Class-Agnostic Continual Learning of Alternating Languages and Domains

Germán Kruszewski ∗
germank@gmail.com
Ionut Teodor Sorodoc
Universitat Pompeu Fabra
ionut.sorodoc@gmail.com
Tomas Mikolov
CIIRC CTU
tmikolov@gmail.com

Abstract

Continual Learning has been often framed as the problem of training a model in a sequence of tasks. In this regard, Neural Networks have been attested to forget the solutions to previous task as they learn new ones. Yet, modelling human life-long learning does not necessarily require any crisp notion of tasks. In this work, we propose a benchmark based on language modelling in a multilingual and multi-domain setting that prescinds of any explicit delimitation of training examples into distinct tasks, and propose metrics to study continual learning and catastrophic forgetting in this setting. Then, we introduce a simple Product of Experts learning system that performs strongly on this problem while displaying interesting properties, and investigate its merits for avoiding forgetting.

1 Introduction

Neural Network systems are often trained once and for all to solve any given fixed task. This gives rise to an evaluation paradigm where data is split in two parts so that one part is used for training the system and the other is used to estimate its performance on any new examples. Continual Learning, has emerged as the problem of incrementally training the system on new tasks. Accordingly, Neural Network systems have been shown to suffer from “catastrophic forgetting” of previous tasks as they are trained on new ones (McCloskey and Cohen, 1989; Ratcliff, 1990). Even though several solutions have been proposed to alleviate the problem, most often they rely on an explicit signal identifying the working task (Kirkpatrick et al., 2017; Zenke et al., 2017; Sodhani et al., 2018; Serra et al., 2018; Lopez-Paz and Ranzato, 2017; Fernando et al., 2017; Lee et al., 2017; Rusu et al., 2016; Li and Hoiem, 2018; Aljundi et al., 2017). However, it is unclear whether it is necessary to segment the learning experience into clear-cut tasks to realistically model the act of continual learning.

Instead, learning could proceed as a continuous stream of situations, each demanding the agent to act to the best of its ability, and then, to learn from feedback in the hope of performing better next time. In this view, understanding the impact of catastrophic forgetting on a learning systems implies assessing how an agent’s performance may be affected by long sequences of correlated examples, followed by other uncorrelated ones. For example, consider the experience of the daughter of a French-American couple living in Spain: The child may talk to her father in French in the morning over breakfast, then go to school and speak to her classmates in Spanish and then go back home in the evening where she will discuss her day with her mother in English. Different linguistic knowledge will be required for each of these situations, and context alone, rather than some explicit signal, will dictate what is needed at each given moment. Furthermore, the child’s brain needs to carefully store learned information from each of these languages so that they are kept separate as distinct skills.

Here, we make a two-fold contribution towards studying the process of continual learning in Neural Networks. First, we introduce to the community the class-agnostic continual language modelling problem (Figure 1), a multilingual/multidomain online language modelling evaluation framework featuring alternating languages and domains, and where the learner’s performance is continuously evaluated on each example before it can learn from it. Catastrophic forgetting is thus measured in terms of adaptation time after a switch. We propose two variants. The first is a character-based language modelling benchmark with text written in 5 different languages that randomly switch between one
Our experimental setup aims to establish whether models are able to adapt to a continuous stream of circumstances in which it needs to develop, improve and use a wide range of skills. While most previous work interested in continual learning considered sequences of tasks that were unambiguously identified by a marker given as an extra input to the model, here we pursue a more realistic setup where only context can dictate which skills are required at a given time. For this, we introduce a lifelong language modelling task where the model is continually exposed to a novel linguistic stream that switches between different classes of inputs without any explicit marker signalling the change. More specifically, we propose two language modelling benchmarks: One is word-level and multi-domain whereas the other is character-level and multilingual. Both benchmarks feature conflicting learning signals when moving between domains or languages, making the learning systems susceptible to catastrophic forgetting.

As we are interested in evaluating the continual adaptation to incoming non-i.i.d. data, a situation that is closer to the experience of any human being, the traditional train-test split approach is not adequate here. Instead, we adopt an online learning paradigm (see Algorithm 1). This means that at each time step the model receives an instance $x_t$ and makes a prediction $\hat{y}_t$. Then, the true target $y_t$ will be observed and the model incurs in a loss $L(\hat{y}_t, y_t)$, which both plays the role of an evaluation metric and a numeric reward used for training. Thus, after reporting the loss value, the model is trained, possibly for multiple ($m$) iterations, on minimizing the loss on the just observed example.

