# CONTINUAL POST-TRAINING OF LANGUAGE MODELS

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## ABSTRACT

Language models (LMs) have been instrumental for the recent rapid advance of natural language processing. Existing research has shown that post-training or adapting an LM using an unlabeled topical/domain corpus can improve the end-task performance in the domain. This paper proposes a novel method to *continually post-train* an LM with a sequence of unlabeled domain corpora to adapt the LM to these domains to improve their end-task performances. The key novelty of our method is a soft-masking mechanism that directly controls the update to the LM. A novel proxy is also proposed to preserve the general knowledge in the original LM. Additionally, it contrasts the representations of the previously learned domain knowledge (including the general knowledge in pre-trained LM) and the knowledge from the current full network to achieve knowledge integration. The method not only overcomes *catastrophic forgetting*, but also achieves *knowledge transfer* to improve end-task performances compared to post-training each domain separately. Empirical evaluation demonstrates the effectiveness of the proposed method. [1]

## 1 INTRODUCTION

Pre-trained language models (LMs) like BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019b) significantly advanced NLP recently. A common way of applying an LM is to fine-tune it using the end-task data. However, researchers have shown that using a large unlabeled domain corpus to further train an LM using the same training loss (e.g., the *masked language model* (MLM) loss) to adapt the LM to the domain can help end-tasks in the domain to do even better (Gururangan et al., 2020; Xu et al., 2019). This further training of an LM is called *post-training* or *domain-adaptive pre-training*.

This paper studies continual learning (CL) of post-training or *continual post-training* to incrementally post-train a sequence of domain corpora $D_1, D_2, ....$ Once a domain is trained, its data is no longer accessible. In CL, each $D_i$ is called a *task*, but we use the term *domain* to be consistent with post-training. Continual post-training is important as in the real world, data shifts constantly and new domains keep emerging (Gururangan et al., 2020). For example, one may adapt an LM trained over a general domain (e.g., News) to some science domains (e.g., ACL and AI papers). This requires LMs to continually learn new domains. This problem has some similarity to *task-incremental learning* (TIL) of CL where the task id (domain id in our case) is needed in both training and testing. However, we do not need domain ids in testing (i.e., end-task fine-tuning) to identify the right model to use.

Ideally, the proposed method should have the following properties: **(1)** It can maximally preserve the general language knowledge in the original LM. This is important because if it is forgotten in continual post-training, the knowledge learned from each domain alone will not be sufficient for good end-task performances. **(2)** It can overcome CF so that after post-training on a new domain, the knowledge learned for previous domains is not forgotten. **(3)** It should encourage knowledge transfer across domains to achieve improved end-tasks performances compared to post-training each domain separately. **(4)** It should not need the user to provide domain id for each end-task fine-tuning.

A highly effective TIL approach is *parameter-isolation* (PI) (Serrà et al., 2018; Wortsman et al., 2020), which has almost no *catastrophic forgetting* (CF).[2] It learns *binary/hard masks* to isolate a sub-network for each task/domain. However, PI is not suitable for continual post-training of an LM. The key issue is that PI is designed for supervised end-task CL. For CL post-training, we cannot

[1] The code has been uploaded as supplementary materials.

[2] *Catastrophic forgetting* (McCloskey & Cohen, 1989) in CL means that the training of a new domain needs to update the existing network, which may cause the performance degradation of the domains trained previously.

isolate a sub-network for each domain simply because it means that end-tasks will not be able to use the general knowledge in the original LM, which results in very poor end-task performances (Sec. 4).

This paper proposes a novel technique with all 4 desired properties. The key idea is that instead of employing hard/binary masks as in PI, we propose *soft-masks* that do not isolate a sub-network for each domain and as a result, the knowledge in the full model can be leveraged for end-task fine-tuning. The proposed method is called CPS (*C*ontinual *P*ost-training of LMs with *S*oft-masking). CPS directly updates the LM by exploiting the over-parameterization property of LMs as a large number of parameters in an LM are unimportant and can be pruned (Li et al., 2021; Michel et al., 2019). In learning each new domain based on its unlabeled corpus, CPS overcomes CF by computing the importance of attention heads and neurons in Transformer layers for previous domains and soft-mask them based on their importance values to control the backward gradient flow to protect the knowledge learned for previous domains (for simplicity, we use the term *units* to mean both *attention heads* and *neurons* below). However, this method cannot be applied to maximally preserve the general language knowledge in the original LM as we cannot directly find their important units (see Sec. 3.1). A novel proxy is proposed to solve the problem. In the forward pass, soft-masking is not applied, which encourages knowledge transfer across domains. CPS also contrasts the past domain (including both the general knowledge in the pre-trained LM and previously learned domain knowledge) representations and the full knowledge (including both the past domains and the current domain knowledge) representation to learn an integrated representation (Sec. 3.2).[3] In end-task fine-tuning, unlike existing TIL methods, CPS does not need the domain id as the end-task data can automatically choose the right knowledge to use. Note that soft-masking has some resemblance to the regularization based approach to CL, but it is quite different, which we detail in Sec. 2.

