CONTINUOUS LEARNING FOR MONOLINGUAL END-TO-END AUTOMATIC SPEECH RECOGNITION

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Abstract
Adapting Automatic Speech Recognition (ASR) models to new domains leads to a deterioration of performance on the original domain(s), a phenomenon called Catastrophic Forgetting (CF). Even monolingual ASR models cannot be extended to new accents, dialects, topics, etc. without suffering from CF, making them unable to be continually enhanced without storing all past data. Fortunately, Continual Learning (CL) methods, which aim to enable continual adaptation while overcoming CF, can be used. In this paper, we implement an extensive number of CL methods for End-to-End ASR and test and compare their ability to extend a monolingual Hybrid CTC-Transformer model across four new tasks. We find that the best performing CL method closes the gap between the fine-tuned model (lower bound) and the model trained jointly on all tasks (upper bound) by more than 40%, while requiring access to only 0.6% of the original data.

Index Terms—end-to-end automatic speech recognition, continual learning, monolingual speech recognition

1. INTRODUCTION
Automatic Speech Recognition (ASR) has greatly progressed in recent years, moving from Hidden Markov Model (HMM) to End-to-End (E2E) models. However, like the Artificial Neural Networks (ANN) they use, E2E ASR models suffer from Catastrophic Forgetting (CF) [11] when adapted to a new task. This new task need not be a new language: it may consist of new dialects, accents, topics, etc. It suffices that the data distributions of the old and new tasks differ for CF to occur.

Fortunately, many Continual Learning (CL) methods have been proposed in the image classification community, enabling ANNs to learn continually without suffering from CF. Following [2], CL methods can be categorized into three groups: i) the regularization-based methods use a regularization loss to train new tasks such that it does not hurt the performance of previous tasks. [3, 4, 5] do this by estimating the importance of each parameter to previous tasks and using these importance weights in a weighted L2 regularization to learn new ones. [6] uses knowledge distillation [7] on the new tasks’ data to transfer knowledge from the old to the new model; ii) the replay-based methods store a set of representative samples in a memory to rehearse old tasks when learning new ones. Most straightforward are [8, 9, 10], which train on the new task and the memory jointly. Another line of work [11, 12, 13] focuses on gradient alignment between old and new tasks; iii) the architectural-based methods increase the capacity of the model when learning new tasks. The latter are not considered in this paper.

Regarding ASR and, especially, E2E ASR, CL is a very new and unexplored topic. [14, 15] apply CL to the acoustic model of a HMM-based ASR model. [16] considers CL for the pre-trained wav2vec2 model [17] by freezing all learned parameters and using adapters for new tasks. [18] combines a Text-to-Speech and ASR model to prevent forgetting. [19] applies Learning without Memorizing [20] to E2E ASR, focusing on a scenario where subsequent tasks are much smaller than the initial one. Finally, [21] implements four existing CL methods for E2E ASR. Compared to [21], we implement an extra seven CL methods for E2E ASR. We test and compare their ability to continually extend and enhance a monolingual E2E ASR by training it on new data. To make the experiments more realistic, we run the methods without assuming access to validation sets of previous tasks to optimize hyper-parameters. Since for many CL methods, both regularization-based and rehearsal-based, the weight of the regularization is a crucial hyper-parameter, we propose, based on [2], a simple and efficient way to determine this weight.

2. CONTINUOUS LEARNING SET-UP
First, we elaborate on the CL setup of our experiments, which were all done using the ESPnet library [22].

Data. We consider the Corpus Gesproken Nederlands (CGN) dataset [23]. The CGN dataset consists of 900 hours of Dutch speech from both the Netherlands (NL) and Belgium (BE), divided into 15 components: we consider all except four components which consist of more spontaneous speech. Based on the dialect of the speakers, we split the remaining components into four tasks: NL-main, VL-main, NL-rest, VL-rest; which are learned in this order. Each task is further split into a training set (with 59k to 101k utterances per task), validation set and test set.

