Is It Worth the (Environmental) Cost?
Limited Evidence for the Benefits of Diachronic Continuous Training

Giuseppe Attanasio♣, Debora Nozza♣, Federico Bianchi♦, Dirk Hovy♣

♣Bocconi University, Milan, Italy
♦Stanford University, Stanford, CA, USA
{giuseppe.attanasio3,debora.nozza,dirk.hovy}@unibocconi.it
fede@stanford.edu

Abstract

Language is constantly changing and evolving, leaving language models to quickly become outdated, both factually and linguistically. Recent research proposes we continuously update our models using new data. Continuous training allows us to teach language models about new events and facts and changing norms. However, continuous training also means continuous costs. We show there is currently limited evidence for the benefits of continuous training, be it for the actual downstream performance or the environmental cost. Our results show continuous training does not significantly improve performance. While it is clear that, sooner or later, our language models need to be updated, it is unclear when this effort is worth the cost. We call for a critical reflection about when and how to use continuous training and for more benchmarks to support this research direction.

1 Introduction

Language models are trained on a static sample of data fixed in time. Because BERT was trained on the 2019 version of Wikipedia, it is unaware that Joe Biden is the current President of the United States or that the coronavirus has caused a pandemic. It is intuitively problematic if language technologies do not acknowledge recent facts since these events are the driving force behind the conversation on the internet, from social media to news broadcasts.

Recently, Loureiro et al. (2022a) introduced DALMs (Diachronically Adapted Language Models) to solve this problem. DALMs are language models that are updated via a continuous pretraining scheme using recent data – for example, tweets – fed to the model to update its weights. The most recent model showed decreased perplexity and gains in downstream task performance compared to the model created with the oldest data. Nevertheless, this study suffers from two primary issues: (1) a lack of a thorough examination of the changes throughout all periods, and (2) continual training necessitates using a significant amount of computer resources, which impacts the environment.

In this paper, we tackle the question, “Do our models really need to be updated?”. We perform several experiments by comparing DALMs for each period with other pre-trained PLMs on the downstream tasks used in Loureiro et al. (2022a), presence of bias, and factual knowledge coverage. This comparison demonstrates that DALMs do not consistently improve performance, especially over time. In fact, DALMs obtain worse performance compared to regular large models. This finding suggests that the “one model fits many use-cases” strategy is still valid: a large model, trained once, can be better in terms of results and environmental sustainability than many DALM counterparts. Table 1 shows the carbon footprint produced by fine-tuning a large version of BERTweet vs. the continuous training and tuning of DALMs. We also raise the question of whether DALMs are a cost we

| Model       | kgCO₂eq | F1  |
|-------------|---------|-----|
| BERTweetBASE | 0.14     | 58.60 |
| BERTweetLARGE | 0.68     | 61.68 |
| DALM 2020-1  | 6.38 (x9) | 58.72 |
| DALM 2022-2  | 61.91 (x91) | 58.91 |

Table 1: Carbon footprint (kgCO₂eq) and downstream performance (F1 macro) on the TWEETEVAL benchmark (Barbieri et al., 2020). 2020-1 and 2022-2 DALMs require, respectively, x9 and x91 consumption of the best-performing model.

1Code available at https://anonymous.4open.science/r/cost-continuous-training-EC4B.
are willing to pay for.

While we believe it is the right question to ask, it might be that DALMs are not the right answer. However, we also point out that the current datasets do not help us understand the advantages introduced by DALMs.

**Contributions** We reproduce the experimental configurations of Loureiro et al. (2022a) to extensively evaluate DALMs for each time frame. We show a lack of significant improvement at high environmental costs. Moreover, we tested for the presence of biases in LMs and the coverage of factual knowledge and find they become less perplexed by stereotypes and do not reliably retain knowledge about the world.

2 **Diachronic Continuous Training**

Diachronic Continuous Training (DCT) is the process of updating language models by further pretraining on data sampled from a time after the initial collection. Similar to initial pretraining, the DCT regime uses a linguistically motivated training objective, such as Masked Language Modeling, to update the model’s weights in reaction to new words used to describe new events and facts about the world. This paper focuses on DALMs on Twitter, a good test bed with ever-evolving language.

While DCT suggests a straightforward way to update the model’s weights, we argue it poses two types of risks: one practical, related to the knowledge encoded in the model, and the problem of forgetting; one broader that relates to pollution considerations, bearing the question do DCT benefits outscore its environmental costs?