The goal is minimizing the average loss $\frac{1}{T} \sum_{t=1}^{T} L(\hat{y}_t, y_t)$.

### Algorithm 1 Online learning loop

```
procedure ONLINELEARN(\langle x_i, y_i \rangle; i = 1, \ldots, T)
for t := 1 \ldots T do
    \hat{y}_t \leftarrow M_0(x_t) \triangleright Act / Predict
    L_t \leftarrow L(\hat{y}_t, y_t) \triangleright Observe
for i := 1 \ldots m do \triangleright Learning iterations
    \Theta \leftarrow \text{LEARN}(\Theta, \nabla L(\hat{y}_t, y_t))
    \hat{y}_t \leftarrow M_0(x_t)

return $\frac{1}{T} \sum_{t=1}^{T} L_t$
```

Our benchmarks involve learning from sequences of training pairs $(x_i, y_i)$ belonging to different distributions or classes $[D_1, \ldots, D_n]$, which are observed as sequences $i_1, i_2, \ldots, i_N (1 \leq i_j \leq n)$ with lengths $T_1, T_2, \ldots, T_N$, respectively.

A model that is prone to forgetting will display a spike in the loss after a sequence switch, even if returning to a distribution observed in the past. In contrast, a good model should be very good at transitioning between classes, while still maintaining good overall performance for online language modelling.

### 3 Dataset

For our first dataset (multi-lingual and character-based) we build on parts of the news corpus developed for the 2009 Workshop of Machine Translation (Callison-Burch et al., 2009). We extracted text from five languages: English, French, Spanish,
German and Czech because they all have similar character sets, while also showing interesting linguistic variability. In particular, they belong to three different Indo-European branches: Romance (French and Spanish), Germanic (English and German) and Slavic (Czech). Compared to earlier multilingual corpora (Kawakami et al., 2017), our dataset was carefully constructed to include only linguistically valid characters, in order to prevent non-linguistic noise from interfering with our experiments. For this, we removed all lines from the input that contained characters appearing less than 100 times on the full corpus. The resulting character vocabulary consists of 211 characters.

The second dataset is an English word-level multi-domain dataset. For this, we used four different source corpora: news (same as above), europarl (Koehn, 2005), the British National Corpus (Consortium et al., 2007) and Wikipedia (Merity et al., 2017). We kept in the vocabulary the top 25K words for each corpus, which after merging yielded a vocabulary size of 58K words.

We then created the final multilingual and multi-domain corpora by joining $N = 100$ different fragments evenly distributed among the different classes (languages or domains) with lengths sampled from a (truncated) exponential distribution: $T_1 \sim \text{Exp}(\lambda)$. Thanks to this distribution’s memorylessness property, it is virtually impossible to estimate when the next switch is going to happen. Furthermore, to simplify the future analysis, we split these fragments into an integer number of batches of length $w$. We constructed two different variations with shorter or longer fragment lengths. For the multilingual case, we constructed 1M and 10M-characters-long corpora with expected fragment lengths of $\lambda = 10k$ and $\lambda = 100k$ characters, respectively. For the multi-domain dataset we followed the same procedure, extracting 100 alternating sequences with mean lengths of $\lambda = 10k$ and $\lambda = 20k$, for a total of 1M and 2M words. We used a smaller corpus in the latter to allow for faster experimentation as the models have now to predict over a larger vocabulary, and thus they require more training time. Samples from all source corpora are included in the supplementary material.

4 Models

To tackle the above described problem, we propose a simple architecture based on the Product of Experts (PoE) (Hinton, 1999). A PoE is composed of modules operating in concert to compute the network’s output by means of a weighted combination of their predictions. Modular architectures, such as this, could display good continual learning skills thanks to only applying first, and learning second, the modules that are more relevant to the current context. In its standard implementation, the combination weights are produced by a third module as a function of the current inputs. While, in principle, this architecture could quickly adapt to changes in the environment, learning to do so is far from trivial, sometimes requiring pre-training to distinguish inputs types (Aljundi et al., 2017) or using large amounts of training experience (Shazeer et al., 2017). Instead, we propose a model where weights are another trainable parameter that is constant with respect to the input. In contrast to a large neural network, these weights are much easier to optimize and thus they can be quickly adapted.