Model. The model is the Hybrid CTC/Transformer from [24]. Its loss during training is thus computed as:

$$L(X, y; \theta) = c \cdot L_{ctc}(X, y; \theta) + (1 - c) \cdot L_{dec}(X, y; \theta)$$  (1)

where $L(X, y; \theta)$, $L_{ctc}(X, y; \theta)$ and $L_{dec}(X, y; \theta)$ are, respectively, the total, CTC and Decoder loss of the model with parameters $\theta$ on utterance $X$ with ground truth $y$. As in [24], the weight of CTC for both training and decoding is 0.3, i.e. $c = 0.3$. Unlike [24], we do not use a Language Model during decoding. The output of the model are 300 word pieces, generated by the Sentence Piece model
3. METHODS

3.1. Regularization-based methods

The regularization-based methods compute a regularization loss which is added to \( L(X, y; \theta) \) from Eq. [2] during training.

**Elastic Weight Consolidation (EWC).** After training task \( t \), EWC \([3]\) computes the diagonal of the Fisher information matrix, denoted \( \Omega^t \). \( \Omega^t \) is considered the importance weight of parameter \( \theta^t \) for task \( t \). Next, \( \Omega^t \) is added to \( \Omega^{\leq t} = \Omega^{\leq t-1} + \Omega^t \) as in \([27]\), and used in the regularization loss to learn task \( t + 1 \):

\[
L_{ewc}(\theta) = \frac{\lambda}{2} (\theta - \theta^t)^T \Omega^{\leq t} (\theta - \theta^t)
\]

Since \( \Omega^t \) is diagonal, Eq. [3] reduces to a weighted L2 regularization, with weight \( \Omega^t \) for parameter \( \theta^t \).

**Memory-Aware Synapses (MAS).** MAS \([4]\) works similar as EWC, but computes the (diagonal of) \( \Omega^t \) differently. Given that the ASR model has both a CTC and Decoder output, we compute \( \Omega^t \) for MAS as follows:

\[
\Omega^t_{i,i} = \mathbb{E}_{X \sim D_t} \left[ \left( \frac{\partial f^{dec}(X; \theta^i)}{\partial \theta_i} \right)^2 + (1 - c) \left( \frac{\partial f^{dec}(X; \theta^i)}{\partial \theta_i} \right)^2 \right]
\]

Next, the loss is exactly the same as for EWC (Eq. [3]).

**Continual learning with Sampled Quasi-Newton (CSQN).** CSQN \([28]\) was recently proposed to extend EWC by considering interactions between parameters. Starting from EWC’s \( \Omega^t \), CSQN considers sampled Quasi-Newton \([29]\) methods to compute low-rank approximations of the Hessian of the loss, which are then used as in Eq. [3] to regularize training. We consider both the standard version and the reduced version which was called BTREE in \([28]\) and which we here denote CSQN-BT.

**Learning Without Forgetting (LWF).** LWF \([5]\), when learning task \( t + 1 \), uses knowledge distillation \([7]\) between the old model (with parameters \( \theta^t \)) as teacher and the current model (with trainable parameters \( \theta \)) as student, on the new task’s data:

\[
\mathcal{L}_{lwf}(X; \theta) = \lambda \cdot \left( e \sum_{i=1}^{L} \sum_{j=1}^{o} f^{dec}_{ij}(X; \theta^t) \log \frac{f^{dec}_{ij}(X; \theta)}{\gamma} \right) + (1 - e) \sum_{i=1}^{W} \sum_{j=1}^{o} f^{dec}_{ij}(X; \theta^t) \log \frac{f^{dec}_{ij}(X; \theta)}{\gamma}
\]

With \( \gamma \) called the temperature. In our experiments, \( \gamma = 1 \).

3.2. Rehearsal-based methods

The rehearsal-based methods use a small memory of exemplars of previous tasks to enable CL.

**Experience Replay (ER).** We consider three variants of ER \([8]\). In the standard variant, the mini-batch from the current task is augmented with a mini-batch sampled from memory. The augmented mini-batch is sent through the model and the loss is computed on the augmented mini-batch. As this may result in overfitting on the memory, an alternative is to use the loss of the mini-batch sampled from memory a weight \( \lambda \in (0, 1) \), denoted ER (\( \lambda \)). Finally, as in \([9]\), we merge the training set and memory and train on the resulting set, referred to as BER (Batch-level ER).