**Forgetting** While changing their internal distributional representations, DALMs can incur different types of “forgetting”:

- representational: while the goal of DCT is to adapt to new words and contexts, there are no guarantees that the model preserves its ability to generalize. Indeed, new weights and representations can lead to worse models in downstream tasks;
- factual: the upcoming data collection can introduce false facts alongside new events, possibly overriding previous, correct knowledge;
- catastrophic: this phenomenon is a well-known issue caused by further lengthening training of neural networks (Goodfellow et al., 2013). When models are trained on one task, and then on a second one, they can lose the ability to solve the former. In language models, specifically DALMs, DCT can lead to models that fail to fill the blank coherently.\(^2\)

This paper focuses on the representational and factual aspects and inspects how well DALMs perform in different downstream tasks and retain factual knowledge about the world. We leave catastrophic forgetting evaluation to future work.

**Environment** Despite recent success in hardware optimization and efficiency, training large-scale neural networks incurs substantial energy consumption and, in turn, a non-negligible environmental cost (Strubell et al., 2019; Bender et al., 2021).

Diachronic adaption does not entail pretraining from scratch, as recent work starts from a pre-trained checkpoint and tunes it over new temporal data. However, this same formulation hides a long-term effect: a commitment to update DALMs periodically puts us on a track where the carbon footprint will grow and accumulate at the same pace.

We argue that DALMs resulting from continuous training should be measurably better than already existing checkpoints to justify the environmental cost. In the spirit of transparency and to raise awareness on the matter, we study the relationship between carbon footprint and in-domain downstream performance on eleven DALMs from Loureiro et al. (2022a), which we compare to state-of-the-art models in Table 1 and discuss in Section 3.2.1.

3 **Experimental Setup**

We test diachronic continuous training under several lenses. First, we study the downstream performance of these trained models: ideally, newer models achieve better performance by incorporating new information about the world. Second, we investigate these results with respect to their environmental cost. Third, we measure diachronic models’ perplexity on stereotypical and anti-stereotypical sentences from two established benchmark sets. This metric gives us a measure of their bias and ability to incorporate new knowledge.

\(^2\)We refer the reader to Table 6’s last row in Loureiro et al. (2022a), where the model completes the sentence Looking forward to watching <mask> Game tonight! with Squid.
Table 2: F1 macro performance (↑) on TWEETEVAL (Barbieri et al., 2020) split by classification task. Results of DALMs (20-1 through 22-2) are relative (±%) to the first checkpoint (19-4).

| Model               | Emoji | Emotion | Hate  | Irony | Offensive | Sentiment | Stance | Avg   |
|---------------------|-------|---------|-------|-------|-----------|-----------|--------|-------|
| RoBERTa             | 30.04 | 76.77   | 43.05 | 65.86 | 79.54     | 71.69     | 26.73  | 56.24 |
| BERTweet<sub>BASE</sub> | 29.53 | 73.73   | 50.99 | 76.32 | 80.34     | 72.18     | 26.73  | 58.60 |
| BERTweet<sub>LARGE</sub> | 35.48 | 81.65   | 52.30 | 78.22 | 81.14     | 73.08     | 29.92  | 61.68 |
| 19-4                | 31.81 | 79.08   | 50.95 | 73.24 | 80.56     | 71.84     | 26.73  | 59.17 |
| 20-1                | -1.73 | -0.70   | -3.00 | -2.20 | +1.12     | +0.26     | 0.00   | -0.76 |
| 20-2                | -2.20 | -0.94   | -2.53 | -1.63 | +1.32     | +0.52     | 0.00   | -0.60 |
| 20-3                | -2.10 | -0.64   | -2.98 | -3.17 | +0.82     | +0.56     | 0.00   | -0.95 |
| 20-4                | -2.01 | -0.80   | -2.53 | -2.61 | +0.96     | +0.59     | 0.00   | -0.79 |
| 21-1                | -2.00 | -1.61   | -3.75 | -2.07 | +0.54     | +0.54     | 0.00   | -1.09 |
| 21-2                | -1.60 | -1.54   | -5.13 | -1.23 | +0.57     | +0.55     | +0.59  | -1.02 |
| 21-3                | -1.75 | -1.29   | -3.65 | -1.01 | +0.85     | +0.37     | +3.29  | -0.57 |
| 21-4                | -0.64 | -0.85   | -2.59 | -1.42 | 0.00      | +0.42     | +4.36  | -0.43 |
| 22-1                | -0.65 | -0.94   | -2.52 | -0.81 | +0.20     | +0.31     | +5.73  | -0.22 |
| 22-2                | -0.71 | -1.10   | -2.96 | -1.75 | +0.08     | +0.08     | +7.24  | -0.44 |

In total, we test fourteen models on three English benchmarking suites. We aim for a fair comparison, so we allocate a fixed computing budget and resources to all models. Please find all training details in Appendix A and B.