In summary, this work makes the following contributions. **(i)** It discovers that the popular *parameter-isolation* approach to TIL is unsuitable for continual post-training. **(ii)** It proposes a novel soft-masking method to overcome CF and to encourage knowledge transfer. It further proposes to integrate knowledge across domains. To our knowledge, none of these has been done before. CPS also learns within an LM with no added structures or need for replay data. **(iii)** To preserve the general knowledge in the LM, a novel proxy is proposed. Again, it has not been used before. **(iv)** Experiments have been conducted to demonstrate the effectiveness of CPS. Due to its ability to overcome CF and to transfer knowledge, we believe CPS has a great potential for practical applications.

## 2 Related Work

**Post-training** (also known as domain-adaptive pre-training). Researchers have applied post-training to many domains, e.g., reviews (Xu et al., 2019; Sun et al., 2019), news and academic papers (Gururangan et al., 2020), and shown improved end-task results. However, they are not about CL.

**Continual learning.** Many approaches have been proposed to overcome CF: (1) *Regularization methods* (Kirkpatrick et al., 2016; Seff et al., 2017) computes the importance of each parameter to previous tasks and uses a regularization term to penalize the sum of changes to the important parameters. Our CPS method is related to the regularization method EWC (Kirkpatrick et al., 2016), but it is different. First, CPS does not control each parameter/weight, but only attention heads or neurons based on their importance scores. This gives less forgetting (see the forgetting rate in Table 2) because even a small change to each parameter for a neuron can give a large total change to the neuron's activation. Second, CPS directly controls the backward gradient flow on each neuron, which is more fine-grained and effective than the sum of changes of all parameters in the entire network. Our experimental results confirms EWC is significantly poorer than CPS (see Table 2). (2) *Replay methods* retain (Rebuffi et al., 2017; Wang et al., 2020) or generate some data of old tasks (Shin et al., 2017; He & Jaeger, 2018) and use them in learning a new task; (3) *parameter-isolation methods* (Serrà et al., 2018; Wortsman et al., 2020) allocate neurons and parameters for different tasks and mask them in task learning. None of these approaches is for continual post-training, which needs a different method in the context of an LM as we elaborated in the introduction section.

In NLP, CL has been used for slot filling (Shen et al., 2019), language learning (Li et al., 2019), embedding (Liu et al., 2019a), translation (Khayrallah et al., 2018), cross-lingual modeling (Liu

[3]Contrasting the past domain and only the domain-specific knowledge gives poorer results (see Sec. 4.2) as it causes the two types of knowledge to split rather than to integrate.

et al., 2020b), sentiment analysis (Shu et al., 2017), topic modeling (Gupta et al., 2020), question answering (Greco et al., 2019) and text classification (Sun et al., 2020; Huang et al., 2021; Chuang et al., 2020). But none of these is for post-training. Several recent CL papers concern LMs. Pfeiffer et al. (2020) proposed to learn an adapter for each end-task separately. This work is not on CL. A similar method is used in (Madotto et al., 2020) for CL. Since it learns separate adapters, it has no CF or knowledge transfer. In post-training, DEMIX (Gururangan et al., 2021) is similar to (Madotto et al., 2020) but initializes the new adapter with the closest previously trained adapter. Jin et al. (2021) compared several CL methods for continual post-training. CPS is closely related to ELLE (Qin et al., 2022), which does *continual pre-training*. The key difference is that ELLE starts from random initialization, while our CPS post-trains a pre-trained LM.

**Neural network pruning.** Many parameters in a neural network are redundant and can be pruned (Li et al., 2021; Lai et al., 2021). This has also been shown for pre-trained Transformer (Chen et al., 2020a; Lin et al., 2020; Gao et al., 2021b; Michel et al., 2019; Voita et al., 2019). A popular pruning method is to discard the parameters with small absolute values (Han et al., 2015; Guo et al., 2016). Other methods include accumulated gradient (Michel et al., 2019), dropout rate (Gomez et al., 2019), and lottery ticket hypothesis (Brix et al., 2020). However, these methods are not directly applicable because (1) we compute importance for soft masking, not for pruning, and (2) post-training works on unlabeled data, while the above approaches work with *labeled data*.