**Product of Experts** More formally, a PoE is composed of a set of modules $M = \{M_1, \ldots, M_n\}$ with parameters $\Theta_{M_1}, \ldots, \Theta_{M_n}$, which are used to compute a unique prediction as follows. When an input $x$ (with target $y$) is observed, it is fed to all modules $M_1, \ldots, M_n$, obtaining log-linear outputs $\hat{y}^{(1)} = M_1(x), \ldots, \hat{y}^{(n)} = M_n(x)$.

An additional vector of mixture weights $w \in \mathbb{R}^n$ is used to linearly combine them. This vector is typically computed by a separate “gating” module $w = G(x)$ with parameters $\Theta_G$, which can be trained jointly with the rest of the network. The output of the full model $y$ is then computed as a linear combination of the individual modules outputs $\hat{Y} = [\hat{y}^{(1)}, \ldots, \hat{y}^{(n)}]$ weighted by $w$:

$$\hat{y} = \text{softmax} \left( \hat{Y}^\top w \right)$$ (1)

Note that since we are combining the model un-normalized predictions before the application of the softmax, we are effectively computing a geometric combination of each individual module’s un-normalized probabilities: $\exp(\hat{y}_j) \propto \prod_{i=1}^n \exp(\hat{y}_j^{(i)})^{w_i}$. Compared to a Mixture of Experts (Jacobs et al., 1991; Eigen et al., 2013), this approach does not require to normalize the output of each individual model, thus being more efficient to compute.

Our model departs from a standard product of experts in that we introduce two simple modifications: fixed weights and fast adaptation. We call the resulting architecture Fast-adapting Fixed-weights Products of Experts (FF-PoE).
Fixed weights  
By this, we mean that the gating network is the constant function \( G(x) = w \). The weights are adapted jointly with the rest of the model through gradient descent on each example. Yet, we must allow these weights to change swiftly when a domain switch happens, which is why we introduce the next mechanism.

Fast adaptation  
We allow the gating function to be trained for multiple steps for each learning step of the expert modules. Thus, the standard gradient descent algorithm is modified as shown in Algorithm 2.

Algorithm 2 Learning

\[
\text{procedure } \text{LEARN}(\Theta, \nabla_{\Theta} L(\hat{y}_t, y_t)) \\
\text{for } i=1 \ldots n \text{ do } \quad \triangleright \text{ train } n \text{ modules} \\
\Theta_M \leftarrow \Theta_M - \alpha \nabla_{\Theta_M} L(\hat{y}_t, y_t) \\
\text{for } i=1 \ldots k \text{ do } \quad \triangleright \text{ fast adaptation} \\
\Theta_G \leftarrow \Theta_G - \alpha \nabla_{\Theta_G} L(\hat{y}_t, y_t) \\
w \leftarrow G(x) \\
\hat{y} \leftarrow \text{softmax}(\hat{Y} w) \\
\text{return } \Theta
\]

Note that it is not necessary to recompute each module’s output for each update of \( \nabla_{\Theta_G} L(\hat{y}_t, y_t) \) and thus, adaptation steps are not expensive.

4.1 Parametrization for Language Modelling

In this work we instantiate the PoE and FF-PoE for an online language modelling task. For this we adopt double-layered LSTM networks (Hochreiter and Schmidhuber, 1997) as modules. Their predictions can then be written as:

\[
\hat{y}^{(i)}, h_{t+1}^{(i)} = \text{LSTM}_i(x_t, h_t^{(i)}) \tag{2}
\]

where \( h_t^{(i)} \) is the hidden vector of each LSTM module and initialized with 0. For the FF-PoE architecture, the weight vector \( w \) is a trainable parameter. Instead, for the base PoE architecture (Eigen et al., 2013), we use a single-layer LSTM network as a gating function. That is, \( w_t, h_{t+1} = \text{LSTM}(x_t, h_t) \). Then, the rest of the computation proceeds as in Equation 1 and the models are trained using the cross-entropy loss.

5 Experiments

5.1 Experimental Setup

We evaluated models on their learning performance on the class-agnostic continual language modelling task (see Section 2).

Every model observes data as a sequence of pairs of token batches \((x_t, y_t)\) where \( x_t, y_t \in V_{b \times w} \), \( V \) is the token vocabulary, \( b \) or “batch size” is the number of streams concurrently observed by the models, and \( w \) is the “window size” for the current batch. Unless explicitly noted, we keep \( w = 20 \) and \( b = 10 \) fixed.

