Pitfalls of Static Language Modelling

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Abstract

Our world is open-ended, non-stationary and constantly evolving; thus what we talk about and how we talk about it changes over time. This inherent dynamic nature of language comes in stark contrast to the current static language modelling paradigm, which constructs training and evaluation sets from overlapping time periods. Despite recent progress, we demonstrate that state-of-the-art Transformer models perform worse in the realistic setup of predicting future utterances from beyond their training period—a consistent pattern across three datasets from two domains. We find that, while increasing model size alone—a key driver behind recent progress-does not provide a solution for the temporal generalization problem, having models that continually update their knowledge with new information can indeed slow down the degradation over time. Hence, given the compilation of ever-larger language modelling training datasets, combined with the growing list of language-model-based NLP applications that require up-to-date knowledge about the world, we argue that now is the right time to rethink our static language modelling evaluation protocol, and develop adaptive language models that can remain up-to-date with respect to our ever-changing and non-stationary world.1

1 Introduction

A language model defines a distribution over utterances. Whether these are sentences, documents, or whole conversations, we usually aim to learn a language model from a set of observations so that it assigns high probability to utterances observed in the future. In this decidedly simple definition lurks a crucial yet often overlooked detail: Language modelling is a **dynamic** task in which experience of the *past* is used to predict the *future*. In contrast, the current practice in large-scale language modelling is to draw training and test data from large web crawls that *overlap in time*.

In this work, we demonstrate that such static evaluation protocol provides an overly optimistic assessment of a language model's efficacy. Hence, throughout this paper, we argue for embracing the temporal dynamics at the heart of language modelling in order to maximize their real-world potential, as reflected by the growing list of NLP applications—many of which currently rely on language model pretraining (Devlin et al., 2019) that require up-to-date factual knowledge of our ever-changing world. Examples of such tasks include flagging the most recent batch of fake news (Thorne and Vlachos, 2018; Zellers et al., 2019; Augenstein et al., 2019, inter alia), and answering questions like "How many people have been infected by COVID-19 worldwide?", "Has there ever been a female Vice President of the USA", and "Is Pluto a planet?", whose answers can vary depending on when the question was posed. Furthermore, the vast majority of practical NLP today happens within the context of commercial systems, such as machine translation and automatic speech recognition, that are deployed on future utterances whilst being trained on past ones.

Given the practical importance of building *adaptive* language models that update their knowledge in response to our non-stationary world, combined with the compilation of ever-larger language modelling benchmarks that do *not* necessarily assess how well our language models can generalize over time (Chelba et al., 2013; Radford et al., 2019;

^{*} Equal contribution. ♠ Project initiation. △ Paper writing. ♦ Project technical infrastructure. ♥ Model design and experiments. ♣ Project support and advice.

¹To track progress and encourage the development of adaptive language models, we release our dynamic (streaming) language modelling benchmark for WMT and ARXIV at https://github.com/deepmind/deepmind-research/tree/master/pitfalls_static_language_models.

Brown et al., 2020; Gao et al., 2021), we argue that now is the right time to revisit the question of whether, and to what extent, our current state-of-the-art Transformer (Vaswani et al., 2017) language models are able to generalize well across time in a dynamic streaming setup (Jelinek et al., 1991; Wang et al., 2008; Yogatama et al., 2014; Osborne et al., 2014, inter alia), which can help measure progress and spur further advances in this direction.

More concretely and as a first step, we stress-test the current state-of-the-art static language models by evaluating their **temporal generalization** ability on two English domains: News and scientific articles—two sources of data with a rapidly changing distribution, where new content with reliable time information is generated in a continuous fashion (§2). To assess how well these models can generalize across time, we design a **time stratification** evaluation protocol where Transformer-XL models (Dai et al., 2019) are trained on the past, but are asked to predict future articles that are published *after* the end of their training period.

We find that, despite remarkable recent progress on language modelling benchmarks that draw training and evaluation sets from overlapping time periods, the same models perform worse in the more realistic use case where models trained on the past are evaluated on their ability to generalize well to future data (§3.1). We further observe an alarming trend where the model performs increasingly badly when it is asked to make predictions about test documents that are further away from the training period, demonstrating that model performance degrades more substantially with time. Given these findings, we conduct a comprehensive analysis on what kinds of predictions the model is struggling with, and observe that model performance degrades most substantially for open-class words, including nouns and verbs (§3.2), rapidly changing topics such as sports (§3.3), and emerging concepts that occur frequently in the test period, but only rarely (or sometimes never) occurred in the training period, such as "Novichok" and "5G" (§3.4).

Since temporal generalization poses a challenge for current large-scale language models, what, then, is the remedy? One option is to periodically *retrain* the model from scratch with the new and old data, although this approach is expensive in terms of both computational resources and carbon emissions (Strubell et al., 2019), and further runs the risk of the model getting outdated in-between long

retraining cycles. More recently, increasing the size (i.e. number of parameters) of language models has been shown to improve perplexity and downstream task performance (Kaplan et al., 2020), and constitutes a key driving factor behind recent language modelling progress (Brown et al., 2020). Hence, we ask: Can increasing model size also improve temporal generalization? We find that increasing model size alone is *not* a solution for the temporal generalization problem (§4), which highlights the need for approaches that more directly tackle some of the problems introduced by an ever-changing world, and can rapidly adapt and integrate new information as it becomes available. We then explore a simple way of keeping our models up-to-date and mitigate this temporal degradation by performing dynamic evaluation (Mikolov et al., 2010; Krause et al., 2018, 2019, §5) incrementally on streams of new data. We find that this approach can mitigate, but not completely eliminate, the temporal degradation problem—leaving a large potential room for improvement, such as through better continual and lifelong learning approaches (§6).

