Drinking from a Firehose: Continual Learning with Web-scale Natural Language

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Abstract

Continual learning systems will interact with humans, with each other, and with the physical world through time – and continue to learn and adapt as they do. Such systems have typically been evaluated in artificial settings: for example, classifying randomly permuted images. A key limitation of these settings is the unnatural construct of discrete, sharply demarcated tasks that are solved in sequence. In this paper, we study a natural setting for continual learning on a massive scale. We introduce the problem of personalized online language learning (POLL), which involves fitting personalized language models to a population of users that evolves over time. To facilitate research on POLL, we collect massive datasets of Twitter posts. These datasets, Firehose10M and Firehose100M, comprise 100 million tweets, posted by one million users over six years. Enabled by the Firehose datasets, we present a rigorous evaluation of continual learning algorithms on an unprecedented scale. Based on this analysis, we develop a simple algorithm for continual gradient descent (ConGraD) that outperforms prior continual learning methods on the Firehose datasets as well as earlier benchmarks. Collectively, the POLL problem setting, the Firehose datasets, and the ConGraD algorithm enable reproducible research on web-scale continual learning.

1 Introduction

Continual learning (CL) calls for learning from data that evolves over time, such that the system adapts to new data while retaining past experience. A variety of algorithmic approaches for CL have been proposed [27]. However, these approaches are typically evaluated on synthetic datasets with artificially defined tasks and simulated non-stationarity. The distribution of tasks is synthetic and the datasets are often small, low-dimensional, and simplistic [8, 26, 34].

A key limitation of existing evaluation protocols is an unnatural definition of the problem setting. A common formulation of the continual learning problem involves discrete tasks that are solved sequentially, one at a time. Yet the world does not present us with neat, sharply demarcated tasks, conveniently arranged in sequence, with no temporal overlap. Humans and other animals are confronted with multiple objectives at any given time and must pursue these objectives in the face of continually evolving circumstances. The environment evolves continually, rather than discretely. A natural model involves a dynamic data distribution that presents an evolving portfolio of tasks.

In this paper, we explore a new setting for continual learning that has these characteristics: a continually evolving data distribution and an evolving set of tasks that naturally arises from the data itself. Our benchmarking environment is social media, in which users post commentary in natural language. Specifically, we consider the popular social media platform Twitter. We define the problem of fitting a personalized language model to each user and refer to this as Personalized Online Language Learning (POLL).

∗Work was mostly done while the author was at Intel Labs.

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Temporal dynamics in POLL assumes multiple forms. First, the usage of language itself evolves: new topics arise, new terms are coined, older terms and topics fade away. Second, users evolve as individuals, acquiring new interests, beliefs, and patterns of expression. Third, the set of active users changes over time: new users join the platform, others drop out, and some are active intermittently. In POLL, we treat personalized language modeling for each individual user as a distinct task. Thus POLL is an instance of continual multi-task learning: the data distribution evolves over time and the set of tasks evolves with it.

Real data for POLL is available on a massive scale and does not require extrinsic labeling. We collect a dataset of more than 100 million tweets with more than 1.5 billion tokens, posted by one million users over six calendar years. We refer to this dataset as Firehose. Using Firehose, we investigate architectures for POLL and describe an effective baseline model that can be used to benchmark continual learning algorithms.

POLL, Firehose, and our baseline architecture enable controlled evaluation of continual learning algorithms on web-scale data. We conduct such an evaluation and uncover deficiencies in current CL algorithms. In particular, the evaluated CL algorithms are significantly worse than their offline counterparts even when they are evaluated in the online setting (i.e., on the most recent datapoints). Offline algorithms that fit all the data outperform CL algorithms even on the most recent datapoints, which CL methods are designed to fit best. This suggests that CL algorithms not only forget the past but also underfit the present. We conjecture that the fault is with the optimizer, and conduct a detailed investigation of gradient-based optimization in CL.

The standard optimizer for CL is online gradient descent with a fixed number of gradient steps at each time step. The number of gradient steps per iteration is critical as it directly affects learning and generalization. An excessive number of gradient steps hurts generalization, while an insufficient number of steps impairs learning. We propose to adaptively control the number of gradient steps using an online validation buffer. The key idea is to use part of the online data to measure generalization and adapt the optimization accordingly. We present a simple strategy to maintain this buffer without wasting data. The resulting continual gradient descent method (ConGraD) significantly outperforms prior continual learning schemes on Firehose and earlier benchmarks.

In summary, our contributions include the following. (i) A new problem setting for continual learning that features real data produced naturally on a massive scale, with natural temporal dynamics (POLL). (ii) A massive web-scale dataset (Firehose) that can support research on POLL. (iii) An effective continual gradient descent algorithm (ConGraD) that addresses the weaknesses of prior methods.

2 Continual Learning

Continual learning (CL) is an umbrella term used to describe a learning setting with the following properties. i) **Online:** Learning from streaming data. There is no direct access to past data. ii) **Dynamic:** The data distribution changes over time. iii) **Transfer:** Data observed in the past should benefit the system in the future. iv) **Retention:** Incorporating new data should not destroy valuable experience acquired in the past.

Existing benchmarks for CL are often based on Sequential Image Classification (SIC) [8, 26, 34]. Three of the most common SIC settings are pixel-permuted SIC (e.g. permuted MNIST), single-head split SIC (e.g. single-head split MNIST), and multi-head split SIC (e.g. multi-head split MNIST). In pixel-permuted SIC, the sequence of tasks is generated by applying a sequence of fixed pixel permutations to the images while their labels stay the same. In single-head split SIC, the sequence of tasks is constructed by partitioning the data and creating disjoint sets of labels. In the learning of each task, the learner is presented with the current task data and must predict over the entire label space. Multi-head split SIC constructs the task sequence in the same way as the single-head variant, but differs in the information presented to the learner. Specifically, the multi-head learner is presented with the current task data and its task identity, and asked to predict labels specific to the current task.

These evaluation protocols for CL are all based on artificial sequences of discrete tasks. This is arguably not a natural model for an intelligent agent that is embedded in a complex dynamic environment. Such an agent should be able to address multiple tasks at any given time, and successfully develop its abilities using data that continuously evolves. The set of tasks itself may evolve: new tasks may be added and some may drop out as the data distribution shifts. The dynamic nature of the
environment and the adaptive nature of the agent can be expressed in terms of dynamic distributions over data and tasks.

