EXPLORING THE JOINT USE OF REHEARSAL AND KNOWLEDGE DISTILLATION IN CONTINUOUS LEARNING FOR SPOKEN LANGUAGE UNDERSTANDING

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ABSTRACT

Continual learning refers to a dynamical framework in which a model or agent receives a stream of non-stationary data over time and must adapt to new data while preserving previously acquired knowledge. Unfortunately, deep neural networks fail to meet these two desiderata, incurring the so-called catastrophic forgetting phenomenon. Whereas a vast array of strategies have been proposed to attenuate forgetting in the computer vision domain, for speech-related tasks, on the other hand, there is a dearth of works.

In this paper, we turn our attention toward the joint use of rehearsal and knowledge distillation (KD) approaches for spoken language understanding under a class-incremental learning scenario. We report on multiple KD combinations at different levels in the network, showing that combining feature-level and predictions-level KDs leads to the best results. Finally, we provide an ablation study on the effect of the size of the rehearsal memory that corroborates the appropriateness of our approach for low-resource devices.

Index Terms— Continual Learning, Spoken Language Understanding, Experience Rehearsal, Knowledge Distillation

1. INTRODUCTION

Nowadays speech-related applications, such as voice assistants and home devices, have become ubiquitous in our society. Although current acoustic models can be trained on very large datasets consisting even of hundreds of thousands of hours, it is often necessary to adapt these models to domains and scenarios never seen during training, and so deviating from the standard i.i.d. paradigm. Unfortunately, deep models tend to completely erase the past knowledge when data from a new domain emerge, leading to the so-called catastrophic forgetting phenomenon [1]. This effect is also detrimental for large-scale speech pre-trained models, such as [2][3], for which a retraining phase is computationally very costly [4].

A possible solution is represented by continual learning (CL) (or life-long learning) [5][6]: a set of machine learning tools, largely investigated in computer vision [7][8][9][10], aimed at learning without forgetting. The goal of CL is to adapt a given model to the task required by a new, never seen, domain while preserving the ability to handle the tasks of previous domains. CL approaches proposed in the literature can be divided into three categories: a) methods based on a regularisation loss [7][11] that prevents the parameters from changing widely; b) rehearsal methods based on the replay of historical data [12][8] (either training samples [13] or model weights [14]), and c) methods that apply some modifications to the architecture of the model [15][16].

Similarly to what has been done in [17] for keyword spotting (KWS), we apply CL in a class-incremental learning (CIL) setting, derived from a spoken language understanding (SLU) domain, where a given speech utterance is to be mapped into one, among \( N \), intent using an end-to-end framework. Intents are seen incrementally, along successive training steps (also called tasks).

Many works [13][8][18] have proven that an extremely effective approach to reducing catastrophic forgetting relying on a set of rehearsal data, chosen in each adaptation step and stored in the rehearsal memory, that contribute to the loss function together with those in the actual task. The additional use of a distillation loss [7], which alone falls through in a CIL scenario, is not always beneficial to the model, as pointed out in [19][20], who contend that it can even lead to a deterioration in the performance.

For this reason, inspired by our previous work on porting models on edge devices [21], we investigate the interrelationship between applying the knowledge distillation (KD) at different levels in the model, namely in the predictions and in the feature space, and the rehearsal approach. We demonstrate that the joint use of predictions-level and feature-level KDs leads to the best results.

Our contributions to the CL problem are the following: i) we define a CIL scenario for SLU over the Fluent Speech Command dataset [22]; ii) we provide a thorough analysis of the combination of rehearsal and KDs for 4 CL strategies, and we prove its efficacy in our scenario; iii) we point out that a careful design of the KD weights is crucial for obtaining optimal results, and we foster the CL community to place more emphasis on this aspect; iv) we provide an ablation study about the size of the rehearsal buffer, and we conclude that our approach attains larger gains for smaller sizes, thus making it appealing for low-resource devices.

2. RELATED WORK

As mentioned above, CL strategies can be categorized into three main groups [22][5]: regularization, rehearsal, and architectural approaches.