**Average-Gradient Episodic Memory (A-GEM).** Consider \( g = \frac{\partial L(X, y; \theta)}{\partial \theta} \) with \( (X, y) \) a mini-batch from the current task. Before \( g \) is used to update the model, A-GEM \([12]\) samples a mini-batch \( (\hat{X}, \hat{y}) \) from memory, and computes \( g_{ref} = \frac{\partial L(X, \hat{y}; \theta)}{\partial \theta} \). If \( g \) and \( g_{ref} \) interfere, i.e. if \( g^T g_{ref} < 0 \), it updates \( g \) with \( g \leftarrow g - \frac{g^T g_{ref}}{g_{ref}^T g_{ref}} g_{ref} \) such that both gradients align. The resulting gradient is used to update the model.

**Knowledge Distillation (KD).** KD uses the same loss as LWF in Eq. [5] not computed on a mini-batch of the new task, but on a mini-batch sampled from the memory.

4. RESULTS

**Determining \( \lambda \).** Many of the CL methods require selecting a hyperparameter \( \lambda \), which is the weight of the regularization. Based on \([2]\), we propose a simple and efficient way to determine \( \lambda \) for E2E ASR. We proceed as follows. First, we consider \( \tau^{\text{init}} \), the TER (on the validation set of the new task) of the initial model. Next, we adapt the model for five epochs without regularization, and compute its TER, obtaining \( \tau^{\text{no}, \text{reg}} \). Then, we set \( \lambda \) to a high value and run the model for five epochs with regularization with weight \( \lambda \). We compute the TER and obtain \( \tau \). If \( (\tau^{\text{init}} - \tau^{\text{no}, \text{reg}}) / (\tau^{\text{no}, \text{reg}} - \tau^{\text{init}}) > a \), i.e. if the gap between \( \tau^{\text{init}} \) and \( \tau^{\text{no}, \text{reg}} \) is closed for at least 100\%, we use \( \lambda \) for the regularization; else, we set \( \lambda \leftarrow \lambda \cdot p \) with \( p \in (0, 1) \) and repeat the process. As such, determining \( \lambda \) is done in a fast and efficient way and does not require access to a validation set of previous tasks. We determine \( \lambda \) only for the first adaptation and then fix it. In our experiments, we set \( p = 0.85 \) and \( p = 0.10 \). Moreover, for each method, the initial value of \( \lambda \) is a power of 10.

**Memory.** After learning a task, we sample 500 utterances from the training set and add them to the memory. While sampling uniformly, we only consider utterances whose output length (i.e. number of word pieces in output) exceeds 0.40 \( \cdot \text{mean}\_\text{length} \), where \( \text{mean}\_\text{length} \) is the average output length of the utterances in the training set.
Baselines. Following baselines are considered: (i) Fine-Tuning (FT): the model is adapted without CL method (lower bound); (ii) Joint (JT): trained from scratch on all tasks jointly; (iii) Continued Joint (CJT): adapted from previous task and trained on current and previous tasks jointly (upper bound).

Metrics. For each method, we report the average WER (AVG) (averaged over all learned tasks), backward transfer (BWT) and forward transfer (FWT) [11], and Coverage (COV) [14]. Assuming $T$ tasks have been learned and $R_{i,j}$ is the WER on task $j$ after learning up to task $i$, the BWT is:

$$BWT = \frac{1}{T-1} \sum_{i=2}^{T} (R_{T,i} - R_{i,i})$$ (6)

Note that using this definition, negative BWT indicates forgetting. Furthermore, we define FWT as:

$$FWT = \frac{1}{T-1} \sum_{i=2}^{T} (R_{i,i} - R_{i,j}^T)$$ (7)

where $R_{i,j}^T$ is the WER on task $j$ after learning up to task $i$ with FT. FWT measures to which extent the model can exploit previously acquired knowledge to learn new tasks better. Positive FWT indicates better learning than FT. Finally, COV measures the extent to which the given method closes the gap between FT (lower bound) and CJT (upper bound) in terms of AVG. It is $0\%$ when the method performs as poor as FT, and $100\%$ when the method performs as well as CJT. In addition to AVG, BWT, FWT and COV, we report the storage requirements (Storage), expressed in number of models (one model requiring 105 MB).