Altogether, our findings: (i) empirically highlight the limitations of current language models with respect to temporal generalization, (ii) demonstrate the need to rethink our static language modelling evaluation paradigm that trains and evaluates models on data from the same, overlapping time periods, (iii) provide a benchmark to systematically measure progress and encourage more research on temporal generalization and adaptive language modelling, and (iv) highlight the fact that succeeding in this setup necessitates approaches that go above and beyond scaling models in terms of parameters or amounts of training data, thus paving the way for better and more efficient continual learning approaches.

2 Time-stratified language modelling

In a non-stationary and rapidly changing world like ours, any model begins to become outdated immediately after training concludes. In this section, we propose an experimental setup that enables us to assess *whether*, and *to what extent*, the performance of state-of-the-art Transformer language models degrades if they are asked to generalize to future data based on the past. Indeed, the question of how we can better measure generalization in large-scale language models is a timely one given the current trend of training on ever-larger collections

of web-crawled data, in which "test data contamination" (Brown et al., 2020) can present an impediment towards fair and reliable evaluations.

2.1 Datasets

Concretely, we identify news and scientific articles as two sources of dynamic streaming data with a naturally changing distribution over time, which lend themselves well to evaluating how well language models generalize over time. For the scientific domain, we use the publicly available arXiv abstracts (ARXIV).² For the news domain, we use the publicly available WMT News Crawl corpus (WMT).³ We ensure that any trends we observe also generalize well to models trained on larger datasets—which improve language modelling and representation learning performance (Liu et al., 2019)—by compiling a larger news corpus that we term CUSTOMNEWS. This dataset consists of crawled English news sources from the web covering the 1969-2020 period and includes a variety of topics, e.g. politics, financial news, sport, and lifestyle. We conduct all experiments in English, although we show that our findings generalize well to another language, German, in Appendix D. We apply minimal preprocessing through: (i) Removal of non-English documents, (ii) deduplication using a custom implementation of the MinHash algorithm, and (iii) tokenization using Moses.⁴ Table 1 summarizes key statistics of our datasets.⁵

2.2 Experiment: A model up to 2 years stale

We now describe our training and evaluation protocols in more detail.

Evaluation period and test set. For each dataset, we pick the last two years (i.e. 2018 and 2019) as our evaluation period,⁶ and sub-sample a test set of 24k test documents (1k per test month).

TIME-STRATIFIED setup. In order to assess temporal generalization, we design a **time stratification** evaluation protocol, where we construct training and evaluation splits from large corpora

by taking into account the timestamp of each document, such that models trained on the past (i.e. the training set) are evaluated on their ability to predict future articles that are published after the time period of its training data (i.e. the test set). More concretely, we use all documents from the beginning of each dataset's time period up until September 2017 as training data, and use the last 3 months of 2017 as our validation period, where we sub-sample a total of 9k validation documents for WMT and CUSTOMNEWS, and 15.6k for ARXIV; we refer to this as the TIME-STRATIFIED setup. We then evaluate the model on the 2018-2019 test set as described above, which in practice evaluates the model's ability to generalize well across time by predicting articles up to two years after the end of their training period—a realistic time frame for which we expect large-scale language models to be used without retraining on more recent corpora.⁷ We argue that such time stratification procedure is a natural way to evaluate models on out-of-sample distributions and truly unseen data—above and beyond distribution shifts in terms of topic or domain (Daumé III, 2007; Gururangan et al., 2020, §6).

CONTROL setup. We assess whether time stratification (i.e. generalizing to the future based on the past) poses a challenge for current language model by comparing it with a CONTROL setup, where we construct the training and evaluation sets from *overlapping* time periods. This setup is similar to the prevailing (static) language modelling evaluation protocol; more concretely, the training set in the CONTROL setup includes documents that come from the *same* 2018-2019 period as the evaluation set (naturally excluding the test documents themselves), which means that the CONTROL setup does *not* present the same temporal generalization challenges as its TIME-STRATIFIED counterpart.

Crucially, we control such that the two setups differ only in the *time periods* of their training data rather than the absolute training data size: Both the TIME-STRATIFIED and CONTROL training data are of the *exact same size*. Concretely, we construct the CONTROL training data by taking the most recent documents starting from the end of the evaluation period (excluding the test documents and including the same number of documents per test month), and keep including documents from previous time

²https://arxiv.org/help/oa/index We limit the dataset to papers with a single version only.

³http://data.statmt.org/news-crawl/ README

⁴https://github.com/alvations/
sacremoses

⁵In Appendix A we present a simple frequency analysis over time conducted in **WMT** and **ARXIV**.

⁶In Appendix B we demonstrate that our findings hold for other test year periods beyond the 2018/2019 one.

⁷In Appendix C, we observe an even stronger trend as we increase the gap between their training and test periods beyond the two-year gap.

					Prop. of CONTROL's
			#Words per Doc	Training Size	Training Data
Dataset	Domain	Time period	(Average)	(in GB)	from the Test Period
WMT	News	2007 - 2019	551	22.65	6.3%
CUSTOMNEWS	News	1969 - 2020	491	395.59	34.8%
ARXIV	Scientific text	1986 - 2020	172	0.72	14.5%

Table 1: Statistics and time periods of the datasets used in this study.

periods until we reach the TIME-STRATIFIED setup training data size. In Table 1, we report the proportion of documents in the CONTROL setups' training data that come from the same 2018-2019 time period as the evaluation set, which constitutes the only effective difference between the two setups: For the TIME-STRATIFIED setup, this proportion is exactly zero. For validation, we sub-sample a total of 9k for WMT and CUSTOMNEWS and 15.6k for ARXIV from the 2018-2019 evaluation period (again, excluding the 24k test documents). Note that we evaluate both the TIME-STRATIFIED and CONTROL models on the *exact same* test set from the 2018-2019 period, which facilitates a fair perplexity comparison between the two setups.