We argue that the standard formulation of continual learning in terms of discrete tasks that are solved one at a time is holding the field back. In particular, this formulation leads to artificial evaluation and benchmarks, since naturally-occurring data does not fit the problem definition.

We now present a formulation of continual multi-task learning with dynamic distributions over data and tasks. Consider the problem of multi-task learning defined via a task-specific data distribution \( x^u, y^u \sim \mathcal{P}^u \) for each task \( u \). Consider specifically the continual multi-task setting in which tasks are distributed through time in a non-stationary manner via \( u \sim \pi_t \) at time \( t \). We are interested in learning the parameters of a model over a hypothesis class \( h_u(\cdot; \theta^{sh}, \theta^u) \), with shared parameters \( \theta^{sh} \) and task-specific parameters \( \theta^u \). To facilitate learning, we also consider a task-specific loss functions \( I^u : \mathcal{Y} \times \mathcal{Y} \rightarrow \mathbb{R} \). Consider the time-varying multi-task data at time \( t \) as \( \mathbf{D}_t = \{x^i_t, y^i_t, u^i_t\}, \ldots, \{x^N_t, y^N_t, u^N_t\} \), where \( N_t \) is the batch size. Define the empirical loss over a set of data points \( S \) as \( \mathcal{L}^S(\theta) = \frac{1}{|S|} \sum_{x,y,u} I^u(h_u(x; \theta^{sh}, \theta^u), y) \). The aim of continual learning is to learn the parameters of the model to minimize the following objectives at time \( T \). i) Backward transfer: \( \frac{1}{T-1} \sum_{t=1}^{T-1} \mathcal{D}^D(\theta_T) \). ii) Forward transfer: \( \mathbb{E}_{D_{T+1}}[\mathcal{D}^{D_{T+1}}(\theta_T)] \). iii) Online fit: \( \mathcal{L}^{D_T}(\theta_T) \).

This formulation is general and can be used to instantiate other learning settings. For example, when the distributions over time stays the same (\( \pi_t = \pi^* \)), the formulation reduces to supervised multi-task learning. In a different instantiation, if we only optimize the online fit and let an adversary choose \( \pi_t \), we obtain the online multi-task learning setting. Moreover, if we choose a singleton distribution as \( \pi_t(u) = 1_{u=\hat{u}} \), which is 1 for a specific task \( \hat{u} \) and 0 for others, we get continual learning over a sequence of discrete tasks. Hence, our setting generalizes the discrete continual learning setting that is operationalized in current SIC evaluation protocols.

We add a constraint on the learner to formalize the online nature of CL. We are only interested in learners that can carry a limited amount of data (memory buffer \( M_t \)) across iterations. In other words, the learner plays the following \( T \)-step game with Nature at each time instant \( t = 1, \ldots, T \):

- **Nature** determines \( \pi_t \) and samples \( \{x^i_t, y^i_t, u^i_t\} \) via \( u^i_t \sim \pi_t \), and \( x^i_t, y^i_t \sim \mathcal{P}^{u^i_t} \)
- **Nature** reveals \( \{x^i_t, u^i_t\} \)
- **Learner** decides \( \{\hat{y}^i_t = h^{u^i_t}(x^i_t; \theta^{sh}, \theta^{u^i_t})\} \)
- **Nature** reveals \( \{y^i_t\} \) and learner pays the online fit loss
- **Learner** decides \( \theta_{t+1} \) and \( M_{t+1} \) using \( \theta_t, x^i_t, y^i_t \), and \( M_t \)

Finally, at time \( T \), Nature computes the forward and backward transfer losses. To play this game successfully, the learner needs to remember the past using its model parameters and the limited memory buffer, fit the online stream as closely as possible, and generalize to the future.

### 3 Personalized Online Language Learning

In this section we develop personalized online language learning (POLL) as a concrete instantiation of the continual learning setting formalized in Section 2.

Consider a stream of tweets. Our aim is to learn a personalized language model for each user. Language modeling is an unsupervised problem. In terms of the formalism presented in Section 2, take \( x^u_t \) to be the observed part of the sentence and \( y^u_t \) the predicted part at time \( t \) for user \( u \).

We are interested in learning personalized language models that share some parameters between users: \( \hat{h}(\cdot; \theta^{sh}, \theta^u) \) where \( \theta^{sh} \) is shared between users and \( \theta^u \) is specific to each user \( u \in [U] \triangleq \{1, \ldots, U\} \). We consider a dataset of inputs \( \hat{x} \in \mathcal{X} \) and labels \( \hat{y} \in \mathcal{Y} \) sampled from a user data distribution \( \hat{x}, \hat{y} \sim \mathcal{P}^u \). We also consider a distribution of activity \( \tilde{\pi}_t \) across users at any given time \( t \).

To show that POLL is an instance of continual learning, we formally describe the continual learning problem corresponding to it. The input is the concatenation of user ID with the data: \( x = (\hat{x}, u) \). The distribution over users is the task ID: \( d_t = \tilde{\pi}_t \). The parameters of the model are concatenated into \( \theta = (\theta^{sh}, \theta^1, \ldots, \theta^U) \). Finally, the data distribution \( \mathcal{P}^{d_t} \) can be defined as a generative model: first sampling \( u \sim d_t \) and then sampling \( \hat{x}, \hat{y} \sim \mathcal{P}^u \). This construction shows that POLL is an instance of CL. In the rest of the paper, we use the notation of continual learning for the sake of generality.
3.1 Why is POLL a good problem for continual learning?

We define a set of **desiderata for CL** based on the work of Farquhar & Gal [8].

- **Free of task label.** Task labels should not be explicitly given to the learner. Distributional shift over tasks happens naturally through time without the control of the learner. Therefore, having explicitly provided task labels is unrealistic. The learner should infer the changes in the tasks.
- **Coherence.** Tasks should have enough shared structure for inductive transfer. If the tasks share no inductive bias, forward and backward transfer are not possible. The real world has such coherence in the form of physical laws, norms of behavior, and other regularities.
- **Continuous dynamics.** Tasks should change continuously over time rather than go through discrete phases. Crisply demarcated task boundaries are unlikely to occur in a real application.
- **Long horizon.** Continual learning should extend over a long time span. We envision agents that can function in changing environments for long periods of time (months, or even years).
- **Real data.** The benchmark should be based on real data, with naturally occurring temporal dynamics. We want to evaluate continual learning on real distributional shifts that actually occur in the world, not on synthetic dynamics posited by researchers. Synthetic non-stationarity can bias experimental results and skew research agendas [8, 26].