We explored models featuring different degrees of modularization, while keeping the number of parameters approximately constant. On one extreme, we had both a large two-layers LSTM network and a Transformer model. Next, we considered a Products of Experts model (PoE) with weights computed by an LSTM gating network, as described in Section 4.1. We studied both a more centralized network composed of 5 modules and larger hidden dimensionality (PoE 5) and a more distributed network with 30 modules but with smaller hidden sizes (PoE 30). Finally, we explored the Fast-adaptation with Fixed weights variants of the PoE model (FF-PoE 5 and FF-PoE 30), using \( k = 100 \) adaptation steps for the weights (see Algorithm 2).

As reference points, we also trained independent LSTMs (Ind. LSTM), one for each class, which enabled us to compare the performance of our model to a situation where there is no forgetting from conflicting learning signals, but also where there is no possibility of transferring learned representations across possibly related domains.

Within each of the multilingual and the multi-domain experimental setups we controlled the number of model parameters to remain constant. In particular, models for the multilingual dataset feature around 21M parameters, while there are roughly 570M parameters in the models for the multi-domain setup (the difference in size is explained by the larger vocabulary sizes in the latter). Thus, we adjusted the hidden dimensionality accordingly, as reported in Table 1.

| Model            | multilingual | multi-domain |
|------------------|--------------|--------------|
| LSTM             | 1300         | 5200         |
| Ind. LSTM        | 550          | 1800         |
| (FF-) PoE 5      | 550          | 1600         |
| (FF-) PoE 30     | 200          | 200          |

Table 1: Number of hidden units per model

For the Transformer we allowed a larger window size \((w \in [20, 100])\) and tuned the number of layers \((1, 2, 3 \text{ or } 6)\), the feed-forward network hidden size \((768 \text{ or } 2048)\), the number of heads \((16, 32 \text{ or } 64)\) and the embedding dimensionality \((768 \text{ or } 2048)\) for the multilingual setup and 768 or 4608 for multi-domain), finding that smaller models (often 768 units with a single layer) perform
best (viz. Section 5.3). Furthermore, we considered both training with default Adam parameters \((\alpha = 10^{-3}, \beta = (0.9, 0.999))\) or with the curriculum described in Vaswani et al. (2017) tuning the warmup parameter from 1, 40, 400 and 4000. We tuned these and other hyperparameters (see supplementary material for details) for all the models on a development set for each corpus. We performed all our experiments using PyTorch (Paszke et al., 2017) with the standard available implementations for the underlying models.

5.2 Metrics

We keep track of the following metrics in order to assess whether models are efficient at adapting when there is a switch in the class of data while remaining competitive in terms of overall performance. In order to observe the asymptotic behaviour of the models, we restrict our analysis by reporting measures pertaining only to the second half of the data.

- **Online perplexity (ppl):** This is the general perplexity over the data measured during model training as described in Algorithm 1. Note that since the task is framed as an online learning one, the training loss serves as a test measure because no example is seen twice.
- **Perplexity after switch (ppl@sw):** We further compute the perplexity restricted to the first 10 batches after the switch. If the model is spiking at these specific points, then this measure should capture it.
- **Recovery time after switch (rec):** Finally, we compute the time that it takes the model to recover after a switch back to a normal regime, as measured by the number of batches that it takes to reach the mean cross-entropy of the previous fragment within the same domain.

5.3 Results

We report our experimental results for both the multilingual task and for the multi-domain data in Table 2. Recall that the Independent LSTM row is trained per-class and thus, it is not a valid solution for our benchmark. Nonetheless, it provides a reference point for the performance of a model that does not suffer from forgetting, but also cannot share knowledge between classes.