Learning the four tasks. Table 1 shows the results after learning the four tasks from Section 2 in sequence.

| Model   | AVG | BWT | FWT | COV | Storage |
|---------|-----|-----|-----|-----|---------|
| JT      | 21.3| -   | -   | -   | 260.54  |
| CJT     | 21.9| +2.5| +0.5| 100.0\% | 260.54  |
| FT      | 27.3| -4.2| -   | 0.0\%| 0.00    |
| EWC     | 28.3| -0.7| -4.8| -18.9\%| 2.00    |
| MAS     | 28.3| -1.1| -4.4| -18.9\%| 2.00    |
| CSQN    | 27.7| -1.5| -3.2| -8.7\%| 32.00   |
| CSQN-BT | 27.8| -1.7| -3.2| -9.8\%| 22.00   |
| LWF     | 26.6| -3.3| -   | 12.4\%| 1.00    |
| A-GEM   | 26.1| -2.5| -0.0| 22.0\%| 2.24    |
| ER      | 28.0| -3.4| -1.7| -13.1\%| 2.24    |
| ER ($\lambda$) | 25.8| -1.9| -0.3| 27.2\%| 2.24    |
| BER     | 26.4| -2.8| -0.2| 16.7\%| 2.24    |
| KD      | 25.0| -1.2| +0.0| 41.7\%| 3.24    |

Table 1: Results after learning the four tasks in sequence.

First, we note that FT indeed suffers from CF, while both JT and CJT are able learn the tasks well, with the latter reaching a positive BWT and FWT.

Considering the regularization-based methods, we find that the methods estimating which parameters are important experience difficulties learning the four tasks. This is especially true for EWC and MAS, which both perform equally poor and even much worse than FT. While CSQN and CSQN-BT, thanks to considering interactions between parameters, perform slightly better, they still underperform FT. We hypothesize that the poor performance of these methods is due to the tasks (as they are very similar) having the same important parameters, which gives the model two options: either it updates these parameters, resulting in CF of the previous task(s); or it leaves them unchanged, resulting in poor learning of the new tasks. In this experiment, EWC, MAS and CSQN are able to limit forgetting, but fail to learn the new tasks well. While EWC achieves the best BWT of all methods, it also attains the worst FWT. Note that the performance of EWC is in line with [21], which also found EWC underperforming FT. Compared to EWC, MAS and CSQN, LWF performs much better, even learning the new tasks better than FT and achieving the best FWT. However, its COV is only 12.4\%, as it is able to reduce FT’s forgetting (BWT) by only 21\%.

Comparing LWF to KD, which uses the same regularization but computed on the memory instead of on the new task’s data, we find that having access to a memory, even though it is only 0.6\% of the original data when learning the fourth task, yields big improvements. KD attains a COV of over 40\%, and learns the new tasks as well as FT, while reducing the latter’s forgetting by more than 70\%. It outperforms the other rehearsal-based methods by a large margin. A-GEM, while it learns the new tasks well, still suffers from severe forgetting, reaching a COV of 22\%. These results are again consistent with [21], which found Gradient Episodic Memory [11] (of which A-GEM is a more efficient variant) outperforming LWF, while both improved the performance of FT. Finally, ER performs worse than FT, as it overfits on the memory, achieving 0.0 WER on its utterances, thus completely memorizing them. Both BER, and especially ER ($\lambda$), perform much better, reaching a COV of 16.7\% and 27.2\%, respectively.

Figure 1 shows the COV after training the tasks with each CL method.

![Figure 1](image-url)
NL-main’s important parameters, they are unable to exploit NL-rest to further improve these parameters.