**Contrastive Learning.** Contrastive learning (Chen et al., 2020b; He et al., 2020) learns good representations by maximizing the similarity of positive pairs and minimizes that of negative pairs:

$$\mathcal{L}_{\text{contrast}} = -\log \frac{e^{(\text{sim}(q_i, q_i^+)/\tau)}}{\sum_{j=1}^{N} e^{(\text{sim}(q_i, q_j^+)/\tau)}}, \tag{1}$$

where $N$ is the batch size, $\tau$ is a temperature parameter, $\text{sim}(\cdot)$ is a similarity metric, and $q_i$ and $q_i^+$ are representations for positive pairs $x_i$ and $x_i^+$. Our CPS contrasts the learned knowledge from previous domains and pre-trained LM (general knowledge) with the full knowledge (including both the previous domains and current domain knowledge) to achieve a complementary effect.

## 3 Proposed CPS Technique

Continual post-training in CPS is based on two main ideas: (1) preserving the important general language knowledge in the LM and knowledge learned from previous domains to overcome CF by soft-masking units based on their importance, which also facilitates cross-task knowledge transfer, and (2) encouraging the model to learn complementary representations of the current domain and previous domains to achieve knowledge integration. Figure 1 gives an overview of CPS.

The whole learning consists of two main functions: (i) ***initialization*** and (ii) ***continual learning***. (i) computes the importance of units to the general language knowledge in the LM. It is the initialization step because it is computed based on the original pre-trained LM and is done before the continual learning starts. (ii) is for continual learning, which consists of two steps: (a) ***task training*** and (b) ***importance computation***. (a) takes the importance scores accumulated so far (including those to general knowledge and to the learned domains) and the input data of the current domain to learn the domain and to achieve (1) and (2) above, while (b) computes the importance scores for the current domain for future use. The following sub-sections present each function and step in detail.

### 3.1 Initialization: Computing importance of units to The General Knowledge

This initialization function computes the importance of units (attention heads and neurons) in the Transformer for the *general* knowledge in the original LM. The key components of a Transformer are *multi-head attention layer*, *intermediate layer* and *output layer*. Below, we use "layer" or $l$ to indicate any of these three layers because our method treats the three layers similarly.

**Layer importance.** Researchers have found that not all units in a layer are important (Michel et al., 2019). We introduce a *gate vector*, $\boldsymbol{g}_l$, for computing the importance of unit in a layer $l$.

$$\hat{\boldsymbol{o}}_l = \boldsymbol{g}_l \otimes \boldsymbol{o}_l, \tag{2}$$

where $\boldsymbol{o}_l$ refers to the output of layer $l$ (which can be any of the three layers mentioned above). The $\otimes$ refers to element-wise multiplication, i.e., each gate variable $g_{l,i}$ in $\boldsymbol{g}_l$ corresponding to a unit (a

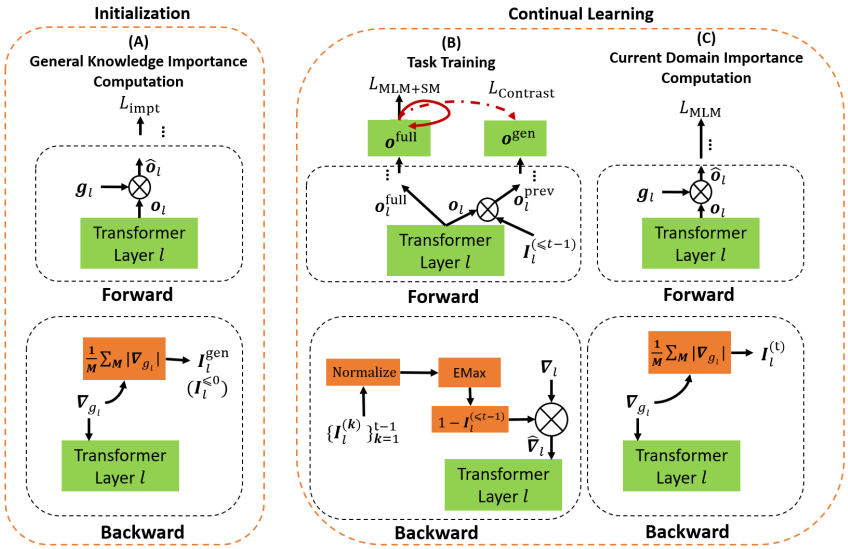


Figure 1: Illustration of CPS. (A) **Initialization** (Sec. 3.1) learns the importance of units (attention heads and neurons) for the general knowledge in the LM. (B) **Training** (Sec. 3.2) trains the new domain using the importance scores as soft-masks and contrasts the previous learned domain knowledge (including the general knowledge) and full knowledge (including both previously learned domain and current domain knowledge). (C) **Importance Computation** (Sec. 3.3) learns the importance of units for the current domain.