First, higher values of \(\lambda\) correspond to lower perplexities, as expected from the fact that these corpora with longer sequence lengths are also proportionally larger in total length (as described in Section 3). For the multilingual case (left panel), we can see that in terms of overall perplexities most models perform almost on-par, with the FF-PoE and Large LSTM being the best ones in the 10k and 100k settings, respectively. Transformer, on the other hand, performs comparatively worse. Moreover, contrary to recent findings in which the largest transformers perform best, here we found that smaller configurations often yielded the best performance, and yet still far from other models. We attribute this apparent contradiction to an important, but often ignored, distinction between learning and processing. While large Transformer networks, trained for many epochs in vast amounts of text can yield state-of-the-art natural language processing systems, when it comes to them as tabula rasa natural language learning systems they seem to be requiring more steps than the other here considered architectures. Next, when we examine the adaptation efficiency of the models after a language switch, we see that the FF-PoE model always performs best (with 5 modules for 10k and 30 modules for 100k). Figure 2a shows this fact in more detail, by representing the mean cross-entropy of each different model for the 15 batches occurring immediately after a switch. There, we can see that the FF-PoE model shows a large spike on the first batch because its adaptation mechanism, depending on this error signal, has not kicked-in yet. However, in the following batch its performance increases sharply outperforming all other models.

On the multi-domain case, we observe a more clear advantage for the PoE-like architectures, which perform better than a simple large LSTM, and within them of the ones with 30 modules over those with 5. Thus, higher modularization seems to be even more advantageous. This is possibly related to the fact that word-level language modelling is a more complex problem than character-level, and thus it can be more easily fitted by combining the judgements from multiple experts (Hinton, 2002; Yang et al., 2018). We also note that while the multi-lingual benchmark switches between classes that have quite different statistical properties, here the differences between the classes are much more nuanced. Thus, even though the Independent LSTM model does not suffer from forgetting of switching domains, it also misses the training signal from not-completely-different train-
Table 2: Average perplexity (ppl), perplexity for 10 batches after a switch (ppl@sw) and recovery time after a switch in batches (rec) for the multilingual (left) and multi-domain (right) datasets per mean sequence length (λ).

| Alternating Languages | Alternating Domains |
|-----------------------|----------------------|
| λ = 10k               | λ = 100k             | λ = 10k               | λ = 20k               |
| ppl, ppl@sw, rec     | ppl, ppl@sw, rec     | ppl, ppl@sw, rec     | ppl, ppl@sw, rec     |
| Ind. LSTM             | LSTM                 | FF-PoE 30             | FF-PoE 30             |
| 7.1                   | 7.1                  | 356                   | 349                   |
| 7.16                  | 1.15                 | 1.11                  | 1.11                  |
| 4.7                   | 4.73                 | 296                   | 292                   |
| 1.18                  | 1.18                 | 1.15                  | 1.15                  |
| Large LSTM            | Large LSTM           | Transformer           | Transformer           |
| 7.78                  | 10.4                 | 7.68                  | 10.5                 |
| 6.82                  | 2.37                 | 7.06                  | 7.06                 |
| PoE 5                 | PoE 5                | FF-PoE 5              | FF-PoE 5              |
| 7.96                  | 10.7                 | 7.33                  | 7.33                 |
| 5.17                  | 9.9                  | 5.02                  | 7.54                 |
| FF-PoE 30             | FF-PoE 30             | 5.04                  | 7.03                 |
| 9.03                  | 9.03                 | 285                   | 316                   |
| 2.68                  | 2.68                 | 241                   | 287                   |
| 3.54                  | 3.54                 |                      |                      |

Figure 2: Mean cross-entropy for the first 15 batches after a switch averaged over all occurrences.