Regularization approaches mitigate catastrophic forgetting by supplying the standard cross-entropy (CE) loss with regularization terms to avoid abrupt changes in the model weights. Learning without forgetting (LwF) [7] employs a weighted knowledge distillation loss [24] that forces the outputs of the model to be similar to those obtained by the model trained in the previous task. The work by [11] resorts to the Fisher information matrix to estimate the importance of the model weights and protect them afterward to prevent forgetting, while [25] advance a spatial-based distillation loss computed for every intermediate layer of the model.

Rehearsal or Experience Replay methods keep in memory some of the past data to mitigate forgetting. A key aspect lies in the selection strategy for retaining past data. The simplest, but relatively effective, approach randomly chooses some samples from the last task [9]. ICaRL [8] fosters the samples whose features are the closest to
their moving center of gravity. Gradient Episodic Memory (GEM [13]) attenuates forgetting by projecting the gradient update along a direction that does not interfere with the previously acquired knowledge. [26] select the rehearsal samples by maximizing the mutual information between the predictions and the posterior of the model’s parameters using Monte Carlo dropout.

Finally, Architectural methods apply modifications to the network architecture, such as adding layers or freezing specific parts of the model, to handle new incremental tasks. An example is [16], where, at each new task, a novel feature extractor is instantiated, while the previous one is frozen, and pruning is applied to shrink the model. Similarly, [27] learn a subnetwork in each task, called supermask. At inference time, the weighted combination of the supermasks that minimizes the entropy of the output distribution is evaluated. These methods, although successful, do not scale to the number of seen tasks, thus limiting their application in practical scenarios.

Although the literature is mainly related to computer vision, CL has also been investigated in the speech domain. For example, [17] address a KWS incremental-learning task, creating a sub-network for each new task and keeping in memory the processed features from the past tasks. It is also worth noting the use of CL in Automatic Speech Recognition (ASR). The work in [28] proposes an online GEM method for model updates together with a selective sampling strategy.

If we narrow it down to SLU, we can find few works that only consider a domain-incremental CL scenario. [29] propose a progressive architecture for the slot-filling task that expands the network for each new task; [30] consider the combination of rehearsal and regularization techniques for natural language generation. Nevertheless, to the best of our knowledge, we are the first to explore SLU in a CIL scenario, in particular, we study the adoption of the KD at a features and predictions level, and applied to only the rehearsal data or the rehearsal data plus the current data.

3. PROPOSED APPROACH

![Fig. 1: Complete overview of our proposed CIL approach.](image)

In a CL scenario, a classification model, which comprises a multilayered feature extractor ENCφ and a classifier FCφ, is trained over a sequence of T distinct training phases, that is \( D = \{ D_0, \ldots, D_{T-1} \} \). The dataset \( D_t \) related to the \( t^{th} \) training step is interpreted as a task defined by audio signals \( X_t \) and associated class labels \( Y_t \), i.e. \( D_t = (X_t, Y_t) \). In CIL scenarios all task label sets are mutually exclusive, i.e. \( Y_i \cap Y_j = \emptyset, i \neq j \).

At the end of task \( t-1 \) we select a set of data \( R_{t-1} \subset D_{t-1} \) for the rehearsal memory. Then, all the rehearsal data, from task 0 to task \( t-1 \), \( R_{0}^{t-1} = \{ R_0, \ldots, R_{t-1} \} \) are joined with the training data \( D_t \) in order to train the model for the \( t^{th} \) task. A naive CL strategy optimizes the CE loss computed over \( D_t \cup R_{0}^{t-1} \):

\[
\mathcal{L}_{CE}^{t} = - \sum_{(x,y) \in D_t \cup R_{0}^{t-1}} \log(p[y|x; (\theta_t, \phi_t)]),
\]

where \( p[y|x; (\theta_t, \phi_t)] \) is the output probability distribution of the model given the parameters \( \theta_t \) and \( \phi_t \) at task \( t \).