neuron or attention head) in the layer. A gradient-based importance detection method is proposed in (Michel et al., 2019). Given a dataset $D = \{(\boldsymbol{x}_m, y_m)\}_{m=1}^{M}$ of $M$ samples ($y_m$ is the class label of $\boldsymbol{x}_m$ as Michel et al. (2019) worked on supervised learning), the importance of neurons or heads in the layer is estimated with a gradient-based proxy score

$$\boldsymbol{I}_l = \frac{1}{M}\sum_{m=1}^{M}\left|\frac{\partial \mathcal{L}_{\text{impt}}(\boldsymbol{x}_m, y_m))}{\partial \boldsymbol{g}_l}\right|, \tag{3}$$

where $\mathcal{L}_{\text{impt}}$ is a task-specific loss function. Note the gate vector $\boldsymbol{g}_l$ is initialized as all 1's, and is not changed. This is because we need only its average gradient $\nabla_{\boldsymbol{g}_l}$ (the term within $|\,|$ in Eq. 3) over all the data to compute the importance and will not use the gradient to update the gate vector. In training (Sec. 3.2 and Fig 1 (B)), the gate vector can be discarded.

Recall that the goal of the *initialization* function is to learn the importance of units $\boldsymbol{I}_l^{\text{gen}}$ to the *general knowledge* in the LM. Although Eq. 3 offers a way to compute the units importance w.r.t. a given loss $\mathcal{L}_{\text{impt}}$, it is not directly applicable. If we use the domain data at hand and employ the MLM loss as $\mathcal{L}_{\text{impt}}$, $\nabla_{\boldsymbol{g}_l}$ only indicates the importance score for the *domain-specific* knowledge. However, to compute the importance of units to the general knowledge in the LM (which is our goal), we need the original data used in pre-training the LM to compute the $\mathcal{L}_{\text{impt}}$. In practice, such data is not accessible to users of the LM. Further, label is needed in Eq. 3 but our domain corpus is unlabeled in post-training. To address these issues, we propose a *proxy KL-divergence loss* ($\mathcal{L}_{\text{proxy}}$) to replace $\mathcal{L}_{\text{impt}}$ to learn units importance for the general knowledge.

**Proxy KL-divergence loss.** We propose to use model *robustness* as the proxy, i.e., we try to detect units that are important for LM's *robustness*. Their gradients, $\nabla_{\boldsymbol{g}_l}$, then indicate the robustness and thus the importance to the LM model. Our rationale is as follows: If an $I_{l,i}^{\text{gen}}$ (the importance of unit $i$ in layer $l$) has a high value, it indicates that it is important to the LM's robustness because its change can cause the LM to change a great deal. It is thus an important unit. In contrast, if $I_{l,i}^{\text{gen}}$ has a small value, it is a less or unimportant unit.

To compute the *robustness* of the LM, we take a subset of the current domain data $\{\boldsymbol{x}_m^{\text{sub}}\}$ (no label in post-training) and input $\boldsymbol{x}_m^{\text{sub}}$ twice to the LM and do distillation between the two resulting representations using KL-divergence,

$$\mathcal{L}_{\text{impt}} = \text{KL}(f_{\text{LM}}^{1}(\boldsymbol{x}_m^{\text{sub}}), f_{\text{LM}}^{2}(\boldsymbol{x}_m^{\text{sub}})), \tag{4}$$

where $f^1_{\text{LM}}$ and $f^2_{\text{LM}}$ are the LM with different dropout masks. We don't need to add any additional dropouts to implement these two as the Transformer already has dropout masks placed on fully-connected layers and attention probabilities. Thus, simply feeding the same input to the Transformer twice will get two representations with different dropout masks. Since dropout is similar to adding noise, the difference between the two representations can be regarded as the *robustness* of the LM.

### 3.2 Training: Learning a New Domain via Soft-masking and Contrastive Loss

**Soft-masking units.** Recall we want to preserve the learned knowledge in the LM during post-training using the accumulated importance $\boldsymbol{I}_l^{(\leq t-1)}$ when we learn domain $t$, which includes both the importance for the general knowledge $\boldsymbol{I}_l^{\text{gen}}$ (Sec. 3.1) and learned domain-specific knowledge $\boldsymbol{I}_l^k$ of each domain $k$ ($k$ can be any domain in $\{1...t-1\}$) that has been learned (Sec. 3.3). This is achieved by soft-masking the learning based on accumulated importance as follows.