Table 1 compares POLL and prior CL settings in terms of the stated desiderata. Both multi-head split SIC and POLL require task labels. Next, every setting except pixel-permuted SIC satisfies the coherence criterion, which enables inductive transfer. POLL is the only setting that has continuous dynamics and does not presume discretely demarcated phases (although the other settings can be modified to have this property [1]). POLL spans a long time horizon: multiple years. Finally, and most importantly, in contrast to all other settings, POLL uses real data with real temporal dynamics produced by natural behavior in the wild.

| Free of task label | Coherence | Continuous dynamics | Long horizon | Real data |
|-------------------|-----------|---------------------|-------------|-----------|
| ✓                 | ✓         | ✓                   | ✓           | ✓         |
| Single-head split SIC | ✓         | ✓                   | ✓           | ✓         |
| Multi-head split SIC | ✓         | ✓                   | ✓           | ✓         |
| POLL (our setting) | ✓         | ✓                   | ✓           | ✓         |

Table 1: Comparison of continual learning benchmark protocols. (SIC: Sequential Image Classification. †: can be modified to.)

3.2 A Model Architecture for POLL

In order to enable learning for POLL, we need a multi-task model, $h^u(\cdot; \theta^s, \theta^u)$. A model for POLL must fulfill two requirements. First, we need a high-capacity sequence model that can fit linguistic patterns within a long context. We use Transformer-XL for this purpose [7]. Our second requirement is to control the operation of the model to represent the differences in content and style between users. To this end, we study different multi-task natural language processing architectures. This study is reported in Appendix A. Based on the results, we use residual adapters [12, 29] to model user-level personalization. The adapters produce user-specific residual tensors that modulate intermediate representations in the model. The overall structure is shown schematically in Figure 1. Further details are provided in Appendix A.

![Figure 1: Architecture for POLL.](image-url)
4 Continual Gradient Descent

In gradient descent (GD), the number of iterations is directly relevant to generalization. A higher number of GD steps increases algorithmic complexity and decreases generalization, as discussed by Schmidhuber [33] from a Kolmogorov complexity perspective and by Yao et al. [43] for reproducing kernel Hilbert spaces. We analyze the role of the CL optimizer in this light.

At time \( t \), given the observed data \( D_t \) and the replay buffer \( M_t \), the learner must determine the parameters \( \theta_{t+1} \). The backward transfer loss \( \frac{1}{t} \sum_{s=1}^{t} L_{D_s}(\theta_{t+1}) \) and the forward transfer loss \( \mathbb{E}_{D_{t+1}}[L^{NT}_{t+1}](\theta_{t+1}) \) can be decomposed as follows:

\[
\frac{1}{t} \sum_{s=1}^{t} L_{D_s}(\theta_{t+1}) = \frac{1}{t} \sum_{s=1}^{t} L_{D_s}(\theta_{t+1}) - L_{NT}(\theta_{t+1}) + \frac{1}{t} \sum_{s=1}^{t} L_{NT}(\theta_{t+1}) \tag{1}
\]

\[
\mathbb{E}[L^{D_{t+1}}_{t+1}(\theta_{t+1})] = \mathbb{E}[L^{D_{t+1}}_{t+1}(\theta_{t+1}) - L^M_{t}(\theta_{t+1}) + \frac{1}{t} \sum_{s=1}^{t} L^M_{s}(\theta_{t+1})] \tag{2}
\]

where \( M_t = M_t \cup D_t \) denotes combination of the replay buffer and the data from time \( t \).

We refer to the difference between the loss over the replay buffer and the history as the core-set loss in (1) since the replay buffer functions as a ‘core set’ that summarizes past data. As long as the replay buffer is chosen effectively, the core-set loss will be small for any \( \theta_{t+1} \), making forgetting behavior independent of the chosen \( \theta_{t+1} \). Thus the optimizer can optimize the online fit without concern for catastrophic forgetting.

Optimization for the online fit in (2) is trickier because it requires careful control of complexity. Consider taking multiple GD steps over the loss in (2) in order to find \( \theta_{t+1} \). With a higher number of iterations, the training loss will decrease. On the other hand, each iteration is expected to increase algorithmic complexity and decreases generalization. Consider two extremes. 1) Performing a single GD step (common practice for CL): \( \theta_{t+1} = \theta_t - \eta \nabla L^M_t(\theta_t) \). 2) Optimizing the current fit to the stationary point by repeated GD steps until \( \|\nabla L^M_t(\theta_{t+1})\|_2 \leq \delta \) for a tolerance parameter \( \delta \). This corresponds to smoothed online GD, proposed and analyzed by Hazan et al. [11]. The theory [33, 43] indicates that the first option will result in a high training loss and good generalization, while the second option will result in a low training loss and poor generalization.

We propose an adaptive strategy to find the right trade-off between the two options dynamically in a streaming setting. The key idea is to use the validation loss in an online manner. We keep an online first-in first-out (FIFO) validation buffer \( (V_t) \) and modify the game as follows. Given the data \( (x_i, y_i) \) at time \( t \), the learner makes predictions and pays the online fit loss. Then, the learner pushes the new data to \( V_t \) and pops \( \{\bar{x}, \bar{y}, \bar{v}\} \) from the validation buffer. Finally, the learner sets the next model and replay buffer \( (\theta_{t+1} \text{ and } M_{t+1}) \) using \( \theta_t, \{\bar{x}, \bar{y}, \bar{v}\}, \text{ and } M_t \).