Relative perplexity comparison. One of our goals is to measure *temporal degradation* (i.e. whether LM performance degrades more when predicting test documents further into the future). Unfortunately, *absolute* perplexity degradation over time (e.g., comparing the perplexity of January 2017 vs December 2018) is *not* a reliable measure due the inherent variability of different test months, e.g. some months have longer documents than others, resulting in higher perplexities. Hence, we report *relative* perplexity changes between the TIME-STRATIFIED and the CONTROL models.

2.3 Model

We perform our experiments on autoregressive, left-to-right language modelling, and leave the extension to the representation learning case through masked language modelling (Devlin et al., 2019) to future work. More concretely, we conduct our experiments using the state-of-the-art Transformer-XL model (Dai et al., 2019). We use 18 layers and set the model size to 1,024, resulting in 287M parameters—roughly 15% smaller than the second smallest GPT-2 model (Radford et al., 2019) and BERT-Large (Devlin et al., 2019), although we experiment with larger models in §4. For both training and test sets, we set the sequence length to 1,024; we set the memory attention length to 384

Setup	WMT	CUSTOMNEWS	ARXIV
CONTROL	21.11	18.38	21.38
TIME-STRATIFIED	22.45	21.33	23.07
Δ , absolute	+1.34	+2.95	+1.79
Δ , relative (%)	6.34	16.04	8.37

Table 2: Perplexity of Transformer-XL when trained in two the two different setups regimes and evaluated on the same test set from 2018/2019 period.

during training and 1,600 during test. We use a vocabulary of 50,259 subwords, as obtained through a SentencePiece tokenizer (Kudo and Richardson, 2018) trained on a random subset (up to 15GB) of the training data of each respective experiment, i.e., CONTROL and TIME-STRATIFIED. Whilst training and validation are done on subword tokens, all reported perplexities are computed over **actual test word tokens** as produced by the Moses tokenizer; we compute these per-word probabilities by summing the log-probabilities of the subword tokens that form each respective word.

3 Results

In this section, we empirically validate our hypothesis that state-of-the-art Transformer language models would perform worse in the realistic case where models trained on the past are tested on their ability to generalize to the future. We begin by comparing the perplexity of the TIME-STRATIFIED setup against the CONTROL setup, and demonstrate how the perplexity of the TIME-STRATIFIED model degrades more over time (§3.1). We then perform a fine-grained analysis that helps better understand what kinds of predictions the model is struggling with §3.2-3.4, and identify that increasing model size alone—a key driver behind recent language modelling success (Brown et al., 2020)—does not solve the temporal degradation problem (§4).

⁸In Appendix E we assess the effect of an outdated tokenizer on the language modeling perplexity; having an outdated tokenizer harms performance, but not being able to *update* the weights of the language model is a larger problem.

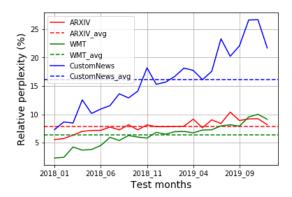


Figure 1: Relative perplexity increase across test months of the TIME-STRATIFIED model over the CONTROL one. The former has *not* seen documents from the test period, but the latter *has*.

3.1 Temporal degradation of stale models

Table 2 presents the results of our first experiment, with a clear pattern across all datasets. Although we train both models: (i) On the exact same dataset sizes, and (ii) use the same model architectures, a stale TIME-STRATIFIED model performs markedly worse than the CONTROL model, which has seen training data from the test period and thus does not have to make the same temporal generalization. We attribute the higher relative degradation on CUSTOMNEWS and ARXIV to their recent exponential growth of new documents, resulting in a higher proportion of documents from the test period being present in the training data (i.e., 34.8% for CUSTOMNEWS, 14.5% for ARXIV, and 6.3% for WMT). Compared to prior work on streaming (n-gram) language modelling (Yogatama et al., 2014; Osborne et al., 2014), the magnitude of the perplexity numbers is overall much lower in this work—although the exact perplexity values are not directly comparable. This finding suggests that current neural LMs are, to some extent, already able to mitigate some of the problems posed by temporal generalization; in fact, we later discuss how conditioning on long-range information in Transformer-XL is beneficial for this challenging task (§3.4).

Nevertheless, analyzing the performance of the model across test months yields a troubling trend, where the stale models become increasingly outdated with time. Fig. 1 plots the relative perplexity increase of the TIME-STRATIFIED over the CONTROL model. As evidenced by the *upward slope* on all three lines, the model deteriorates more as we ask it to predict data further away from the end of the training period (i.e., September 2017).

3.2 Perplexity and open-class words

We plot the relative perplexity increase of the TIME-STRATIFIED over the CONTROL model broken down by part-of-speech (POS) tags in Fig. 2; we also plot the corresponding perplexity change across time in Fig. 3.

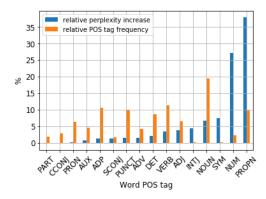


Figure 2: Relative perplexity increase of the TIME-STRATIFIED over CONTROL models per POS tag, alongside the relative POS tag frequency, on WMT.

First, we see that common nouns, the most frequent POS tag in our test set, are contributing among the largest perplexity increases and drive the overall trends observed in Figure 1. We also observe a large temporal performance degradation for other open-class categories, such as adjectives and verbs. In contrast, conjunctions and pronouns—closed word classes containing mostly function words—are unaffected by this degradation (Fig. 2).