Note that the importance values in each layer $l$ for a domain $k$ is normalized via

$$\text{Norm}(\boldsymbol{I}_l^{(k)}) = |\text{Tanh}(\frac{\boldsymbol{I}_l^{(k)} - \text{Mean}(\boldsymbol{I}_l^{(k)})}{\sqrt{\text{Var}(\boldsymbol{I}_l^{(k)})}})|. \tag{5}$$

With this normalization, $\boldsymbol{I}_l^{(k)}$ has the mean of 0 and standard deviation of 1. Absolute value of Tanh ensures that $\boldsymbol{I}_l^{(k)}$ takes values in the interval $[0, 1]$. To simplicity the notation, we use the same $\boldsymbol{I}_l^{(k)}$ to represent the normalized importance. Given the normalized importance, we accumulate the importance after task $t-1$ was learned is done as follows:

$$\boldsymbol{I}_l^{(\leq t-1)} = \text{EMax}(\{\boldsymbol{I}_l^{t-1}, \boldsymbol{I}_l^{(\leq t-2)}\}), \tag{6}$$

where $t$ refers to the current task-ID and $\boldsymbol{I}_l^{(\leq t-2)}$ refers to the previously accumulated importance at task $t-2$. When we learn task 1, $\boldsymbol{I}_l^{(\leq 0)}$ is $\boldsymbol{I}_l^{\text{gen}}$. We do not need to save $\boldsymbol{I}_l^{\text{gen}}$ and all $\{\boldsymbol{I}_l^{(k)}\}_{k=1}^{t\text{-}1}$ for Eq. 6. We only save the incrementally accumulated importance after training of each task.

For soft-masking, given the accumulated importance $\boldsymbol{I}_l^{(\leq t-1)}$ of layer $l$ and the post-training loss $\mathcal{L}_{\text{post-train}}$ (typically the MLM loss; we also propose an additional loss in Eq. 11), we constrain (or soft-mask) its corresponding gradient ($\nabla_l$) flow as follows,

$$\hat{\nabla}_l = (1 - \boldsymbol{I}_l^{(\leq t-1)}) \otimes \nabla_l, \tag{7}$$

As mentioned in Sec. 3.1, we expand (by copying) the importance $\boldsymbol{I}_l^{(\leq t-1)}$ to match the dimensions of $\nabla_l$ to apply it to all associated parameters. This is *soft-masking* because each element in $\boldsymbol{I}_l^{(\leq t-1)}$ is a real number in $[0, 1]$ (instead of binary $\{0, 1\}$), which gives the model the flexibility to adjust any unit. This is useful because although some units are important, they may conflict with the knowledge in the current domain and thus need some small adjustments.

We note that the above soft-masks are only applied in the backward pass, but not in the forward pass, which encourages knowledge transfer across domains as each domain training can leverage the knowledge learned from all past domains. To further encourage the model to learn a good representation from both the accumulated knowledge ($\boldsymbol{I}_l^{(\leq t-1)}$) and the full knowledge (both accumulated and current domain knowledge) , we next introduce a contrastive learning method to encourage complementary representation.

**Contrasting the previously learned and new domain knowledge.** We now present how to integrate the previously learned knowledge and the current domain knowledge by contrasting the previously learned knowledge and the full knowledge (both previously learned knowledge and the current domain knowledge). Note that this is done based on the current domain data. Below we first introduce how to obtain the required types of knowledge for input $\boldsymbol{x}$, and then discuss how we contrast them to achieve their integration.

**(1)** *Obtaining previously learned knowledge in the current LM using the input* $\boldsymbol{x}$. This is done by extracting the representation of $\boldsymbol{x}$ from the network learned from previous domains by combining the units in the layer and their importance scores $\boldsymbol{I}_l^{(\leq t-1)}$ in a *forward pass*. The intuition is that

since the importance scores show how important each unit is to the previously learned knowledge (including the general knowledge in the *initialization* functions), the resulting representation reflects the main previously learned knowledge used by $\boldsymbol{x}$. Formally, we use $\boldsymbol{I}_l^{(\leq t-1)}$ to gate the output of layer $l$ (similar to Eq. 2),

$$\boldsymbol{o}_l^{\text{prev}} = \boldsymbol{I}_l^{(\leq t-1)} \otimes \boldsymbol{o}_l. \tag{8}$$

Given the units in layer $l$ for the previously learned knowledge $\boldsymbol{o}_l^{\text{prev}}$, we can plug it into the whole language model to obtain the final learned knowledge or representation, taking the average of each token's output in the input sequence $\boldsymbol{x}$ (see $\boldsymbol{o}^{\text{prev}}$ in Figure 1 (B)),

$$\boldsymbol{o}^{\text{prev}} = f_{\text{LM}}(\boldsymbol{o}_l^{\text{prev}}). \tag{9}$$

**(2)** *Obtaining full (both learned domains and current domain) knowledge in* $\boldsymbol{x}$. This is similar to the above except that we extract the representation by using all units in the layer without considering their importance (the gates are removed) , i.e., $o_l^{\text{full}} = \boldsymbol{o}_l$.