**Increasing vs. fixed memory.** The rehearsal-based methods from Table 1 had access to a memory with 500 utterances per task. In practice, it may be more desirable to have a memory with fixed size, especially as the number of tasks becomes large. To this end, we fix the size of the memory at 500. Table 2 shows the results for A-GEM, ER (λ) and KD.

| Model     | AVG ↓ | BWT ↑ | FWT ↑ | COV ↑ | Storage |
|-----------|-------|-------|-------|-------|---------|
| A-GEM     | 26.2  | -2.8  | -0.0  | 18.9% | 0.72    |
| ER (λ)    | 25.6  | -1.6  | -0.4  | 29.8% | 0.72    |
| KD        | 25.2  | -1.5  | +0.1  | 38.3% | 1.72    |

Table 2: Results for the rehearsal-based methods with fixed memory after learning the four tasks in sequence.

We find that the differences with Table 1 are negligible. For A-GEM and KD, we observe a slight increase of AVG and a slight decrease of BWT. For ER (λ), on the other hand, there is even a minor improvement, which we attribute to random effects. Nevertheless, we can conclude that the benefits of having an increasing memory, with, when learning the fourth task, access to 0.6% of the training data, are negligible compared having a fixed memory, which has access to only 0.2% of the training data. However, one can expect the benefits to increase as more tasks are learned, and as the number of utterances per task in the fixed memory becomes smaller.

**Storage requirements.** Table 1 shows the storage requirements for the CL methods. After four tasks, the rehearsal-based methods require storing an equivalent of 2.24 models, as they need to store the utterances in the memory. KD even needs to store 3.24 models, compared to the memory it also requires storing the previous model. Compared to the rehearsal-based methods, the regularization-based methods are generally more storage efficient (in addition to not requiring some data from previous tasks to be stored in a memory, which may not always be allowed due to e.g. privacy concerns). While LWF requires storing the previous model, EWC and MAS require storing the previous model and the importance weights, which are the equivalent of one model. Compared to EWC, MAS and LWF, CSQN and CSQN-BT are less storage efficient. The former requires, in addition to EWC’s importance weights and the previous model, 10 models per task (in our experiments) for the Hessian approximations. Consequently, CSQN’s storage requirements increase linearly with the number of tasks. CSQN-BT was proposed to alleviate this; while only negligibly worse in terms of performance than CSQN, its storage requirements increase only logarithmically with the number of tasks. Nevertheless, this is still not as good as EWC, MAS and LWF, whose storage requirements remain constant with the number of tasks.

With an increasing memory, as in Table 2, the rehearsal-based methods’ storage requirements also increase linearly with the number of tasks. However, as we saw in Table 1, this can be overcome by fixing the memory size, with only a negligible deterioration in performance, enabling A-GEM, and, especially, ER (λ) and KD, to achieve excellent performance while being very storage efficient. While A-GEM and ER (λ) need to store an equivalent of only 0.72 models, KD requires storing 1.72 models. While for KD, this is still more than LWF, A-GEM and ER (λ), KD’s very good performance might make it worth the cost. Finally, note how JT and CJT, which need access to all data the model was ever trained on, require storing an equivalent of 260.54 models, making them clearly not a practical solution to overcome CF.

5. CONCLUSION

In this paper, we implemented an extensive number of CL methods, and tested and compared their ability to extend a monolingual E2E ASR model across four tasks. Having access to a memory, though very small compared to the original training set, proved to be very beneficial, as the rehearsal-based methods generally performed much better than the regularization-based methods. To assure the former’s storage requirements do not increase with the number of tasks, the memory size can be fixed with only a negligible degradation in performance. In general, thus, the rehearsal-based methods seem the best and most practical way to currently overcome CF in monolingual E2E ASR models; in particular KD, which closes the gap between the Fine-Tuned (lower bound) and Continued Joint model (upper bound) for 41.7% and 38.3% while having access to only 0.6% and 0.2%, respectively, of the original data. In case storing utterances from previous tasks is not allowed, LWF seems to be the best option, as the other regularization-based methods, which have higher storage requirements, were unable to improve the Fine-Tuning lower bound.

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