5.4 Analysis

Catastrophic forgetting To get some further insights into the workings of the FF-PoE model we analyzed its weight vectors while processing the multilingual dataset (λ = 10k). As we observed in the previous section, this model seems to be more robust to forgetting. Figure 3 hints upon the reasons for the improved performance. As we can see, when a language switch occurs, the model adapts its weights to use the modules that are fitter to the corresponding domain. (Only absolute values matter for considering whether a module is active at a given time, thus both positive and negative values can be construed to be activating their corresponding module.) Consider, for instance, the 10th, 12th and 19th modules, which seem to activate with French, but not, for instance, with Spanish. Other modules (e.g. 24th) behave in the opposite way, being more active for Spanish than for French. Thus, the model seems to be effectively adapting to different classes thanks to activating the best combination of modules. Furthermore, when the weight associated with a module is close to 0, it is also protected from catastrophic forgetting, as this gating value is also multiplied to each module’s gradients. Moreover, we hypothesize that modules are protected even when their corresponding weight is set to the opposite sign (see, for instance, module 16 on English and Spanish), because the incoming training data serves as negative training data, namely, something not-to-be-predicted. Thus, this...
Module clustering Finally, to further understand how the information associated to each class was distributed by the FF-PoE across different modules, we computed the correlations between the weights produced while processing the last 100 batches of each class. Results are shown in Figure 4. Recall from Section 3 that the languages in our dataset are derived from different linguistic families. Interestingly, for the multilingual case, we observe that Czech seems to be using the most distinct set of modules. Spanish and French correlate quite strongly in the modules they use, and while English also correlates with French, it also does so with German, with the latter correlating to a lesser extent with the other languages. Indeed, applying a simple hierarchical clustering algorithm over this matrix recovers the underlying linguistic families! This reveals that the model seems to be sharing information between different modules in ways that reflect the similarities between the modelled languages. Conversely, correlations in the multi-domain case are much weaker. Moreover, they are weak even within a same class: When we measure the weight autocorrelation by comparing the ones corresponding to the last 100 batches with the preceding 100 ones we obtain values in the order of 0.65. In contrast, these are in the order of 0.96 when computed for the multilingual data. This shows that the model usage is less consistent per-class, which is probably explained by the fact that classes are much more nuanced than before and their corresponding distributions are far more complex. These results are also consistent with our previous observation that models trained independently on each stream reach the lowest perplexity on the multilingual benchmark, but not on the multi-domain one. In the former case, even though there is some very sensible sharing of modules in the multilingual case, each language is encoded as a self-consistent weighted combination of modules. In contrast, domains are less clearly defined as units, and thus, the model distributes the information learned from each of them in a more even fashion. In this context, our results indicate that the Wikipedia domain is the most idiosyncratic in terms of the modules that are most typically recruited for it, sharing some positive correlation with BNC. On the other hand, Europarl and the News corpora also display some positive correlation in terms of the modules they use. Nonetheless, these correlations are weak and thus, harder to interpret.

6 Related work

Studying learning in animals and machines and its modeling as a Continual Learning loop goes back
to the dawn of the field of Artificial Intelligence (Minsky, 1961) and Cybernetics (Wiener, 1948). This feedback loop is still core to the theory of Reinforcement Learning (Sutton and Barto, 1998), and Online Learning (Bottou, 1998; Shalev-Shwartz and Ben-David, 2014).

Our work is related to the efforts aimed at having Neural Networks learn continually through their lifetime, and the associated problem of catastrophic forgetting (McCloskey and Cohen, 1989; Ratcliff, 1990; French, 1999; Goodfellow et al., 2013). Approaches to attack this problem range from discovering free capacity within the network (Kirkpatrick et al., 2017; Zenke et al., 2017; Serra et al., 2018; Lopez-Paz and Ranzato, 2017) to growing the structure (Rusu et al., 2016; Li and Hoiem, 2018; Aljundi et al., 2017; d’Autume et al., 2019), or both at once (Sodhani et al., 2018). However, all of these require an explicit notion of tasks. Much more in the spirit of our work, some recent work has started tackling continual learning in a more realistic task-agnostic way (Aljundi et al., 2019). Differently from them, who focus on Computer Vision, here we study a language learning problem.

Finally, our study falls within the line of language modelling using Neural Network models (Bengio et al., 2003; Mikolov et al., 2010). In this context, adaptation to the recent past has been studied in the context of cache models (Grave et al., 2017; Merity et al., 2017). In contrast to cache models, our system learns from recent statistics and applies them in its predictions in the exact same way it operates with long-term ones.

7 Conclusions

We have argued that life-long language learning must be framed as a continuous process, without requiring any explicit separation of experiences into tasks. Under this view, the fact that neural networks are susceptible to catastrophic forgetting translates into a de-adaptation effect when learning from different classes of inputs presented in sequence. To foster empirical work in this optic, we have introduced to the community two lifelong language modelling tasks that require adaptation to switching classes. One, character-based and multilingual, and other, word-based on multiple domains. We have also presented a simple and effective mechanism for gating the contributions of different modules in a PoE architecture that helps the system to seamlessly adapt to different contexts, while preserving good predictive power. Furthermore, this gating mechanism contributes to making the system more resilient to catastrophic forgetting thanks to the fact that it modulates either conflicting or complementary training signals to learn from them without interference. In the multilingual case, this allows the model to distribute different languages in a sensible way across modules (actually recovering the linguistic families in the underlying languages). In the multi-domain scenario, the model can take advantage of the complementarity across different domains and learn better models. In the future, we see as a pressing problem to understand how learning systems can bootstrap on their knowledge to improve their learning skills, so they can learn more effectively from fewer data points. In Section 5.4 we have discussed on such example, where a more sophisticated gating strategy could be learned from the simpler one. In time, we expect that this route should bring about more effective learning systems that will not only be able to acquire knowledge from different sources in a seamless way, but also get better at it as they go.
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A Supplementary Material