Similarly, we can plug it into the Transformer (see $\boldsymbol{o}^{\text{full}}$ also in Figure 1 (B)),

$$\boldsymbol{o}^{\text{full}} = f_{\text{LM}}(o_l^{\text{full}}). \tag{10}$$

Note that it is possible to use $(1 - \boldsymbol{I}_l^{(\leq t-1)})$ as the importance of domain-specific knowledge and contrast it with the previously learned knowledge. However, this produces poorer results (see Table 3) as explained in footnote 3.

**(3)** *Contrasting learned and full knowledge.* Contrastive learning helps learn a good isotropic representation that is good for down-stream tasks, with the help of positive $\boldsymbol{o}_m^+$ and negative $\boldsymbol{o}_m^-$ instances. In our case, such instances are representations of the input $\boldsymbol{x}$ for both the full knowledge ($\boldsymbol{o}^{\text{full}}$) and the previously learned domain knowledge ($\boldsymbol{o}^{\text{prev}}$) in the current LM. This enables us to contrast the two representations, which essentially makes the two representations *complementary* as they represent two aspects of the same input. It thus encourages the current domain representation of $\boldsymbol{x}$ in $\boldsymbol{o}^{\text{full}}$ to learn knowledge that is not already in the learned knowledge in previous domains and yet related to and integrated with the learned knowledge ($\boldsymbol{o}^{\text{prev}}$).

We construct the contrastive instances as follows: for an input $\boldsymbol{x}_m$, three contrastive instances are produced. Anchor $\boldsymbol{o}_m$ and positive instance $\boldsymbol{o}_m^+$ are both the full knowledge from Eq. 10, obtained based on two independently sampled dropout masks in Transformer (recall that this can be achieved by inputting $\boldsymbol{x}_m$ twice, see Sec. 3.1). $\boldsymbol{o}_m^+$ and $\boldsymbol{o}_m$ are positive instances as the dropout noise has been shown good positive instances for improving alignment in training sentence embedding (Gao et al., 2021a). Negative instance $\boldsymbol{o}_m^-$ is the representation of $\boldsymbol{x}_m$ in the previously learned knowledge obtained by Eq. 9. Contrastive learning pushes the positive and negative instances away, forcing them to be different and covering different aspects (full and previously learned knowledge) of the same input, resulting in knowledge integration.

Formally, with $\boldsymbol{o}_m$, $\boldsymbol{o}_m^+$, and $\boldsymbol{o}_m^-$, our contrastive loss is (sim$(\cdot)$ is the cosine similarity),

$$\mathcal{L}_{\text{contrast}} = -\log \frac{e^{\text{sim}(\boldsymbol{o}_m, \boldsymbol{o}_m^+)}/\tau}{\sum_{j=1}^{N}(e^{\text{sim}(\boldsymbol{o}_m, \boldsymbol{o}_j^+)/\tau} + e^{\text{sim}(\boldsymbol{o}_m, \boldsymbol{o}_j^-)/\tau})}. \tag{11}$$

Compared to Eq. 1, the second term is added in the denominator, i.e., representation in the previously learned knowledge as additional negative instances. Figure 1 (B) shows a red arrow pointed from $\boldsymbol{o}^{\text{full}}$ to itself, indicating the positive instances are from inputting twice. The dashed red arrow pointing to $\boldsymbol{o}^{\text{prev}}$ indicates the negative instances contrasting the full and previously learned knowledge.

**Final Loss Function**. The final post-training loss combines the Masked Language Model (MLM) loss after applying the proposed soft-masking for the general knowledge (we call $\mathcal{L}_{\text{MLM+SM}}$, where SM is for soft-masking) (Sec. 3.1) and the proposed contrastive loss ($\lambda$ is a hyper-parameter),

$$\mathcal{L}_{\text{post-train}} = \mathcal{L}_{\text{MLM+SM}} + \lambda \mathcal{L}_{\text{contrast}} \tag{12}$$