3.1 Models

We study eleven pretrained diachronic models from Loureiro et al. (2022a), covering a period from the last quarter of 2019 to the second quarter of 2022. The authors train the models as follows. For the first checkpoint (19-4 in this paper), they start from a pretrained RoBERTa (Liu et al., 2019) and continue training on an initial set of 90M English tweets sampled from 2018 and 2019. Next, they train and release a new checkpoint using continuous training every quarter (20-1 to 22-2 in this paper). Each subsequent DALM is obtained by starting from the previous one and training on 4.2M additional tweets sampled in the new quarter.

We compare diachronic models to RoBERTa (i.e., with no additional training) and BERTweet (Nguyen et al., 2020). We test the latter in the two configurations BASE (110M params) and LARGE (335M params).

3.2 Twitter Benchmarks

Following Loureiro et al. (2022a), we test the models on the TWEETEVAL benchmark (Barbieri et al., 2020). The suite collects existing English Twitter datasets into a unified evaluation benchmark. It contains seven sentence classification tasks, namely 1) Emoji prediction, 2) Emotion, 3) Hate Speech, 4) Irony, 5) Offensive Language detection, 6) Sentiment classification, and 7) Stance detection. We train and test models separately per task using the official splits.

We report results on each task in Table 2. Top rows represent baseline models with no diachronic adaptations; 19-4 is the first release by Loureiro et al. (2022a) corresponding to the adaptation of RoBERTa<sub>BASE</sub> (Liu et al., 2019) on 90M tweets. The bottom rows correspond to the remaining DALMs. We identify two crucial highlights—first, DALMs’ downstream performance does not improve over time. In four tasks – Emoji, Emotion, Hate, Irony – 19-4 outperforms 22-4; except for Stance, 22-2’s improvements over 19-4 are lower than 0.1%. These results clash with the intended use of DCT, i.e., improving language models over time.

Second, BERTweet<sub>LARGE</sub>, trained and fine-tuned once, achieves best performance across the board. On all but the Offensive Language detection task, the model outperforms RoBERTa, BERTweet<sub>BASE</sub>, and all the DALMs. Again, this re-
| Model | Muslims | Black | Disabled | Gay | Immigrants | Trans | Women | Avg |
|-------|---------|-------|----------|-----|------------|-------|-------|-----|
| 19-4  | 79.55   | 74.69 | 83.26    | 73.50 | 79.05      | 77.32 | 79.96 | 78.19 |
| 20-1  | -1.82   | 0.28  | -3.23    | 2.22 | 0.55       | 0.84  | 0.74  | -0.06|
| 20-2  | -1.56   | 0.00  | -2.23    | -1.48| +0.82      | +0.28 | -1.97 | -0.88|
| 20-3  | -1.56   | -0.28 | -1.74    | -2.72| +1.91      | 0.00  | -2.95 | -1.05|
| 20-4  | -2.86   | -0.56 | -2.98    | -2.22| -1.64      | +0.28 | -2.46 | -1.78|
| 21-1  | -2.08   | -0.56 | -3.23    | -1.73| -1.64      | 0.00  | -0.74 | -1.42|
| 21-2  | -2.08   | -0.28 | +0.25    | -1.98| +1.37      | +0.56 | -0.98 | -0.45|
| 21-3  | -0.26   | 0.00  | +0.99    | +2.22| +2.73      | +1.12 | -0.25 | +0.94|
| 21-4  | -1.30   | 0.00  | +0.56    | -1.49| -0.55      | -0.28 | -1.47 | -0.72|
| 22-1  | -0.26   | +0.28 | -2.73    | -0.49| -0.27      | 0.00  | -0.25 | -0.53|
| 22-2  | -2.08   | +0.56 | -1.49    | -3.21| -0.82      | +0.56 | -1.23 | -1.10|
| Avg   | -1.58   | -0.06 | -1.69    | -1.09| +0.25      | +0.39 | -1.15 | -0.70|

Table 3: Accuracy performance (↑) on HATECHECK split by target group. Results of diachronic models (20-1 through 22-2) are relative (±%) to the first checkpoint (19-4).