Notably, the performance of the TIME-STRATIFIED model degrades most rapidly when making temporal generalizations about proper nouns. As proper nouns closely relate to events and facts about the world, this finding indicates that the model requires an up-to-date knowledge about the world to generalize well to these types of predictions. Qualitative analysis indicates that the model performs badly on named entities in politics, whose position changed in some way in our 2018-2019 evaluation period. For instance, "Bolsonaro" was elected to and assumed the office of the Brazilian presidency in 2018 and 2019, respectively, which falls outside of our training period; "Pompeo" was appointed Secretary of State in 2018; while "Khashoggi" was subject to widespread discourse in 2018 following his assassination. Interestingly, we also found the model struggling with concepts associated with cultural and sociological changes on which public perception and discourse have evolved over time, such as "MeToo".

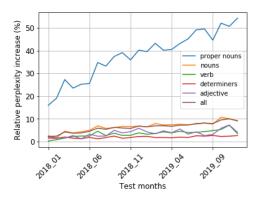


Figure 3: Relative perplexity increase of TIME-STRATIFIED over CONTROL models, broken down by POS tags, across test months on WMT.

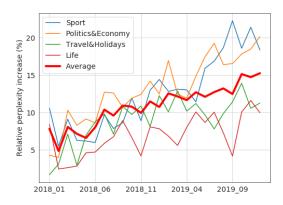


Figure 4: Relative perplexity increase by topic for **WMT**—TIME-STRATIFIED over CONTROL model. Documents are clustered using LDA, and perplexity is aggregated by topic. In the news domain, politics and sports are the topics that change more rapidly than average due to a faster-changing context.

3.3 Perplexity and topics

A priori, we expect the speed of perplexity deterioration to be causally linked to the speed of incoming new information. Here, we aim to understand how the perplexity deterioration is distributed across different topics in the corpora, as we expect different topics to shift more or less rapidly over time. We first cluster the documents using Latent Dirichlet Allocation (Blei and Jordan, 2003, LDA), representing each document as a mixture of topics and each topic as a distribution over words, and then aggregate the perplexity of words by topic. We present the results for **WMT** in Fig. 4.

We see that politics and sports are topics that change more rapidly than the average. Moreover, we find that this is not just caused by new words entering these topics (e.g., named entities), but also by *how* and *what* we choose to talk about in these

topics, i.e., the context around the existing named entities changes too. This problem is directly related to concept drift and out-of-distribution generalization, which we discuss in §6. For instance, we look at one of the sub-topics present in the articles covering politics in WMT, "Brexit", and analyze its changing context: In early 2018, far from the Brexit deadline, the words "remain" and "leave" both frequently occur in the articles, highlighting the fact that the media—and by extension the people—were still ruminating the results of the original referendum. Throughout the second half of 2018 and into 2019, as the deadline loomed and attention shifted towards achieving a Brexit deal, these words ceased to appear as frequently, overtaken by "deal" and "Boris Johnson". While terms like "deal" and "Brexit" were not necessarily rare, the local word co-occurrences and context surrounding these words had changed in a meaningful way, and this change affects the performance of the TIME-STRATIFIED model, which lacks access to more recent information.

3.4 Perplexity and temporal shifts in frequency

Our realistic time-stratification setup entails that there are new data every day, hence resulting in a natural and constant growth of the vocabulary. Indeed, analysis of our datasets suggests that \sim 10-15% of word types each month are previously unseen words in WMT and ARXIV, rising to 27% in **CUSTOMNEWS**. These novel words represent 0.1-0.3% of all tokens in WMT and CUSTOMNEWS, and 0.6-0.8% in ARXIV. Crucially, a substantial number of these remain in our discourse for a while, as 14-35% of these novel words reappear in at least four future months. In ARXIV, examples of these reappearing terms include terms related to new research directions (e.g. "pretrain"). In WMT and CUSTOMNEWS, these words often correspond to political terms (e.g. "Brexiteers") and social movements (e.g., "MeToo"), as well common nouns.⁹ We denote these as EMERGING NEW WORDS.

While it is unrealistic to expect models to be able to handle *all* rare words, we argue that these concepts in particular are of great importance, as they reflect precisely the dynamically-changing nature of our non-stationary world. To ground this observation into the recent global situation, per-

⁹More examples of novel words can be found at https://twitter.com/NYT_First_Said, a resource that has been used for novel word research (Pinter et al., 2020)

Model	Test ppl. on EMERGING NEW WORDS
Time-stratified	109.73
Time-stratified w/ dynamic eval.	66.26

Table 3: **WMT** test perplexity for words in the EMERG-ING NEW WORDS category, which undergo the largest temporal shifts between the training and test periods. We report results with and without dynamic evaluation (Krause et al., 2018, 2019, §5).

haps the most notable EMERGING NEW WORDS is "COVID-19", which has zero unigram probability before the end of 2019, and yet constitutes an extremely important use case of NLP systems today. We continue with assessing how well the TIME-STRATIFIED model is able to predict to these words, by confining the perplexity analysis to these words.

Concretely, we define EMERGING NEW WORDS as those that occur frequently on the test set (at least 50 times), but either: (i) were previously unseen on the training set, or (ii) occurred much less frequently on the training set than on the test set, as indicated by an at least 5 times lower unigram probability, giving rise to 287 EMERGING NEW WORDS and 87,636 mentions. Indeed, many of these words reflect strong temporal dynamics: e.g. "Ardern" (occurring 30 times more frequently on the test set, since Jacinda Ardern became the Prime Minister of New Zealand in late-2017) and "Novichok" (appearing 20,000 times more frequently on our test set, since Sergey and Yulia Skripal were poisoned by Novichok nerve agents in 2018). Table 3 shows that the TIME-STRATIFIED model performs substantially worse for EMERGING NEW WORDS, a ∼5 times worse perplexity than the overall one (see Table 2).

