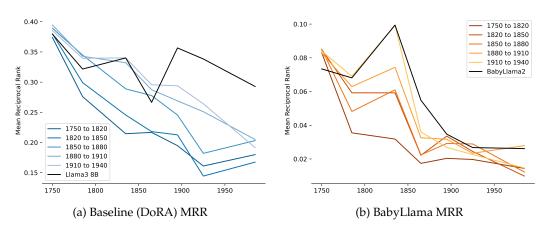


Figure 6: Model performance on the cloze task

# E Further analytical commentary

In a second, more cumulative analysis (Table 8), words with consistently high perplexity differences were highlighted. The underlying reason for these variations is varied. Some words show semantic shifts, such as "car" (automobile) "plane" (airplane) and "inspector" (detective), while others are a part of novel word combinations, which had gained popularity such as "skirt" in the context of "hobble skirt" or "Victoria" in the context "Queen Victoria".

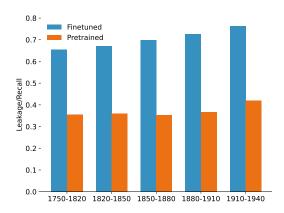


Figure 7: Probability of leakage corrected for model recall.

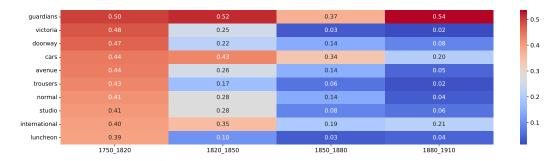


Figure 8: Cumulative perplexity results.

While these insights cannot be pinpointed to a single phenomenon, they offer valuable insights into the training corpora.