A.1 Corpus examples

Figure 5 and 6 present samples from the corpora used for our dataset. As stated in the paper, we can notice a much bigger difference between input class in the case of the multilingual setup, while the differences in the case of the multidomain setup are more subtle and nuanced.

| Dataset samples | Czech | English | French | German | Spanish |
|-----------------|-------|---------|--------|--------|---------|
| Multilingual dataset samples | Madárská INFiNITY Coliseum Lan je pokračováním úspěšného BECU Pu, z něhož si nejeden nás tým v minulosti odvezl medaili. | If Hofmann played the role of paterfamilias, Anaïs Nin was the bad mother to Admiral and De Niro’s group. This one wasn’t close. | Le Beatle s’en est alors emparé pour créer un chef-d’œuvre psychédélique longtemps associé à l’usage du LSD. | Im ersten Jahr hatten sie schon 278 Anfragen, fast 60 ehemalige Manager und Unternehmer wollten mitmachen. | Los despidos serán realizados por medio del plan de GM de cese de empleo, por lo que no se ofrecerán jubilaciones anticipadas |

| Multidomain dataset samples | BNC | Euro | News | Wiki |
|-----------------------------|-----|------|------|------|
| Good weather for the crops. Have your sheep been suffering much from the staggers? Have you contributed a great deal this year to the butter mountain? | I would like your advice about Rule 143 concerning inadmissibility. My question relates to something that will come up on Thursday. | If Hofmann played the role of paterfamilias, Anaïs Nin was the bad mother to Admiral and De Niro’s group. This one wasn’t close. | Otto, Prince of Bavaria, was chosen as the first King of Greece in 1832, under the name Othon. His arrival in Nauplio, then the Greek capital, was hailed enthusiastically by Makriyannis |

Figure 5: Samples from the multilingual dataset

Figure 6: Samples from the multi-domain dataset

A.2 Generated output

In Figures 7 and 8, we present generated samples from different stages of training. These generated examples are produced by sampling one character at a time from the models, and using them as input for the next time step. As quantitatively observed in the paper, it adapts much faster to the current input type (French) in comparison with an LSTM, which generates text resembling the language of the previously seen class even after 10 batches.
Table 3: Table with the hyperparameters tested on the models: LSTM, PoE, and FF-PoE. The bold parameters are the ones chosen for LSTM, PoE-30, FF-PoE30 and the italic parameters are the ones chosen for PoE-5 and FF-PoE5

Table 4: Table with the hyperparameters tested for the transformer architecture

A.3 Hyperparameter search

Tables 3 and 4 present the explored hyperparameters. The parameters in bold are the ones chosen for the final models, with the exception of PoE-5 and FF-PoE5 which are marked with italics.

The meaning of the different hyperparameters for Table 3 is:

- nhid: the size of the hidden state of the base LSTM
- dropout: the dropout value used in the base module of the LSTM
- learn iter.: how many learning iterations over each batch are done before moving to the next batch
- adapt. iter.: it is used in the case of FF-PoE and it shows how many iterations to train the gating weights are done for each learning iteration.
- modules: how many modules does the PoE models contain
- gating nhid: the size of the hidden state for the PoE models
- clear gating hidden: used in the case of FF-PoE
the case of PoE

- clear gating hidden: it is a boolean value which clears the hidden state of the LSTM used for gating weights in the case of PoE

Table 4 presents the range of the hyperparameters test for the Transformer architecture. The meaning of the different hyperparameters in this table is:

- `nemb`: the size of the embedding transformation
- `nhid`: the size of the hidden state
- `dropout`: the value of dropout used across the whole model
- `learn iter.`: how many learning iterations over each batch are done before moving to the next batch
- `nhead`: how many attention heads are used at each step
- `transf warmup`: warmup parameter in the learning rate scheduling mechanism of Vaswani et al. (2017). A dash stands for using a constant learning rate of 0.001.
- `nlayers`: number of layers