### 3.3 Compute importance of units to The current domain

After training the new/current domain $t$, we learn the units importance by applying Eq. 3 for the domain. We do not need any proxy to compute $\mathcal{L}_{\text{impt}}$ as in Eq. 4 because we can directly use the

| Unlabelde Domain Datasets | | | End-Task Classification Datasets | | | | |
|---|---|---|---|---|---|---|---|
| Source | Dataset | Size | Dataset | Task | #Training | #Testing | #Classes |
| Reviews | Yelp Restaurant | 758MB | Restaurant | Aspect Sentiment Classification (ASC) | 3,452 | 1,120 | 3 |
| | Amazon Phone | 724MB | Phone | Aspect Sentiment Classification (ASC) | 239 | 553 | 2 |
| | Amazon Camera | 319MB | Camera | Aspect Sentiment Classification (ASC) | 230 | 626 | 2 |
| Academic Papers | ACL Papers | 867MB | ACL | Citation Intent Classification | 1,520 | 421 | 6 |
| | AI Papers | 507MB | AI | Relation Classification | 2,260 | 2,388 | 7 |
| | PubMed Papers | 989MB | PubMed | Chemical-protein Interaction Prediction | 2,667 | 7,398 | 13 |

Table 1: Statistics of datasets for post-training. More details of their end-task supervised learning datasets are given in Appendix B.

current domain data. Specifically, we randomly sample a subset (a hyper-parameter) of the current domain data $\{(\boldsymbol{x}_m^{\text{sub}}, y_m^{\text{sub}})\}$, where $\boldsymbol{x}_m^{\text{sub}}$ is the input and $y_m^{\text{sub}}$ is the masked token as in MLM self-supervised loss. We can then easily compute the importance $\boldsymbol{I}_l^{(t)}$ by plugging $\mathcal{L}_{\text{MLM}}$ into $\mathcal{L}_{\text{impt}}$ in Eq. 3. The resulting $\boldsymbol{I}_l^{(t)}$ will be used in the next task by accumulating with the previously accumulated importance (Eq. 6) and soft-masking the learning (Eq. 7).

# 4 Experiments

We use RoBERTa (Liu et al., 2019b)[4] as the LM. Following the standard evaluation setup (Lange et al., 2019) and, after a domain is trained, its training data is discarded. After all domains are incrementally learned, the final model is evaluated by fine-tuning the end-tasks in all domains.

## 4.1 Datasets and Baselines

**Datasets:** Table 1 shows the statistics of the *unlabeled domain corpora* for post-training and their corresponding *end-task classification datasets*. We use 6 *unlabeled domain datasets*:[5] 3 of them are about reviews: *Yelp Restaurant* (Xu et al., 2019), *Amazon Phone* (Ni et al., 2019), *Amazon Camera* (Ni et al., 2019); 3 of them are academic papers: *ACL Papers* (Lo et al., 2020), *AI Papers* (Lo et al., 2020), and *PubMed Papers*[6]. Their corresponding *end-task classification datasets* are:[7] *Restaurant*[8], *Phone* (Ding et al., 2008; Hu & Liu, 2004), *Camera* (Ding et al., 2008; Hu & Liu, 2004), *ACL* (ACL-ARC in (Jurgens et al., 2018)), *AI* (SCIERC in (Luan et al., 2018)), and PubMed (CHEMPORT in (Kringelum et al., 2016)).

**Baselines.** We use 15 baselines, including non-continual learning (Non-CL) and continual learning (CL) baselines. All CL baselines are originally for learning supervised data except DEMIX. We adapt them and replace their backbone with RoBERTa. Details of each baseline is given in Appendix C.

**Non-CL Baselines**: Each baseline here builds a separate model for each task. **(1) RoBERTa** (Liu et al., 2019b) uses RoBERTa for end-task fine-tuning without post-training. **(2) Post (RoBERTa)** uses the existing post-training method (MLM) in (Gururangan et al., 2020). **(3) Post (Adapter)** adds adapter layers in Transformer for post-training (Madotto et al., 2020; Houlsby et al., 2019). Only the added adapters are trainable. In end-task fine-tuning, both RoBERTa and the adapters are trainable. **(4) Post (Prompt)** is from (Lester et al., 2021). In post-training, RoBERTa (the LM) is fixed and only the prompts are trained. In end-task fine-tuning, both the LM and the trained prompt are trainable.

**CL Baselines**: We use 2 naive baselines, which keep learning more domains with no mechanism to deal with CF or transfer. **(5) NCL** (Naive CL) continually post-trains the RoBERTa; and **(6) NCL (Adapter)** continually post-trains a set of adapters (Houlsby et al., 2019).

8 baselines are CL systems: **(7) DEMIX** (Gururangan et al., 2021) adds a new adapter for each new domain and initializes it with a previous adapter nearest to the new domain; **(8) BCL** (Ke et al., 2021b) uses capsule networks. **(9) CLASSIC** (Ke et al., 2021a) uses contrastive learning. **(10)**

[4] https://huggingface.co/roberta-base

[5] We down-sampled the *PubMed* due to its huge original size. In general, our datasets are much smaller than those used in (Gururangan et al., 2020) (which used more than 11GB of data for each domain). Our experiments showed that a smaller dataset is sufficient and more data does not help. It also requires less computing power.