**Algorithm 1 ConGrAD: Continual Gradient Descent**

1: Initialize \( \theta_1, M_1, \text{ ValidationBuffer} \).
2: for \( t = 1, \ldots, T \) do
3: \hspace{1em} Observe \( \{x_i\} \) and predict \( \{\hat{y}_i\} = \{h(x_i; \theta_t)\} \)
4: \hspace{1em} Receive label \( y_i \).
5: \hspace{1em} ValidationBuffer.push(\( \{x_i, y_i\} \))
6: \hspace{1em} \{\bar{x}_t, \bar{y}_t\} = ValidationBuffer.pop()
7: \hspace{1em} Set \( M_t = \{\bar{x}_t, \bar{y}_t\} \cup M_t \)
8: \hspace{1em} for \( k = 1, \ldots, K \) do
9: \hspace{2em} \( \theta_{k+1} = \theta_{k-1} - \eta \nabla L^M_t(\theta_{k-1}) \)
10: \hspace{1em} end for
11: \hspace{1em} \( V_t = ValidationBuffer.sample() \)
12: \hspace{1em} \( \theta_{t+1} = \arg \min_{\theta_{t+1} \in M_t} \sum_{s=1}^{K} L^{V_s}_{s}(\theta) \)
13: \hspace{1em} \( M_{t+1} = \text{ReplayBufferUpdate}(M_t, D_t) \)
14: end for

![Figure 2: Illustration of the validation buffer with size 3. Circles are data points. Red: data points used for gradient computation in the past. Green: data points in the validation buffer. Purple: New data that arrives at time \( t \).](image)
In this setting, the online-fit loss is computed using the current data. However, GD does not use it to compute gradients. Instead, new data is first pushed to the validation buffer. Gradient descent is performed on a loss function computed over the replay buffer and the data points from the previous iteration popped from the validation buffer. We visualize this streaming behavior in Figure 2.

In order to choose the number of steps, we first perform the highest number of iterations we can afford and choose the one with the lowest validation error. Formally, we start with \( \theta^{0} \) and perform a sequence of gradient updates using the data \( M_t = \{x_i, y_i\} \cup M_t \) as
\[
\theta_{t+1}^k = \theta_{t+1}^{k-1} - \eta \nabla L^{M_t}(\theta_{t+1}^{k-1}) \quad \text{for} \quad k = 1, \ldots, K.
\]
The next iterate is chosen as \( \theta_{t+1} = \arg \max_{\theta \in \theta_{t+1}^{0}, \ldots, K} L^V(\theta) \). We summarize in Algorithm 1.

5 The Firehose Datasets

Figure 3: User activity distributions. The vertical axis shows the density of posts for each user. Darker means higher. The total number of posts per user is on the top. Distributions are heterogeneous and highly non-uniform.

Data collection and preprocessing. To support the use of POLL for continual learning research, we collected a large dataset of Twitter posts, posted between January 2013 and September 2019. We performed a number of processing steps to clean the data, described in Appendix C. The cleaned data contains more than 110M tweets in total. We subsample it into two disjoint datasets: Firehose10M and Firehose100M, with a total of 10M and 100M tweets, respectively. Firehose10M is intended for rapid development and validation. Firehose100M is intended as a large-scale benchmark.

Table 2 summarizes key statistics of the datasets. We set aside 3 randomly sampled tweets per user for the validation set, and 3 other randomly sampled tweets per user for the test set. Note that the Firehose-level validation sets are different from the online validation buffer maintained internally by ConGraD (Section 4). Figure 3 shows a small sample of the temporal dynamics in the data. The distributions of users’ posts are continuous, span a long time horizon, and are highly heterogeneous.

Figure 4 shows the distribution of word-level tokens in the Firehose datasets, categorized into English, hashtags, mentions, and emoji. (A mention is a direct reference to another user.) In total, Firehose 10M and 100M contain 5.2M and 26.2M unique word-level tokens, respectively. While English dominates in terms of the number of tokens, the number of unique tokens is dominated by mentions and hashtags. The high number of unique mentions and hashtags indicates that many of these only occur a small number of times. The emoji vocabulary is limited but heavily used: a higher number of tokens than hashtags, for a vocabulary that is three orders of magnitude smaller.

Vocabulary. The number of unique tokens in the data is far beyond the capacity of word-based models. To address this, we leverage practices from machine translation [42] and build a subword vocabulary through unigram modeling [17] using the SentencePiece library [18]. This produces a subword vocabulary of size 32,000. We use a subword vocabulary for training only, and report word perplexity for evaluation, since this measure is independent of different tokenizers and vocabularies.
Multi-task structure. We conduct an experiment to evaluate the importance of multi-task modeling on Firehose. To this end, we examine whether a single language model can fit the data as well as a personalized language model. Table 3 shows the performance of a user-agnostic language model versus a personalized (user-conditioned) model on Firehose10M. For this experiment, we trained the models offline, in a batch setting, to specifically evaluate the prevalence of multi-task structure in the data. The personalized model reduces word-level perplexity by 16.3% relative to the user-agnostic model. To further evaluate the multi-task structure, we evaluate each user’s language model on data from 5 other randomly chosen users. Cross-user perplexity is as high as 159.2. This indicates that tasks (users in our setting) differ significantly from each other, validating the multi-task structure. Combined with the strong non-stationarity apparent in Figure 3, Firehose is both multi-task and non-stationary, indicating it is an appropriate dataset for benchmarking CL as formalized in Section 2.

6 Experiments

Baselines. Two aspects of continual learning approaches are the algorithmic model and the optimizer. For the algorithmic model, we experiment with (i) Offline (Oracle): Learner after online-to-offline conversion. This is not a continual learner as it passes over the data multiple times. We include it as an oracle model to compare against. (ii) Online Only: Pure online learner without any memory. (iii) Replay Only: An experience-rollback-based method that adds all the data to a replay buffer and samples from it. (iv) Mixed Replay [6]: Combines a pure online learner and a replay-based learner to take half of the data from the online stream and the other half from the replay buffer. (v) A-GEM [5]: An efficient implementation of Gradient Episodic Memory. For the optimizer, we benchmark Online GD (i.e., applying SGD in an online manner) and ConGraD. We evaluate each algorithmic model × optimizer pair. We report three metrics: test performance, online fit, and backward transfer.

Test performance. We report word perplexity on a withheld test set that is balanced across users. This is a time-independent measure over the full dataset. It measures generalization and learning. Table 5 reports the test performance of each algorithm for Firehose10M and Firehose100M.