A common approach is to further regularize the model adaptation through a KD loss. In this paper, we experiment with two different distillation terms in combination with the CE loss. The first one is the Kullback Leibler Divergence (KLD) between the output probability distribution at task \( t \) and the distribution predicted with the model trained at task \( t-1 \), i.e.:

\[
\mathcal{L}_{KLD}^{t} = \sum_{(x,y) \in D_t} p[y|x; (\theta_{t-1}, \phi_{t-1})] \log(p[y|x; (\theta_t, \phi_t)]).
\]

In the equation above \( I_t \) represents the training set for task \( t \), consisting of only the rehearsal data (\( I_t = R_{t-1}^{0} \)), or the union of the rehearsal and current data of task \( t \) (\( I_t = D_t \cup R_{t-1}^{0} \)). The second regularization term is given by the mean squared error (MSE) loss between the output of the model encoder at tasks \( t-1 \) and \( t \), i.e.:

\[
\mathcal{L}_{MSE}^{t} = \sum_{x \in I_t} ||\text{ENC}_{\theta_{t-1}}(x) - \text{ENC}_{\theta_t}(x)||^2.
\]

Also in this case we experiment with both \( I_t = R_{t-1}^{0} \) and \( I_t = D_t \cup R_{t-1}^{0} \). The total loss to optimize in each task \( t \) is therefore a linear combination of the CE loss in eq. 1 and the regularization losses in eqs. 2 and 3.

\[
\mathcal{L}_{TOT}^{t} = \lambda_{CE} \mathcal{L}_{CE}^{t} + \lambda_{KLD} \mathcal{L}_{KLD}^{t} + \lambda_{MSE} \mathcal{L}_{MSE}^{t}
\]

Figure 1 shows a schematic illustration of the proposed CIL approach.

4. EXPERIMENTS

We evaluate our proposed approach on the Fluent Speech Commands (FSC) dataset [22]. FSC includes 30,043 English utterances, recorded at 16 kHz. The dataset provides 248 different utterances that are mapped in 31 different intents. The CIL scenario consists of 10 tasks, and each task contains some unique intents. The first task has 4 intents, whereas the subsequent 9 tasks include 3 intents each.

Concerning the rehearsal memory, its entire capacity is not exploited since the beginning, but each class has a pre-allocated space that is used when that class is seen for the first time. In this way, we avoid a possible imbalance among the classes between the first and the last tasks.

4.1. Model architecture and KD weights

The neural network architecture used in the experiments is depicted in Figure 2. It is inspired by the temporal convolutional network (TCN) used in the separation block of Conv-Tas-Net [31], a recently proposed model for speech separation.

The network receives in input 40 Mel-spaced log filter-banks, computed using a sliding window of length 25 ms, with 10 ms stride. Then it applies a global layer normalization (gLN) and a bottleneck layer (1x1 conv block) that maps the input features into 64 channels. The input layer is followed by 2 repetitions of 5 consecutive 1-D dilated convolutional residual blocks. Each residual block is formed by
two symmetrical pipelines surrounding a depth-wise separable convolutional layer that maps the 64 bottleneck features into 128 channels. Each pipeline has a point-wise convolution (1x1 conv block) followed by a gLN with Parametric Rectified Linear Unit (PReLU) activation function. A pointwise convolution is applied at the input and as a final operation. A residual branch connects the original input to the output. Mean pooling is applied to the output of the last block, followed by gLN and a linear layer. A softmax activation layer gives the final class scores.

We train the TCN model for 50 epochs per task with Adam optimizer [32], with a learning rate equal to 5e-4. The CIL scenario is implemented with the Continuum library [33], and the rest of the code is based on PyTorch. Table 1 reports the whole set of hyperparameters of the TCN. We also release our code on GitHub.

Table 1: List of the hyperparameters of the TCN.

| Hyperparameter          | Value |
|-------------------------|-------|
| Input channels          | 40    |
| Hidden channels         | 128   |
| Output channels         | 64    |
| # 1-D conv blocks       | 5     |
| # Repetitions           | 2     |
| Kernel size for the depthwise conv | 3 |

The selection of the KD weights deserves special attention. A common choice for the $\lambda_{KD}$ weight is $\frac{n}{n + m}$, where $n$ is the number of old (seen) classes and $m$ is the number of new classes [34][35]. This choice was originally proposed for works that used only KD as CL strategy, and it gives more and more importance to $\lambda_{KD}$ over time because the past model retains the knowledge from more and more past classes. The subsequent works that considered KD and rehearsal together, adhered to this choice. Nonetheless, we speculate that relying on this option gives worse results.