Perplexity of first and subsequent occurrences of EMERGING NEW WORDS It is a well-known fact that language is characterized by burstiness (Church and Gale, 1995; Church, 2000): A word is more likely to occur again in a document if it has already appeared in the same document. We thus argue that models with strong temporal generalization should be able to leverage this property of language and dynamically adapt their knowledge to predict *subsequent* word occurrences in a document better than the first occurrence, something of particular relevance for the EMERGING NEW WORDS—some of which never even appeared on the training

set (e.g. "Skripals", referring collectively to Sergey and Yulia Skripal). Table 4 shows the perplexity obtained by the TIME-STRATIFIED model under two conditions—for the *first* and *second* occurrences of EMERGING NEW WORDS in a document.

We find that, although the model has a high perplexity for generating EMERGING NEW WORDS for the first time in the document (ppl. of 695 compared to the overall ppl. of 22.45 in Table 2), it has a much lower perplexity for generating the same words for the second time, but only if the first word is available in the Transformer context. In this case, the model can simply copy the same word from the context, which is consistent with prior findings on the strong copying ability of the attention block within Transformers (Bahdanau et al., 2015; Vinyals et al., 2015). This means that the ability of Transformer models to condition on long-range context is already a useful feature for facilitating temporal generalization, even when we are not explicitly updating the model parameters to better account for the new data (which we later do in §5).

Nevertheless, the perplexity of the second occurrence is still remarkably high (more than 100 times worse than the overall perplexity) when the first occurrence falls *outside* of the Transformer context, ¹⁰ which highlights the important need to scale Transformers to even longer sequence lengths for achieving better temporal generalization. However, this is challenging because Transformers scale quadratically with the input length, although recent work has made substantial progress in this direction (Child et al., 2019; Correia et al., 2019; Kitaev et al., 2020; Beltagy et al., 2020, *inter alia*).

4 The effect of outdated models persists even when increasing model sizes

Scaling language models in numbers of parameters has led to improved perplexity, downstream task performance, and few-shot learning abilities (Kaplan et al., 2020). Hence, a natural question is: Can increasing model size also help improve the temporal generalization ability of stale models? For this experiment, we train a bigger TIME-STRATIFIED model with 448M parameters, or a 60% increase over the 287M model used thus far. We train the TIME-STRATIFIED 448M model for our bigger datasets: WMT and CUSTOMNEWS.

¹⁰For evaluation, the total context length is 1,024 (standard context length) + 1,600 (extended cached Transformer-XL memory), for a total of 2,624 most recent BPE tokens (§2.3).

Model	Ppl. of first occurrence	Ppl. of second occurrence of EMERGING NEW WORDS		
Wiouei	of EMERGING NEW WORDS	When first occurrence is in Transformer context	When first occurrence is NOT in Transformer context	
Time-stratified	694.95	75.95	2,719.25	
Time-stratified w/ dynamic eval.	357.40	44.21	1,430.34	

Table 4: Test perplexities of EMERGING NEW WORDS in **WMT**, broken down by whether the word is encountered for the *first* time on the test document (high perplexity), or the *second* time (often better perplexity because the model has observed the word before on the test prefix). For the second occurrence, we report perplexity on cases where the first occurrence is in the Transformer-XL context (lower perplexity because the model can *copy* the exact same word from the memory), and where the first occurrence is *not* available in the context (much higher perplexity because the previous occurrence and context is *not* accessible in the Transformer-XL memory due to long-range dependencies). Dynamic evauation (last row; §5) improves performance across the board.

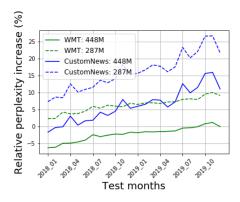


Figure 5: Relative perplexity increase of TIME-STRATIFIED models with 287M (dotted lines) and 448M parameters (solid lines) over the CONTROL model with 287M parameters, for WMT and CUSTOMNEWS.

To assess temporal degradation, we need to look into the performance of the models as more time passes from its training time (see Figure 5). As such, similar to the analysis in Section 3.1 where we reported the perplexity increase of the TIME-STRATIFIED^{287M} model over the CONTROL^{287M} one (here with dotted lines), we report the respective perplexity increase of the newly trained TIME-STRATIFIED^{448M} model over the same CONTROL^{287M} one (solid lines). If increased model size was able to delay temporal degradation, we would expect to see the solid lines produced by the bigger models to have reduced (i.e., flatter) slopes compared to the dotted lines produced by the smaller models.

While larger models, as expected, achieve overall lower perplexities, as indicated by the solid lines being consistently below the dotted ones, model size has **no significant effect** on the slope of these lines (t-test, p > 0.05). In hindsight, this is an expected result in light of our analyses in Section 3: Regardless of the number of its parameters, a *stale* model would not always be able to anticipate and forecast everything that happens in a changing world. Having models that perform well in the realistic setup of predicting future unseen data thus requires solutions that more directly tackle some of the specific challenges we emphasized through our findings so far, and can rapidly adapt to new incoming information about our non-stationary world.

5 Keeping models up to date: Online learning through dynamic evaluation

As state-of-the-art language models perform worse in the realistic scenario of predicting the future based on the past, one way to keep our models upto-date, and hence mitigate this temporal degradation, is to *continually update* their knowledge with new information as new documents arrive into our stream. The simplest way to achieve this is through dynamic evaluation (Mikolov et al., 2010; Graves, 2013; Krause et al., 2018, 2019)—a form of online learning that continually updates the parameters of a pretrained model through gradient descent on the observed test set prefix. Dynamic evaluation has been shown to improve overall perplexity in the standard (non-temporal) language modelling setup, allowing the model to adapt to local topic shifts within a document. Here we aim to use dynamic evaluation to adapt the model to the temporal dynamics that occur within a stream of chronologically ordered documents, allowing the model to capture temporal dependencies across temporallyrelated documents (e.g., news articles published within the same time often describe similar events).