ConGraD outperforms Online GD for all algorithmic models. This indicates that ConGraD is a better optimizer from a test performance perspective. A-GEM does not scale to Firehose100M; hence, it is only included for Firehose10M. Furthermore, mixed replay performs best among the modeling choices, in agreement with Chaudhry et al. [6]. For comparison, the oracle offline learner attains 94.1 perplexity on Firehose10M, which is significantly better than the best-performing continual learner (Mixed Replay with ConGraD). Although part of this gap will remain because online learning is provably harder than offline, we conjecture that significant progress is possible. Moreover, the role of scale is very significant: an 11-point difference in perplexity between Firehose10M and Firehose100M, validating the importance of evaluating continual learning in large-scale settings.

Online fit. We report word perplexity of the next (unseen) batch during training, as defined in Section 2. We average it over time as $\frac{1}{t} \sum_{s=t+1}^{t+L} \mathcal{L}^{D_{s+1}}(\hat{\theta}_s)$ and plot over $t$ in Figure 5(a). This is very similar to average regret in online learning. Online GD in an online-only setting is provably optimal for this metric, as shown by Hazan et al. [11]. ConGraD performs nearly as well as Online GD in the online-only setting and outperforms it in other settings. In terms of algorithmic models, A-GEM and Replay Only fail as they focus exclusively on history without consideration for online fit.

Backward transfer. In order to measure forgetting, we compute the perplexity of the final model on historical data for various time differences as $\frac{1}{t} \sum_{s=t}^{t-L} \mathcal{L}^{D_{s+1}}(\hat{\theta}_s)$ and plot over $t$ in Figure 5(b). As expected, all optimizers and models exhibit forgetting (perplexity increases for older data). Interestingly, the optimizer has a significant effect on forgetting, which suggests that the core-set is not chosen well. ConGraD yields the lowest level of forgetting.

A-GEM retains experience better than other algorithmic models: the difference in perplexity is only 5 points between 2019 and 2013. On the other hand, the perplexity of A-GEM on the latest data is so high that the low level of forgetting is secondary. Other methods yield lower perplexity on historical data.
data despite higher levels of forgetting because they fit the data better. We conclude that the failure of A-GEM reported by Chaudhry et al. [6] is the fault of poor learning, not the fault of forgetting.

**Overall performance.** A successful continual learner needs to optimize all three objectives. Among algorithmic models, A-GEM forgets the least but also learns the least. Online Only learns the most but also forgets the most. Mixed Replay demonstrates a good trade-off between learning and forgetting. From an optimization perspective, our optimization algorithm, ConGraD, yields significantly better generalization. ConGraD outperforms Online GD and Online Only perform similarly in terms of online fit and forgetting. Thus ConGraD is the superior optimizer overall.

### 6.1 Ablation Studies and Analysis

**Effect of \( K \).** Table 6 reports an evaluation of different settings of \( K \) for each learner. ConGraD outperforms the baselines for all \( K \). For Online GD, \( K \) is the number of GD steps. The results indicate that different models and data call for different settings of \( K \). For ConGraD, \( K \) is the maximum number of steps.

**Online validation buffer size.** We evaluate the effect of the validation buffer size in Table 7. We use Mixed Replay × ConGraD for this experiment. The results indicate that a small validation buffer (two data points per user) is sufficient to successfully adapt gradient descent. Although one would expect better performance with a bigger validation set, we see lower performance with large buffer sizes. We hypothesize that larger validation buffer size hurts learning because it creates a delay between the time data is observed and the time it is used for learning.

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**Table 4: Validation buffer strategies.** Word perplexity (↓) of Mixed Replay × ConGraD.

|                | FIFO               | Reservoir sampling | Stratified sampling |
|----------------|--------------------|--------------------|--------------------|
| Data Seen 1e7  | 127.9              | 127.8              | 126.5              |

**Table 5: Test performance.** Word perplexity (↓).

|                     | Firehose10M | Firehose100M |
|---------------------|-------------|--------------|
| Online GD           | A-GEM       | Online Only  |
|                     | 149.7       | 153.1        |
| ConGraD             | 148.1       | 145.7        |
|                     | N/A         | 133.0        |
|                     | 129.7       | 128.2        |

**Table 6: Effect of \( K \).** Word perplexity of test performance (↓). ConGraD outperforms Online GD for all \( K \). The results indicate that setting \( K \) adaptively is beneficial.

|                 | \( K = 1 \) | \( K = 3 \) | \( K = 5 \) | \( K = 3 \) | \( K = 5 \) |
|-----------------|-------------|-------------|-------------|-------------|-------------|
| A-GEM           | 162.1       | 150.7       | 149.7       | 149.0       | **148.1**   |
| Online only     | 153.6       | 153.1       | 164.6       | **145.7**   | 146.8       |
| Replay only     | 142.0       | 158.1       | 176.5       | **139.3**   | 139.9       |
| Mixed replay    | 137.2       | 133.3       | 139.3       | 127.0       | **126.5**   |

**Table 7: Validation buffer size.** Word perplexity (↓) of Mixed Replay × ConGraD.

| \( V = 90K \)   | \( V = 180K \)  | \( V = 270K \)  | \( V = 360K \)  | \( V = 450K \)  |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| 126.5           | 124.8           | 125.5           | 125.9           | 127.3           |
Table 8: Evaluation on earlier continual learning benchmarks. We use final mean accuracy as the metric and report the average over 3 random runs (standard deviation in parentheses). Memory size = 300 for all methods, with one pass over the data as in [1].

|                | GEM [23] | iCARL [30] | Online | Replay | Mix. Replay | Online | Replay | Mix. Replay |
|----------------|----------|------------|--------|--------|-------------|--------|--------|-------------|
| Disjoint CIFAR | 19.1(3.5)| 29.2(5.0)  | 16.0(0.2)| 29.3(0.5)| 27.6(2.7)   | 15.6(0.8)| 31.0(0.7)| **31.3 (1.2)**|
| Disjoint MNIST | 19.1(3.5)| 29.2(5.0)  | 16.0(0.2)| 29.3(0.5)| 27.6(2.7)   | 15.6(0.8)| 31.0(0.7)| **31.3 (1.2)**|
| Permuted MNIST | 79.6(1.3)| 68.2(2.7)  | 56.9(3.2)| 81.3(0.6)| 80.3(1.2)   | 67.5(0.8)| 81.0(0.8)| **81.3 (0.2)**|

**Online validation buffer strategy.** We compare different strategies for maintaining the validation buffer. The results are reported in Table 4. We use the Mixed Replay × ConGraD combination for this experiment. For test performance, stratified sampling is the best strategy.