The result suggests that training a single model once with stronger capacity and generalization capabilities is a better option than adapting smaller models over time.

Finally, note that DALMs are unstable and lead to generally worse performance compared to the initial 19-4 model: the 21-1 checkpoint (a year and three months after the initial release) is worst with a 1.09% F1 decrease, while 22-2 loses 0.44% F1 on average.

3.2.1 Carbon Footprint

As we discussed in Section 2, DCT brings a non-negligible environmental cost. Diachronic models in Loureiro et al. (2022a) are trained by adding new sentences sampled from Twitter: we run an additional analysis in-domain on TWEETEVAL, relating downstream performance and environmental impact.

We compute carbon footprint as follows. For BERTweet models, we consider the CO\(_2\) emissions generated when fine-tuning the whole suite. For DALMs, we consider the DCT cost using the 19-4 checkpoint as a reference, i.e., the initial release as a pre-existing model, on par with RoBERTa and BERTweet checkpoints, plus the cost of fine-tuning. Based on our estimate, each DCT round produces 6.17 kgCO\(_2\)eq.\(^6\) Since each DALM is trained from the preceding checkpoint, we consider the emissions produced by the n-th model to be n times the emission of a single DCT run.

Finally, note that DALMs are unstable and lead to generally worse performance compared to the initial 19-4 model: the 21-1 checkpoint (a year and three months after the initial release) is worst with a 1.09% F1 decrease, while 22-2 loses 0.44% F1 on average.

We report the aggregate comparison on the TWEETEVAL benchmark in Table 1. BERTweet\(_{\text{LARGE}}\) is by a wide margin the best performing model, producing 0.68 kgCO\(_2\)eq. 2020-1 DALM consumes x9 the same energy scoring 2.96 F1 points less. DCT also shows diminishing returns: training the DALM 2020-22 checkpoint requires 61.91 kgCO\(_2\)eq (x91 that of BERTweet\(_{\text{LARGE}}\)), but improvements are brittle compared to 2020-1 and again behind BERTweet\(_{\text{LARGE}}\). These results highlight that DCT is not beneficial for in-domain adaptation and is less sustainable than a “one model, multiple use cases” approach.

3.3 Functional Hate Tests

As models are exposed to new social media data, exploring how their representation change towards hateful and stereotypical language is another exciting direction. We hence test DALMs in the task of Hate Speech Detection.

Hate speech detection models suffer from lexical overfitting to specific identity terms, flagging texts that explicitly mention them as toxic if they are not (Dixon et al., 2018; Kennedy et al., 2020). To avoid this type of technical bias, we fine-tune DALMs on TOXI GEN, a large-scale synthetic corpus with implicit statements about targets (Hartvigsen et al., consider any CO\(_2\) emission offsets.)
The dataset consists of 274k sentences balanced between toxic and benign comments directed to thirteen target groups.

Next, we test fine-tuned models on the HATECHECK benchmark (Röttger et al., 2021). The suite consists of a wide range of functional tests. They are constructed by either slot-filling templated sentences such as “I hate [IDENTITY]” or using spurious clues that can fool the models. Templated sentences use identity terms that refer to seven social groups: Muslims, Black, disabled, gay, immigrants, transgender people, and women.

Table 3 reports results on HATECHECK split by target group. All but one DALMs show worse performance than the 19-4 reference checkpoint. DALM 22-3 is the best-performing model with the greatest improvements in the categories Gay (+2.2%), Immigrants (+2.7%), and Transgender (+1.1%). However, we cannot find a trend over time: after nine months’ worth of DCT, the model is worse (-1.8% on average). After nine more months, it is better (+0.9%), and nine months later, it is worse again (-1.1%). What happens between 21-3 and 22-2 is of particular interest: the 21-3 DCT is “winning” as the new data sample brings meaningful knowledge to solve the downstream task; however, as early as the next run, this “winning” update is lost and never recovered. These results show that DCT is not beneficial for downstream performance on the task of Hate Speech Detection, further suggesting that the updated models can lose some of their representational capacity.