When we use both KD and rehearsal approaches applied to rehearsal and current data ($\mathcal{I}_t = \mathcal{D}_t \cup \mathcal{R}_t^{t-1}$), the importance of the past model is damped by the fact that the current model sees the rehearsal data, so we still would like $\lambda_{KD}$ to increase, but at a slower pace, and this can be accomplished by using a log function. When we use the KD applied only to the rehearsal data ($\mathcal{I}_t = \mathcal{R}_t^{t-1}$), we give it a weight proportional to the fraction of rehearsal data in the mini-batch. Since this number is too small during the first tasks, we apply the square root operation to enlarge it.

We ultimately set $\lambda_{KD}$ as follows:

$$
\lambda_{KD} = \begin{cases} 
\log(1 + \frac{n}{n + m}) & \text{if } \mathcal{I}_t = \mathcal{D}_t \cup \mathcal{R}_t^{t-1} \\
\frac{b_{rehe}}{b_{total}} & \text{if } \mathcal{I}_t = \mathcal{R}_t^{t-1} 
\end{cases}
$$

where $b_{rehe}$ counts the number of rehearsal data in the current mini-batch, and $b_{total}$ is the current mini-batch size. We found empirically that using $\lambda_{KD}$ as defined in eq. [5] brought about a 1% to 2% improvement in the accuracy. This study suggests that a careful choice of the KD weights is essential.

Based on the considered experiment, eq. [4] changes accordingly. When we do not apply any KD loss, then the weights boil down to $\lambda_{KD} = 0$, $\lambda_{CE} = 1$ (in practice, only the CE loss is used). When we use the KD only in the feature space, the KLD loss is not present, $\lambda_{KD}$ follows eq. [5] and $\lambda_{CE} = 1 - \lambda_{KD}$. If we use the KD in the predictions space, the same as before applies with the KLD loss and the MSE loss inverted. Lastly, when both the KLD loss and the MSE loss are employed, their coefficient $\lambda_{KD}$ follows eq. [5] and $\lambda_{CE}$ is set to 1. Note that in this last case the interpolation coefficients in eq. [5] do not sum to 1.

4.2. Results

Table 2 reports the intent classification accuracy for different KD strategies in combination with 4 CL approaches, i.e., a rehearsal approach with 3 different sample selection strategies (random, iCaRL [8], and “closest to mean”, where the samples which are closest to their class mean in the feature space are chosen), and GEM [13]. The rehearsal memory size is 930 (around 4% of the dataset size).

The results we achieve applying solely the KD in the predictions space without rehearsal are in line with the current state-of-the-art methods on the FSC dataset; ii) the results obtained with the naive fine-tuning method, and iii) the results we achieve applying solely the KD in the predictions space without rehearsal.

The lower part of the table shows the accuracies when rehearsal data are employed. The rows show the accuracies for the cases in which the distillation is performed at the feature level, predictions level, and both levels, respectively. For each configuration, the table also reports the performance when distillation is applied to either rehearsal data alone (denoted with $\mathcal{R}$ in the table) or to the union of rehearsal and actual task data (denoted with $\mathcal{D} \cup \mathcal{R}$).

When we endow the model with the KD in the feature space, we see a considerable difference in the accuracy between using only the rehearsal data or the rehearsal and the current data, with the former case that improves both the average accuracy and the last accuracy.

The joint use of rehearsal and current data deteriorates the performance. This can be explained by observing that if we use both rehearsal and new data, we are forcing the current model, $\theta_t$, to produce feature representations that are similar to the ones obtained with the previous model, $\theta_{t-1}$. Whereas this is desirable for the rehearsal data (the previous model has been trained on them), this is not the case for the new data, since we want our model to learn throughout the actual task new clusters which should be far apart from the past clusters.