6.2 Evaluation on Earlier Continual Learning Benchmarks

We evaluate the ConGraD optimizer on earlier continual learning benchmarks. The results are provided in Table 8 and further details are given in Appendix C. ConGraD consistently improves over continual learning methods that leverage Online GD. Even more importantly, we observe that most CL algorithms reach similar accuracy, suggesting that traditional benchmarks are not capable of stratifying different algorithms. This further supports the introduction of POLL as a challenging setting for continual learning at scale.

7 Related Work

**Continual learning.** Existing methods can be categorized into three major families based on how they store and use past data. *Prior-based methods* leverage a data-driven prior from past tasks to regularize the current task [4, 16, 25, 31, 35, 44]. *Replay-based methods* store a small set of samples as a proxy for the past, and leverage them together with the current task [5, 6, 23, 38]. *Structure-based methods* isolate parameters of different task-specific components to prevent interference between tasks [20, 24, 32]. Chaudhry et al. [6] show that the second category (replay-based) achieves superior performance on large-scale datasets while being computationally efficient. We therefore focus on replay-based methods in our work. Since our contributions are independent of the modeling choices, we hypothesize that they are applicable to other categories as well.

**Online learning.** Online learning (OL) [10, 36] is closely related to continual learning. In contrast to continual learning, the focus in OL is on the latest task. Continual fit to past data is not emphasized and catastrophic forgetting is not a primary concern. Furthermore, the non-stationarity is typically governed by an adversary. Most relevant to us is the non-convex OL setting of Hazan et al. [11]. They propose a non-convex optimization method that can be seen as a special case of our method, as discussed in Section 4. Another relevant work that focuses on systems aspects is Carlson et al. [2], which proposes an online data-mining algorithm for learning linguistic knowledge bases.

**Multi-task NLP.** There has been remarkable progress in multi-task NLP due to recent breakthroughs in architectures and unsupervised pretraining [28, 39], multi-task learning [3, 12, 21], and comprehensive evaluation benchmarks [40, 41]. Changpinyo et al. [3] learned a set of task embeddings with a shared sequence model to address 11 sequence tagging tasks. Houlsby et al. [12] utilized residual adapters [29] to adapt Transformers to different tasks. Our work uses these multi-task architectures as a starting point and applies them to the massively multi-task continual setting of POLL.

**Controlled language generation.** Our problem setting can be seen as a form of controlled (conditional) language generation. Existing setups typically learn a generative model over a small set of control factors such as sentiments [13, 37], sentence tense and length [9, 22], or content-derived topics and domains [19]. A recent highlight is the work of Keskar et al. [14], who train a very large Transformer with over 50 control codes, achieving high-quality text generation with attribute control. Compared to this body of work, we use a much larger number of control conditions (hundreds of thousands: each user is a control condition) in a continual streaming setting.
8 Conclusion

We developed personalized online language learning (POLL) as a new setting for continual learning. To support research on this problem, we collected a massive web-scale dataset that comprises 100 million tweets posted over six years (Firehose). We benchmarked continual learning algorithms on this data and contributed an effective algorithm for continual gradient descent (ConGraD). Our experiments indicate that there is significant room for progress in continual learning with real web-scale data.

References

[1] Aljundi, R., Lin, M., Goujaud, B., and Bengio, Y. Gradient based sample selection for online continual learning. In NeurIPS, 2019. 4, 9, 14

[2] Carlson, A., Betteridge, J., Kisiel, B., Settles, B., Jr., E. R. H., and Mitchell, T. M. Toward an architecture for never-ending language learning. In AAAI, 2010. 9

[3] Changpinyo, S., Hu, H., and Sha, F. Multi-task learning for sequence tagging: An empirical study. In COLING, 2018. 9

[4] Chaudhry, A., Dokania, P. K., Ajanthan, T., and Torr, P. H. Riemannian walk for incremental learning: Understanding forgetting and intransigence. In ECCV, 2018. 9

[5] Chaudhry, A., Ranzato, M., Rohrbach, M., and Elhoseiny, M. Efficient lifelong learning with A-GEM. In ICLR, 2019. 7, 9

[6] Chaudhry, A., Rohrbach, M., Elhoseiny, M., Ajanthan, T., Dokania, P. K., Torr, P. H., and Ranzato, M. Continual learning with tiny episodic memories. arXiv:1902.10486, 2019. 7, 8, 9

[7] Dai, Z., Yang, Z., Yang, Y., Carbonell, J., Le, Q. V., and Salakhutdinov, R. Transformer-XL: Attentive language models beyond a fixed-length context. In ACL, 2019. 4, 12, 13, 14

[8] Farquhar, S. and Gal, Y. Towards robust evaluations of continual learning. In ICML Workshops, 2018. 1, 2, 4

[9] Ficler, J. and Goldberg, Y. Controlling linguistic style aspects in neural language generation. In EMNLP Workshops, 2017. 9

[10] Hazan, E. Introduction to online convex optimization. Foundations and Trends in Optimization, 2(3-4):157–325, 2016. 9

[11] Hazan, E., Singh, K., and Zhang, C. Efficient regret minimization in non-convex games. In ICML, 2017. 5, 7, 9

[12] Houlsby, N., Giurgiu, A., Jastrzebski, S., Morrone, B., De Laroussilhe, Q., Gesmundo, A., Attariyan, M., and Gelly, S. Parameter-efficient transfer learning for NLP. In ICML, 2019. 4, 9, 12

[13] Hu, Z., Yang, Z., Liang, X., Salakhutdinov, R., and Xing, E. P. Toward controlled generation of text. In ICMIL, 2017. 9

[14] Keskar, N. S., McCann, B., Varshney, L., Xiong, C., and Socher, R. CTRL: A conditional transformer language model for controllable generation. arXiv:1909.05858, 2019. 9

[15] Kingma, D. P. and Ba, J. Adam: A method for stochastic optimization. In ICLR, 2015. 14