### 3.4 Perplexity on Stereotypical Language

We measure DALMs perplexity on CROWS-PAIRS (Nangia et al., 2020) and STEREOSet (Nadeem et al., 2021), two natural English datasets to measure stereotypes in language models. Following related work, we use pseudo-perplexity (Salazar et al., 2020) to estimate the probability DALMs assign to stereotypical language. Pseudo-perplexity is a common approach to score masked language models. It first uses the model’s MLM score to compute each sentence’s (pseudo) log-likelihood as the sum of probabilities assigned to each token when masked and then averages them over the corpus.

This setup matches Loureiro et al. (2022a)’s, where the authors measure pseudo-perplexity on collections from different time frames. But rather than testing generic text, we focus on the sensitive case of stereotypes and specifically compare stereotypical and anti-stereotypical language. Take the sentences “Women belong to the kitchen.” and “Men belong to the kitchen.” Ideally, we would aim for models to become more perplexed by the former (the stereotype) and less perplexed by the latter. However, new data for DALMs studied in this paper comes from Twitter and a relatively short time span: assuming stereotypes cannot be eradicated entirely in such a short time, we can expect to find some in new time frames. In light of that, we rephrase our objective as such DALMs should become perplexed by stereotypes as much as (or, ideally, more than) they are by anti-stereotypes.

#### 3.4.1 CROWS-PAIRS

CROWS-PAIRS contains 1508 examples of stereotypes common in the United States. Since the authors already provide two distinct sets of stereotypical and anti-stereotypical language, we use them with no changes.

We report pseudo-perplexity and the official score on CROWS-PAIRS in Table 4. DALM 19-4 reports an encouraging lower perplexity on anti-stereotypes than stereotypes. All DALMs improve on the official metric compared to 19-4, and on average, perplexity on anti-stereotypes has a steeper decrease than on stereotypes.

#### 3.4.2 STEREOSet

STEREOSet is a larger dataset composed of almost 17k examples divided into two types of Con-
Table 5: Pseudo-perplexity on STEREOSET intra-sentence (top) and inter-sentence (bottom) CATs divided by target on stereotypical (S) and anti-stereotypical (AS) resolutions. DALMs results (20-1 to 22-2) are relative (±%) to the first checkpoint (19-4). We highlight in bold the resolution (A or AS) that became more likely to the last update.

| Model   | Gender | Profession | Race | Religion |
|---------|--------|------------|------|----------|
|         | S      | AS         | S    | AS       |
| 19-4    | 30.36  | 52.97      | 64.89| 80.72    |
| 20-1    | -12.70 | -8.61      | -12.12| 20.42 |
| 20-2    | -19.46 | -16.52     | -18.50| -18.20 |
| 20-3    | -18.70 | -13.83     | -20.25| -17.08 |
| 20-4    | -16.77 | -13.74     | -20.25| -16.85 |
| 21-1    | -18.01 | -14.29     | -18.66| -19.13 |
| 21-2    | -21.66 | -18.32     | -20.69| -22.41 |
| 21-3    | -22.67 | -18.12     | -22.50| -26.85 |
| 21-4    | -24.49 | -19.78     | -26.57| -41.47 |
| 22-1    | -18.01 | -14.29     | -20.42| -19.39 |
| 22-2    | -21.66 | -18.32     | -20.25| -22.41 |
| Avg     | -20.52 | -15.98     | -24.03| -23.53 |

|         | S      | AS         | S    | AS       |
|---------|--------|------------|------|----------|
| 19-4    | 9.63   | 8.79       | 13.15| 12.54    |
| 20-1    | -15.00 | -1.95      | -16.93| -10.80 |
| 20-2    | -16.17 | -3.73      | -18.66| -12.89 |
| 20-3    | -16.49 | +0.77      | -20.69| -12.34 |
| 20-4    | -14.54 | +0.60      | -20.65| -12.65 |
| 21-1    | -17.43 | -0.09      | -21.33| -12.60 |
| 21-2    | -17.60 | -4.40      | -23.66| -14.29 |
| 21-3    | -19.28 | -3.52      | -26.41| -15.94 |
| 21-4    | -17.76 | -4.21      | -24.77| -16.25 |
| 22-1    | -18.83 | -1.77      | -23.26| -16.45 |
| 22-2    | -18.03 | -0.58      | -21.86| -15.55 |
| Avg     | -14.68 | -0.92      | -18.64| -12.88 |

Table 5: Pseudo-perplexity on STEREOSET intra-sentence (top) and inter-sentence (bottom) CATs divided by target on stereotypical (S) and anti-stereotypical (AS) resolutions. DALMs results (20-1 to 22-2) are relative (±%) to the first checkpoint (19-4). We highlight in bold the resolution (A or AS) that became more likely to the last update.