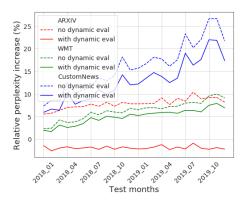


Figure 6: Relative perplexity increase, with (solid lines) and without (dotted liness) dynamic evaluation.

We plot the results in Fig. 6: Dotted lines reflect the perplexity increase when comparing the CONTROL model to the TIME-STRATIFIED model, i.e., the same graph as in Figure 1, whereas solid lines reflect the perplexity increase achieved when comparing the same CONTROL model with the TIME-STRATIFIED model augmented with dynamic evaluation instead (TIME-STRATIFIED dyn). In all datasets, dynamic evaluation reduces the speed of the model becoming outdated, as is evident from their reduced upward slope, with a significant effect for ARXIV and WMT as assessed using a t-test with p < 0.05. The improvements are particularly pronounced in ARXIV, where a more granular analysis over weeks (instead of months) reveals that the model needs only approximately one week worth of data to overtake the CON-TROL model on ARXIV. The fact that the TIME-STRATIFIED dyn . outperforms the CONTROL model on ARXIV hints that the recency bias imposed by dynamic evaluation is particularly advantageous for the TIME-STRATIFIED dyn . model, whereas the CONTROL model does not necessarily see the training documents in order.

When aiming to keep models up-to-date, efficiency considerations are paramount: Lightweight yet effective approaches are preferable because they allow the model to rapidly digest new information with minimal time and computation costs. Since updating the whole model is expensive, we experiment with updating only a smaller subset of the whole model. As our findings identify lexical semantic shifts as one problem, we design a setup where we only update the embedding layer (i.e., 52M parameters). Moreover, following recent work (Ben-Zaken et al., 2021), we also experiment with updating only the bias terms at all layers (i.e.,

type of parameters		CUSTOM	
that get updated	WMT	NEWS	ARXIV
all parameters	22.17	20.72	20.98
only bias	22.16	20.96	21.24
only embeddings	22.32	21.21	22.27
no dynamic evaluation	22.45	21.33	23.07

Table 5: Perplexity results on the three datasets of the TIME-STRATIFIED when updating different subset of parameters with dynamic evaluation.

198K parameters). Table 5 presents the results of this experiment, where we find that, in line with the findings of Ben-Zaken et al. (2021), updating only the bias terms performs nearly on par with the more costly alternative of updating the full model.

Dynamic Evaluation Helps More for Emerging New Words. We now repeat the perplexity analysis on EMERGING NEW WORDS (§3.4) that undergo the largest temporal shifts between the training and test periods. Since dynamic evaluation allows the model to update its parameters based on the test prefix, we hypothesize that it is particularly helpful for predicting EMERGING NEW WORDS. The findings in Table 3 indeed affirm our hypothesis: The perplexity improvements are much more substantial for EMERGING NEW WORDS (a 39.62% perplexity reduction from 109.73 to 66.26), compared to the overall perplexity reduction (a 1.25% reduction from 22.45 to 22.17 for **WMT**; Table 5).

We now repeat our analysis on how the perplexity of EMERGING NEW WORDS evolves between the first and subsequent occurrences of these words. As shown on the bottom row of Table 4, dynamic evaluation reduces the perplexity of both the first and second occurrences. More concretely, we observe the most substantial relative perplexity improvement when predicting the first occurrences of rare words in a document, which we attribute to the fact that dynamic evaluation can store and reuse relevant information about EMERGING NEW WORDS words from previous documents—hence affirming our hypothesis that dynamic evaluation helps the model capture cross-document temporal structures within a stream chronologically ordered documents. Moreover, these improvements are also substantial for predicting the second occurrences when the first occurrence is not in the Transformer memory (bottom right of Table 4), corresponding to a 47.40% perplexity reduction. This is because dynamic evaluation enables the model to store and update its representation of EMERG- ING NEW WORDS directly in the *model parameters*, hence reducing the reliance on the Transformer context length. Nevertheless, the absolute perplexity of such second occurrences is still high (more than 1k), demonstrating a large room for improvement.

Limitations of dynamic evaluation. Dynamic evaluation alone does not completely solve the temporal degradation problem, as evidenced by the prevailing (albeit gentler) upward slopes on WMT and CUSTOMNEWS (Fig. 6). Dynamic evaluation relies on performing gradient descent on the new data, which is prone to catastrophic forgetting (Mccloskey and Cohen, 1989; Kirkpatrick et al., 2017), where the model discards important information from the past. Beyond adapting to local temporal shifts, we want our models to achieve positive forward transfer (Lopez-Paz and Ranzato, 2017), i.e., the longer we train the model, the better the model should be at adapting to new data, which dynamic evaluation alone does not directly optimize for. Hence, the question of better understanding the limitations of dynamic evaluation and whether more sophisticated continual and lifelong learning approaches can achieve even better results—is an exciting avenue for future work.

6 Related Work

Concept drift The problem of detecting changes in data streams, also known as concept drift, has a long history (Kifer et al., 2004; Baena-Garcıa et al., 2006; Dries and Rückert, 2009). In NLP, much of the recent work in this area models lexical change by training word embeddings (Hamilton et al., 2016; Szymanski, 2017; Yin et al., 2018) and deep neural networks (Rosenfeld and Erk, 2018; Bjerva et al., 2019) on data of different time spans.