[16] Kirkpatrick, J., Pascanu, R., Rabinowitz, N., Veness, J., Desjardins, G., Rusu, A. A., Milan, K., Quan, J., Ramalho, T., Grabska-Barwinska, A., et al. Overcoming catastrophic forgetting in neural networks. PNAS, 2017. 9

[17] Kudo, T. Subword regularization: Improving neural network translation models with multiple subword candidates. In ACL, 2018. 6

[18] Kudo, T. and Richardson, J. SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. In EMNLP, 2018. 6

[19] Lample, G., Subramanian, S., Smith, E., Denoyer, L., Ranzato, M., and Boureau, Y.-L. Multiple-attribute text rewriting. In ICLR, 2019. 9
[20] Li, Z. and Hoiem, D. Learning without forgetting. In *ECCV*, 2016. 9
[21] Liu, X., He, P., Chen, W., and Gao, J. Multi-task deep neural networks for natural language understanding. In *ACL*, 2019. 9
[22] Logeswaran, L., Lee, H., and Bengio, S. Content preserving text generation with attribute controls. In *NeurIPS*, 2018. 9
[23] Lopez-Paz, D. and Ranzato, M. Gradient episodic memory for continual learning. In *NeurIPS*, 2017. 9
[24] Mallya, A. and Lazebnik, S. PackNet: Adding multiple tasks to a single network by iterative pruning. In *CVPR*, 2018. 9
[25] Nguyen, C. V., Li, Y., Bui, T. D., and Turner, R. E. Variational continual learning. In *ICLR*, 2018. 9
[26] Nguyen, C. V., Achille, A., Lam, M., Hassner, T., Mahadevan, V., and Soatto, S. Meta-analysis of continual learning. In *NeurIPS Workshops*, 2019. 1, 2, 4
[27] Parisi, G. I., Kemker, R., Part, J. L., Kanan, C., and Wermter, S. Continual lifelong learning with neural networks: A review. *Neural Networks*, 113, 2019. 1
[28] Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., and Sutskever, I. Language models are unsupervised multitask learners. *Technical Report*, 2019. 9
[29] Rebuffi, S., Bilen, H., and Vedaldi, A. Learning multiple visual domains with residual adapters. In *NeurIPS*, 2017. 4, 9, 12
[30] Rebuffi, S.-A., Kolesnikov, A., Sperl, G., and Lampert, C. H. iCaRL: Incremental classifier and representation learning. In *CVPR*, 2017. 9
[31] Ritter, H., Botev, A., and Barber, D. Online structured laplace approximations for overcoming catastrophic forgetting. In *NeurIPS*, 2018. 9
[32] Rusu, A. A., Rabinowitz, N. C., Desjardins, G., Soyer, H., Kirkpatrick, J., Kavukcuoglu, K., Pascanu, R., and Hadsell, R. Progressive neural networks. In *NeurIPS*, 2016. 9
[33] Schmidhuber, J. Discovering neural nets with low Kolmogorov complexity and high generalization capability. *Neural Networks*, 10(5):857–873, 1997. 5
[34] Schwarz, J., Altman, D., Dudzik, A., Vinyals, O., Teh, Y. W., and Pascanu, R. Towards a natural benchmark for continual learning. In *NeurIPS Workshops*, 2018. 1, 2
[35] Schwarz, J., Czarnecki, W., Luketina, J., Grabska-Barwinska, A., Teh, Y. W., Pascanu, R., and Hadsell, R. Progress & compress: A scalable framework for continual learning. In *ICML*, 2018. 9
[36] Shalev-Shwartz, S. Online learning and online convex optimization. *Foundations and Trends in Machine Learning*, 4(2):107–194, 2012. 9
[37] Shen, T., Lei, T., Barzilay, R., and Jaakkola, T. Style transfer from non-parallel text by cross-alignment. In *NeurIPS*, 2017. 9
[38] Shin, H., Lee, J. K., Kim, J., and Kim, J. Continual learning with deep generative replay. In *NeurIPS*, 2017. 9
[39] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. Attention is all you need. In *NeurIPS*, 2017. 9
[40] Wang, A., Pruksachatkun, Y., Nangia, N., Singh, A., Michael, J., Hill, F., Levy, O., and Bowman, S. SuperGLUE: A stickier benchmark for general-purpose language understanding systems. In *NeurIPS*, 2019. 9
[41] Wang, A., Singh, A., Michael, J., Hill, F., Levy, O., and Bowman, S. R. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In *ICLR*, 2019. 9
[42] Wu, Y., Schuster, M., Chen, Z., Le, Q. V., Norouzi, M., Macherey, W., Krikun, M., Cao, Y., Gao, Q., Macherey, K., et al. Google’s neural machine translation system: Bridging the gap between human and machine translation. *Technical Report*, 2016. 6
[43] Yao, Y., Rosasco, L., and Caponnetto, A. On early stopping in gradient descent learning. *Constructive Approximation*, 26(2):289–315, 2007. 5
[44] Zenke, F., Poole, B., and Ganguli, S. Continual learning through synaptic intelligence. In *ICML*, 2017. 9
A Empirical Study on Multi-task Learning Architectures

We perform a study over multiple architectural choices for POLL. We first introduce the principles and concrete instantiations of architectures for POLL in Section A.1. Next, in the Section A.2 we discuss the experimental results and identify the best architectures for POLL.

A.1 Multi-task Learning Architectures for POLL

An architecture for POLL requires a high-capacity sequence model that excels at learning linguistic patterns within a long context, in order to model the language; and, a highly scalable mechanism capable of capturing the personal utterance from a large number of individuals, in order to learn personalization. As a high-capacity model, we use Transformer-XL [7]. Based on it, we adapt a variety of different approaches from the multi-task learning literature to encode user-specific context, such that the Transformer-XL can condition on it. For scalability to a high number of users, we only consider the options which would capture user-specific information as low-dimensional embeddings since anything higher order than linear would not scale. This also allows us to extend to new users, as it only requires new user embeddings.