Text Association Tests (CATs): intra-sentence and inter-sentence. Both categories contain a context sentence and three options the model should choose from to resolve the context. The choice of the model can resolve into a stereotypical, anti-stereotypical, or irrelevant sentence.

To study pseudo-perplexity on CATs, we textualize each sample in its three variants. For intra-sentence CATs, we fill the proposed template and compute pseudo-perplexity on the resulting three sentences. For inter-sentence CATs, we compute pseudo-perplexity on the concatenation between context and each option. Table 5 reports our measurements divided by the four targets present in the dataset, namely Gender, Profession, Race, and Religion. Differently from what we observed on CROWS-PAIRS, DALM 19-4 is less perplexed by stereotypes in all but one case (inter-sentence CATs on Gender). Also, DALM 22-2 has lower perplexity for stereotypical resolutions of CATs in five cases out of eight, and in two cases (intra-sentence Race and Religion), the model is more perplexed by anti-stereotypes than 19-4. These results contrast those on CROWS-PAIRS and pose further questions on the quality of models we are learning through DCT on Twitter data.

3.4.3 Is Perplexity Enough?

In the previous two sections, we studied (pseudo) perplexity on stereotypical language and its trend over time, in many cases a decreasing trend.
However, a decreasing perplexity over time does not necessarily imply that the model will pick up this type of bias to discriminate and ultimately “do more harm” in downstream tasks. While the two aspects can be correlated, perplexity is an intrinsic measure for which we have limited evidence to correlate with extrinsic downstream harm (Goldfarb-Tarrant et al., 2021; Blodgett et al., 2020).

Nonetheless, perplexity is a proxy for model behaviors in tasks where models estimate word or sentence probabilities. Low perplexity on stereotypical language causes the model to prefer undesired associations and resolutions, depending on the task (Rudinger et al., 2018; Nozza et al., 2021, inter alia).

We call for a thorough inspection of the dynamics of (pseudo) perplexity beyond general text and in sensitive contexts: new models can adapt to stereotypical language with the risk of consolidating and reinforcing stereotypical beliefs.

### 3.5 Factual Knowledge Retention

We tested DALMs on recognizing capitals from countries of the world under the form of cloze task (e.g., “The capital of Morocco is <mask>”), and the more general benchmark LAMA (Petroni et al., 2019). The latter is a collection of sentences sampled from four independent knowledge sources, ConceptNet for commonsense knowledge, Google-RE and T-REx about facts from Wikipedia, and the SQuAD question-answering dataset. All LAMA samples are formatted as cloze tasks (e.g., “The theory of relativity was developed by <mask>”, from SQuAD).

Table 6 reports performance considering uncased filling accuracy. Results suggest that there is no clear improvement from continuous training. There does not seem to be a clear pattern suggesting that models either learn new things or forget them, bringing additional questions regarding evaluating DALMs.

### 4 Related Work

Recent work has addressed the issue of large language models becoming outdated over time, focusing on benchmarking their abilities over time and proposing solutions to update them. Lazaridou et al. (2021) question generalization on future data, showing that Transformer-XL models underperform in predicting utterances from beyond their training period and that increasing size does not solve the issue. Jang et al. (2022) test how factual knowledge evolves in LMs. The authors show that models updated via continuous training on the diff between two Wikipedia checkpoints show better perplexity on the proposed benchmark set. While these results match ours (perplexity improves in Tables 4 and 5), we argue that updation.

| Model          | Capitals | ConceptNet | Google-RE | SQuAD | T-REx |
|----------------|----------|------------|-----------|-------|-------|
| BERTweet<sub>BASE</sub> | 35.34    | 12.57      | 20.30     | 10.16 | 38.92 |
| BERTweet<sub>LARGE</sub> | 33.62    | 16.77      | 18.47     | 16.72 | 51.45 |
| RoBERTa<sub>BASE</sub>   | 34.48    | 15.23      | 21.77     | 12.46 | 52.88 |
| RoBERTa<sub>LARGE</sub>  | 35.34    | 18.41      | 23.73     | 20.00 | 58.91 |