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[1] https://github.com/umbertocappellazzo/CL_QUOT
Table 2: Intent classification accuracy with 930 samples in the rehearsal memory, using different distillation strategies. The highest accuracies are reported in bold while we use italics for the best KD of each CL method.

| Baselines       | last acc | avg acc |
|-----------------|----------|---------|
| Offline         | 0.985    | -       |
| Finetuning      | 0.073    | 0.267   |
| Pred. KD (no reh) | 0.080    | 0.272   |

| Feat. KD          | Pred. KD          | Random | Closest_to_mean | iCaRL [8] | GEM [13] |
|-------------------|-------------------|--------|-----------------|---------|---------|
| Feat. KD data     | Pred. KD data     | last acc | avg acc | last acc | avg acc | last acc | avg acc |
| -                  | -                 | 0.660  | 0.720         | 0.650   | 0.694   | 0.682    | 0.740   | 0.573    | 0.710   |
| Feature space KD  |                   |         |               |         |         |         |         |         |         |
| R                  | -                 | 0.737  | 0.779         | 0.728   | 0.740   | 0.789    | 0.802   | 0.773    | 0.789   |
| D ∪ R             | -                 | 0.594  | 0.643         | 0.562   | 0.609   | 0.600    | 0.643   | 0.710    | 0.714   |
| Predictions space KD |                   |         |               |         |         |         |         |         |         |
| -                  | R                 | 0.676  | 0.736         | 0.632   | 0.690   | 0.662    | 0.726   | 0.624    | 0.735   |
| -                  | D ∪ R             | 0.757  | 0.764         | 0.690   | 0.717   | 0.780    | 0.795   | 0.600    | 0.710   |
| Double KDs        |                   |         |               |         |         |         |         |         |         |
| R                  | R                 | 0.752  | 0.770         | 0.728   | 0.739   | 0.788    | 0.787   | 0.764    | 0.799   |
| R                  | D ∪ R             | 0.771  | 0.796         | 0.729   | 0.740   | 0.811    | 0.812   | 0.751    | 0.796   |

Fig. 3: Trend of the avg accuracy for 4 different combinations of the iCaRL method. Each experience has 50 steps (i.e., epochs).

The last two rows of Table 2 consider the combination of feature-level and predictions-level KDs (the configurations with D ∪ R in the feature space are not considered since we have shown they are harmful to the model). The use of the features-space KD applied to R in conjunction with the predictions-space KD applied to D ∪ R gives the best results (0.811 and 0.812 for the last acc and avg acc by iCaRL, respectively), proving the effectiveness of integrating both KDs. Fig. [3] depicts the trend of 4 different configurations for the iCaRL strategy. The concurrent use of both KDs (red curve) leads to the best overall performance, even though the last task accuracy (last acc) is pretty similar to the methods employing single KDs.

Considering the KD in the predictions space, instead, we witness a trend inversion. The jointly use of rehearsal and current data (D ∪ R) achieves better results than just using the data in the memory, albeit the difference is not as pronounced as for the feature-space KD. This can be explained by the fact that in the predictions space the KD forces the current model to make similar predictions as the previous one (the classifier is particularly affected by this), and so the presence of both new and old classes benefits the system. It is worth noting that in almost all cases the feature-level KD attains slightly better results than its predictions counterpart. We point out that GEM achieves slightly better results when only rehearsal data are considered, and this may be because it already employs a regularization on the gradients using only the rehearsal data.

Finally, Figure 4 shows the average accuracies achieved by different KDs approaches when using smaller rehearsal memory sizes. We can note the consistency of the performance trends as the memory size changes. In particular, the gain in accuracy provided by the KDs is larger when a rehearsal memory with a smaller capacity is used, thus showing the effectiveness of the methods also for limited-budget buffers.

5. CONCLUSIONS

This paper describes an approach for class-incremental continual learning in a SLU domain. We have shown that KD on rehearsal data is effective if applied to the encoded features. Furthermore, the feature-level MSE loss, when added to the usual predictions-level KD loss, brings additional performance improvements. The efficacy of the approach is particularly evident when the rehearsal memory has small sizes, making it suitable for low-resources devices. Future work will address the extension of the proposed approach to different neural architectures, as well as its application to KWS and ASR tasks and to more complex SLU datasets, e.g. the Spoken Language Understanding Resource Package (SLURP) [36].
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