We consider three different categories of multi-task architectures (see Figure 6 for illustrative examples). (1) Multi-task Encoder is a model that combines the user-specific information together with the word-embedding, before any sequence modeling happens. It uses a residual MLP to extract such user-specific word embedding, which is then input to the shared sequence model. (2) Multi-user Decoder uses the user embedding and a residual MLP to modulate the contextualized output embedding of the sequence model, similar to the multi-head models. (3) Residual Adapter is a layer-wise deep multi-task model [12, 29]. It makes use of the user embeddings to modulate the output activation of each layers in a deep sequence model (Transformer-XL in our case) by predicting the user-specific residual component of intermediate representations.

Figure 6: Illustrative figure of the multi-task transformer model for a large number of users.
A.2 Quantitative Comparison of Different Architectural Choices

We instantiate the aforementioned options by using the 12-layer base Transformer-XL (with the exact sample configuration of Dai et al. [7]). There is one residual MLP for both Multi-task encoder and Multi-task decoder, which takes the concatenation of the user embedding and the word embedding (or Transformer-XL’s output activation) as input and outputs the user-specific residual component. The dimensionality of the hidden layers for this MLP is set to be 128. For the Residual adapters, it has 12 such residual MLPs (one corresponds to each Transformer-XL layer), with their hidden dimensionality also being 128. We list the parameter of each different architecture in the Table 9.

We compare these architectures after an online to offline conversion as our focus is to study the model architectures, not continual learning. These models are learned offline with multiple epochs over the FIREHOSE10M data and evaluate using the balanced test set from all users in a time-invariant sense. We report average perplexity over the balanced test set in Table 9.

Table 9 suggests that personalization is possible with all of the aforementioned architectures. Moreover, residual adapters significantly improve perplexity over other architectural choices for a modest increase in the number of parameters. Hence, in our setting, the residual adapter is an efficient and effective choice. Therefore, we use it as the standard baseline for continual learning experiments in the main paper.

Table 9: Offline perplexity of multi-user architectures on Firehose10M.

| Architectures            | # Params | Perplexity ↓ |
|-------------------------|----------|--------------|
| User-agnostic LM        | 57.4M    | 112.5        |
| Personalized LM         |          |              |
| Multi-task encoder      | 60.8M    | 100.6        |
| Multi-task decoder      | 60.8M    | 101.4        |
| Residual adapter        | 65.1M    | 94.1         |

B Additional Discussion on Validation Buffer Strategies

ConGraD uses a validation buffer to adaptively control the optimization process. A natural validation buffer maintenance scheme is first-in-first-out (FIFO) as it directly approximates the online fit performance. On the other hand, continual learning is a multi-objective problem as it requires simultaneous optimization of test-performance, backward transfer, and online fit. If the main objective is the test performance which we define as a perplexity over an unseen balanced test-set over users, a balanced validation buffer would be a better choice. This would result in a stratified sampling scheme where the buffer is kept balanced over users. If the main objective is backward-transfer, the intuitive choice becomes reservoir sampling as it ensures the validation buffer is an unbiased estimate of the backward loss. Hence, there is no dominant choice for the validation buffer strategy due to the multi-objective nature of the continual learning problem. We compare these three strategies in terms of test performance in Table 4. As expected, the stratified strategy performs best but the difference between methods is minor. Moreover, we compare them in terms of the backward transfer performance in Figure 7 and conclude that reservoir sampling is the best strategy from a backward transfer perspective. In summary, the choice of validation buffer strategy strictly depends on the partial ordering of the objectives.
C Additional Implementation Details

Data collection and cleaning for Firehose. We perform the following steps of data cleaning. (1) Perform language detection and remove all non-English tweets. (2) Remove tweets that are explicitly marked as retweets and replies. (3) Remove users that have the total number of tweets less than 20. (4) Tokenize and replace all URLs as a special token “<URL>”. (5) Prepend and append the meta-tokens “<SOT>” and “<EOT>” in front of and after each tweet. The preprocessing steps result in 110M tweets in total from more than 920K unique users. We then randomly split the collected data into two datasets, Firehose 10M and Firehose 100M, which contains 10M and 100M tweets, respectively. Meanwhile, we prepare another non-overlapping set of data (with 100M tweets) from Jan 2013 to Dec 2013 as the pretraining dataset, to learn a user-agnostic Transformer-XL that models the Twitter language. We note that the purpose of this model is to serve as an initialization for continual learning the personalized Twitter language model.

Experiments on Firehose. In all our experiments, we use the 12-layer Transformer-XL base model (the same model as Dai et al. [7]) as the backbone architecture for sequence modeling. We pretrain this model on a non-overlapping set of 2013 Twitter data (without using any user information) to serve as initialization for all the experiments (including the study comparing against different architecture choices in Section A.2). We set the dimension of user embeddings to 32, which amounts to 2.8M and 28.0M parameters for Firehose10M and Firehose100M, respectively. The subword vocabulary we used is instantiated with the dimension of 512, which aligns with the settings of the original Transformer-XL.

For replay-based continual learning algorithms, we use a small replay buffer (per user) to store historical data for all the replay-based methods we studied, which is 5 data points per user for Firehose10M and 2 data points per user for Firehose100M. For all the results that use the proposed online validation buffer, we allocate one additional data point per user, which incurs a limited memory cost. We use the Adam [15] optimizer with a constant learning rate of $2.5e^{-4}$. Meanwhile, a warm-up strategy is applied, which linearly increases the learning rate from 0 to $2.5e^{-4}$ in the first 2000 iterations. We also clip the gradient with its $\ell_2$-norm greater than 0.25 to stabilize the training procedure of all experiments. To facilitate the reproducibility of our results, we make our code publicly available on https://github.com/firehose-dataset/congrad.

Experiments on earlier CL benchmarks. We follow Aljundi et al. [1] and implement ConGraD × {Online Only, Replay Only, Mixed Replay} based on the public source code. For a fair comparison, we used the same hyperparameters as Aljundi et al. [1] to construct the three synthetic datasets (Disjoint CIFAR, Disjoint MNIST, and Permuted MNIST) as well as for creating the baseline algorithms. Following the definition of CL, all three datasets are implemented such that only one pass over all the data is available (with randomly permuted data and tasks). We restrict the maximum size of replay memories on each dataset to 300 and use a two-layer perception (with 100 hidden units) as the learning model. For ConGraD, we allocate 50 data points to construct the online validation buffer.

\[^2\text{Available on https://github.com/rahafaljundi/Gradient-based-Sample-Selection}\]