Out-of-Distribution (OoD) generalization. Achieving OoD generalization, primarily to domain shifts, has a long history in NLP (Blitzer et al., 2006; Daumé III, 2007; Axelrod et al., 2011), and has recently been addressed in the context of neural LMs and transfer learning (Fried et al., 2019; Oren et al., 2019; Hendrycks et al., 2020; Gururangan et al., 2020). To this end, prior work has shown that pretraining language models on large datasets has led to substantial improvements and increased robustness compared to non-pretrained models (Hendrycks et al., 2020). Most prior work on OoD generalization, however, puts a greater emphasis on distributional shifts in

terms of topic and domain. In contrast, this work puts an emphasis on distributional shifts in terms of *time*, where models trained on the past must generalize to the future, which is a realistic yet challenging use case of real-world NLP systems. A recent exception comes from Søgaard et al. (2020), who also consider temporal shifts in NLP.

Continual learning & streaming LMs. Our work is closely related to *continual* and *lifelong* learning, which aim to design models that continually accumulate new knowledge without forgetting relevant information about the past (Mccloskey and Cohen, 1989; Thrun and Mitchell, 1995; French, 1999; Mitchell et al., 2015; Rusu et al., 2016; Kirkpatrick et al., 2017; Al-Shedivat et al., 2018; Hadsell et al., 2020). The distribution of words and context in natural language, just like the world around us, changes rapidly with time, and hence constitutes an important test bed for developing and evaluating continual learning systems.

More specific to the language modelling literature, prior work has proposed ways of designing language models that can efficiently adapt their knowledge to continuous streams of new information (Jelinek et al., 1991; Wang et al., 2008; Goyal et al., 2009; Osborne et al., 2014; Yogatama et al., 2014, inter alia)—often known as streaming language models. Despite substantial recent progress in language modelling, we show that state-of-theart Transformer language models similarly suffer from the temporal degradation problem. The use of large-scale neural models also introduces an additional complication: Whereas n-gram models in prior work can be kept up-to-date by updating the counts of each n-gram on the new data, how we can adapt neural LMs without retraining the whole model from scratch remains an open research question, with notable progress in other NLP tasks (d'Autume et al., 2019; Sun et al., 2020).

7 Conclusion and Future work

We systematically evaluated the extent to which our current language models can generalize well in the realistic setup of predicting the future based on the past. Despite substantial recent progress in language modelling, we found that this setup poses a challenge even for state-of-the-art Transformer-XL models, and that model performance degrades more substantially with time. We conducted a thorough analysis to better understand the failure modes of the model with respect to temporal generalization,

and found that increasing model size alone—a key driver behind recent language modelling progress—failed to provide a solution for this task.

We conclude by outlining three broader implications of our findings. First, these findings show that the prevailing language modelling evaluation paradigm—which draws training and evaluation sets from overlapping time periods—provide an overly optimistic assessment of model generalization. Second, as new and ever-larger datasets are presently compiled using web crawls (Radford et al., 2019; Gao et al., 2021), it has never been more timely to rethink how our splits are constructed (Søgaard et al., 2020). We argue that time-stratification is a realistic evaluation setup that enables us to evaluate models on genuinely unseen data, which constitutes a fairer assessment on the out-of-distribution generalization of models. Lastly, a more realistic dynamic language modelling benchmark, such as the one we proposed here in this paper, can be used to measure progress and ultimately encourage the development of models that can handle non-stationary text data and remain up-to-date with respect to the world—an exciting research domain that we believe can spur further advances in continual and lifelong learning.

Future Work. Here we have primarily assessed the effect of outdated language models using an intrinsic perplexity metric, which directly relates to the optimized loss and hence constitutes a natural way to assess language modelling performance. However, a multi-task benchmark is needed to obtain a more holistic picture and better track our progress on downstream tasks—the vast majority of which currently rely on a language model pretraining backbone (Devlin et al., 2019). To this end, one important open question is how we can create and maintain benchmarks that are not static (e.g., see recent attempt that utilize human feedback for adversarial creation of benchmarks (Nie et al., 2019; Potts et al., 2020)) and fixed at a particular point in time, but rather are updated online and reflect the non-stationarity of the real world.

Finally, beyond better evaluations, our findings call for the development of adaptive language models. Due to the computational costs of training large models, brute-force solutions like retraining from scratch are unrealistic in practice, which (among others) runs the risk of the models becoming outdated in-between long retraining cycles. Generalizing to the future necessitates the ability to *quickly*

adapt to the new data, albeit without forgetting the important past—a delicate balance for which continual and lifelong learning techniques can offer promising solutions. Another promising direction is to disentangle the acquisition of up-to-date knowledge (for instance by retrieving external information) from the language learning itself, as recently proposed by Guu et al. (2020) and Yogatama et al. (2021), among others. All in all, above and beyond impressive scaling efforts towards ever-larger language models (Brown et al., 2020; Fedus et al., 2021), we strongly argue for the necessity of adaptive language models that can remain up-to-date with respect to our open and non-stationary world.

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A Frequency analysis on our datasets

A simple frequency analysis reveals a number of interesting phenomena regarding word usage over time, which points to interesting challenges that a model might need to overcome in order to temporally generalize. "Trump" was mostly mentioned in the context of his business and media career prior to 2015, after which the relative frequency of the term had seen a several-fold increase in the WMT dataset and a context-shift towards politics, while the term "Obama" has seen a relative decrease in frequency since then. Moreover, there are many terms that show specific seasonal patterns. The term "Christmas" sees a pronounced increase in frequency every year in December, while the "Olympics" sees an increase every two years. Yet other terms, such as "occupy" (from the Occupy Wall Street movement) peak once or twice before returning to a lower frequency base. Datasets can also undergo a shift in the proportions of individual topics, as shown for example by the growing relative frequency of the word "language" in ARXIV coupled with a relative decrease in frequency of the word "radiation". Some of these frequency patterns are illustrated in Figure 7.