20-1 | +42.11 | +6.23 | -15.60 | +8.33 | +3.20 |
20-2 | +52.63 | +7.69 | -15.85 | +12.50 | +3.60 |
20-3 | +47.37 | +7.80 | -14.62 | +16.67 | +4.72 |
20-4 | +52.63 | +9.26 | -12.78 | +0.00 | +5.20 |
21-1 | +57.90 | +9.32 | -15.85 | +20.83 | +3.29 |
21-2 | +36.84 | +9.67 | -12.90 | +20.83 | +6.23 |
21-3 | +42.11 | +10.72 | -7.13 | +33.33 | +7.97 |
21-4 | +47.37 | +11.71 | -10.20 | +29.17 | +8.38 |
22-1 | +57.90 | +10.89 | -7.25 | +12.50 | +9.21 |
22-2 | +57.90 | +11.94 | -7.00 | +20.83 | +7.64 |

Table 6: Accuracy (↑) on LAMA. Results of DALMs (20-1 through 22-2) are relative (±%) to the first checkpoint (19-4).
ing models via social media data into makes them less perplexed by stereotypes and increases bias. Röttger and Pierrehumbert (2021) show that temporal adaptation on social media leads to better upstream and downstream performance and that updated models are better on past rather than future data. As our findings contrast with these results, we identify a key difference: the authors do not use continuous training but adapt models with data specific from each time frame.

Research on evaluation proposes benchmarks to test pretrained models over new events and facts (Dhingra et al., 2022), and social media data Röttger and Pierrehumbert (2021); Loureiro et al. (2022b). Dhingra et al. (2022) proposed a temporal benchmark to evaluate factual knowledge in T5 (Raffel et al., 2020) models adapted yearly on news data.

Recent work proposes different strategies to factor time in language models. Some model time explicitly: Dhingra et al. (2022) prepend time information as strings in sequence to sequence span completion, Rosin and Radinsky (2022) model add a new time component in the Transformer attention. (De Cao et al., 2021), instead, suggest editing factual knowledge using ad-hoc learned components to update the model’s weights at inference time.

5 Conclusion

This paper bears on the question: is continuous training a viable option to update our language models?

We extensively evaluated eleven Diachronically Adapted Language Models (DALMs) covering a period of thirty months under several lenses. We studied in-domain generalization on Twitter-based English benchmarks, adaptation to hate speech detection, perplexity on stereotypical language, and factual knowledge retention.

All results across the board lead to the same insight: there is little to no evidence supporting the use of diachronic continuous training. New DALMs do not improve in-domain performance on Twitter data and are worse hate speech detectors. Further, over time, DALMs become less perplexed by stereotypes than anti-stereotypes, suggesting they can reinforce the former.

Most importantly, we call for a serious reflection on the environmental cost of continuous training. As our experiments demonstrate, DALMs underperform compared to a single large BERTweet model while producing x91 its carbon emissions.

Limitations

In this work, we have focused on standard benchmark datasets. This analysis is limited because these datasets are not meant to evaluate temporal aspects. Thus we cannot exclude that using datasets that include these temporal aspects would change the results. Nevertheless, our results suggest that currently we do not have evidence about the significant impact of DALMs.

In addition to this, our setup is influenced by the focus on Twitter data, which might not be representative of the events, the passing of time, or the introduction of novel words. We do not know if the results would hold for other DCT setups.

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### A Training Setup

We finetune our models on the TWEETEVAL (Section 3.2) and TOXIGEN (Section 3.3) datasets. We use the same training budget and hyperparameter setup for all the models. We retrieve pretrained models and tokenizers from the HuggingFace Hub (Wolf et al., 2020). We set a maximum sequence length of 256, batch size of 32, and peak learning rate of 0.00002 with linear warmup scheduling, increasing it during 10% of the total training steps. On TOXIGEN, we train for a maximum of 3 epochs, on TWEETEVAL, for a maximum of 10. We evaluate every 500 steps and use the checkpoint with the best validation loss for testing. For TWEETEVAL, we repeat experiments on 5 initialization seeds.

### B Carbon Footprint

Our experiments were conducted using private hardware of type RTX A6000 PCIe 24GB (TDP 230W). Total emissions are estimated to be 16.65 kgCO₂eq.

Estimations were conducted using the Machine-Learning Impact calculator presented in (Lacoste et al., 2019).