B The effect of outdated models persists beyond the 2018/2019 test period.

We test whether the temporal degradation trends we observe in §3 are not an artifact of some particularity of the chosen test period (i.e., Yr1=2018 and Yr2=2019). We design new test sets by shifting Yr1 and Yr2 in increments of one year towards the past, for a total of five such test sets. Following §2.2, we derive different TIME-STRATIFIED Yr1,Yr2 and CONTROL Yr1,Yr2 training and validation splits. Note that each TIME-STRATIFIED Yr1,Yr2 and CONTROL Yr1,Yr2 setups are: (i) trained on the size of training data, and (ii) evaluated on the same test set covering Yr1 and Yr2. Fig. 8 shows similar temporal degradation across all testing years.

C The effect of outdated models persists beyond the two-year gap.

models are evaluated on the same test set introduced in Section 2.2.

In §3, we observe a performance degradation when the TIME-STRATIFIED model is out-of-date for up two years, but would the degradation persist beyond the two-year gap? To answer this question,

we train models with training data from different time periods with increasingly larger gaps from the 2018-2019 evaluation period in §2.2. The most upto-date model covers the same time period as the original TIME-STRATIFIED model, and we "push" the training period back with 6-month increments, up to September 2012, for a total of 11 training sets, of the same size, used to train 11 models. Fig. 9 shows that the perplexity deterioration continues to grow in response to larger gaps between the training and test periods.

D The effect of outdated models persists beyond English: A German study.

We test whether the temporal degradation is a generalizable pattern that holds across languages. We use the German subset of WMT, apply the same preprocessing steps as §2.1, follow the same experimental setup as §2.2, and train two Transformer-XL models on TIME-STRATIFIED de and CONTROL de , achieving 30.87 and 26.79 respective test set perplexities. These perplexities are indeed higher than the ones in Table 2, a pattern consistent with prior findings on the difficulty of modelling German (Mielke et al., 2019). Nevertheless, we still see the exact same pattern where the stale TIME-STRATIFIED de model performs worse than the CONTROL de one (a substantial 15.23% relative increase). Moreover, similar to the English experiment, the model degrades more as the gap between the training and test period widens, an effect particularly pronounced for proper nouns and for words that are broken down by the TIME-STRATIFIED de tokenizer into more tokens.

E Outdated tokenizer does not contribute substantially to performance deterioration

In our current experimental setup, the CONTROL and TIME-STRATIFIED model differ in two aspects; in the time period used to train the *weights* and the *tokenizer* of the language models. A subtle observation is that since the tokenizer in the CONTROL setup is aware of the evaluation period, it also aware its most frequent vocabulary items, whereas the tokenizer in the TIME-STRATIFIED setup is not. Considering only words that have been tokenizer differently by the two tokenizers (cf. Table 6) we see that the TIME-STRATIFIED assigns lower probability to these words than the CONTROL model (cf. 100 vs 650 perplexity respectively). To assess

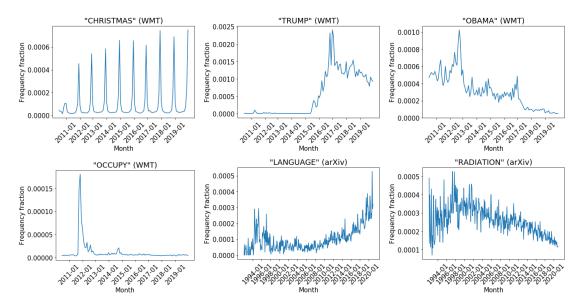


Figure 7: A sample of the types of term frequency through time patterns seen in WMT and ARXIV datasets.

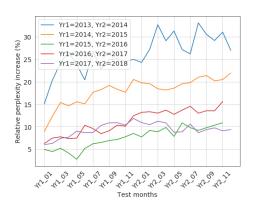


Figure 8: Relative increase of perplexity of TIME-STRATIFIED Yr1,Yr2 over CONTROL Yr1,Yr2 model.

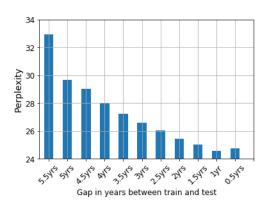


Figure 9: Perplexity of models trained with data covering time periods with increasingly bigger gap from the test set period (2018, 2019).

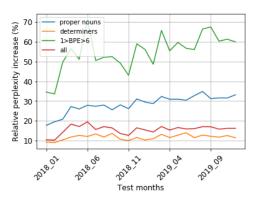


Figure 10: Relative increase of perplexity of TIME-STRATIFIED de over CONTROL de .

CONTROL	TIME-STRATIFIED	
Language model perplexity		
100	650	
Examples		
Brexite+er	Bre+x+ite+er	
Skywalker	Sky+walker	
MeToo	Me+T+oo	
cryptocur+rency	crypt+oc+ur+rency	
reciprocal	reciproc+al	
impeach	impe+ach	
un+biased	un+bi+ased	

Table 6: Examples of words that TIME-STRATIFIED and CONTROL have tokenized differently as well as perplexity for all the words where the two tokenizers differ. The TIME-STRATIFIED model attributes a fragmented tokenization to certain words not seen frequently on the TIME-STRATIFIED training set, e.g., "Me+T+00" or "impe-ach".

the effect of an outdated tokenizer on the language modeling perplexity, we ran an experiment training a Transformer-XL on the TIME-STRATIFIED training data using the CONTROL's tokenizer, resulting in 22.02 perplexity compared to 22.45 of the TIME-STRATIFIED model and the 21.11 of the CONTROL model. From this we conclude that despite having an outdated tokenizer harms performance, not being able to *update* the weights of the language model constitutes a bigger source of degradation.