[6] https://pubmed.ncbi.nlm.nih.gov/

[7] Our results are different from those presented in Table 5 of (Gururangan et al., 2020) because we observe very high variances due to very small test sets and thus enlarge the test set and reduce the training set slightly.

[8] https://alt.qcri.org/semeval2014/task4/

| Category | Domain | Restaurant | | ACL | | AI | | Phone | | PubMed | Camera | | Average | | Forget R. | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Model | MF1 | Acc | MF1 | Acc | MF1 | Acc | MF1 | Acc | MF1 | MF1 | Acc | MF1 | Acc | MF1 | Acc |
| Non-CL | RoBERTa | 79.81 | 87.00 | 66.11 | 71.26 | 60.98 | 71.85 | 83.75 | 86.08 | 72.38 | 78.82 | 87.03 | 73.64 | 79.27 | — | |
| | Post (RoBERTa) | 80.84 | **87.68** | 68.75 | 73.44 | 68.97 | 75.95 | 82.59 | 85.50 | 72.84 | 84.39 | 89.90 | 76.40 | 80.89 | — | |
| | Post (Adapter) | 80.19 | 87.14 | 68.87 | 72.92 | 60.55 | 71.38 | 82.71 | 85.35 | 71.68 | 83.62 | 89.23 | 74.60 | 79.62 | — | |
| | Post (Prompt) | 79.00 | 86.45 | 66.66 | 71.35 | 61.47 | 72.36 | 84.17 | 86.53 | **73.09** | 85.52 | 90.38 | 74.98 | 80.03 | — | |
| CL Post-train | NCL | 79.52 | 86.54 | 68.39 | 72.87 | 67.94 | 75.71 | 84.10 | 86.33 | 72.49 | 85.71 | 90.70 | 76.36 | 80.77 | 1.14 | 1.05 |
| | NCL (Adapter) | 80.13 | 87.05 | 67.39 | 72.30 | 57.71 | 69.87 | 83.32 | 85.86 | 72.07 | 83.70 | 89.71 | 74.05 | 79.48 | 0.15 | -0.02 |
| | DEMIX | 79.99 | 87.12 | 68.46 | 72.73 | 63.35 | 72.86 | 78.07 | 82.42 | 71.73 | 86.59 | 91.12 | 74.70 | 79.66 | 0.74 | 0.36 |
| | BCL | 78.97 | 86.52 | **70.71** | **74.58** | 66.26 | 74.55 | 81.70 | 84.63 | 71.99 | 85.06 | 90.51 | 75.78 | 80.46 | -0.06 | -0.19 |
| | CLASSIC | 79.89 | 87.05 | 67.30 | 72.11 | 59.84 | 71.08 | 84.02 | 86.22 | 69.83 | 86.93 | 91.25 | 74.63 | 79.59 | 0.44 | 0.25 |
| | KD | 78.05 | 85.59 | 69.17 | 73.73 | 67.49 | 75.09 | 82.12 | 84.99 | 72.28 | 81.91 | 88.69 | 75.17 | 80.06 | -0.07 | 0.01 |
| | EWC | **80.98** | 87.64 | 65.94 | 71.17 | 65.04 | 73.58 | 82.32 | 85.13 | 71.43 | 83.35 | 89.14 | 74.84 | 79.68 | 0.02 | -0.01 |
| | DER++ | 79.00 | 86.46 | 67.20 | 72.16 | 63.96 | 73.54 | 83.22 | 85.61 | 72.58 | 87.10 | 91.47 | 75.51 | 80.30 | 2.36 | 1.53 |
| | HAT | 76.42 | 85.16 | 60.70 | 68.79 | 47.37 | 65.69 | 72.33 | 79.13 | 69.97 | 74.04 | 85.14 | 66.80 | 75.65 | -0.13 | -0.29 |
| | HAT-All | 74.94 | 83.93 | 52.08 | 63.94 | 34.16 | 56.07 | 64.71 | 74.43 | 68.14 | 65.54 | 81.44 | 59.93 | 71.33 | 3.23 | 1.83 |
| | HAT (Adapter) | 79.29 | 86.70 | 68.25 | 72.87 | 64.84 | 73.67 | 81.44 | 84.56 | 71.61 | 82.37 | 89.27 | 74.63 | 79.78 | -0.23 | -0.18 |
| | CPS | 80.34 | 87.16 | 69.36 | 74.01 | **70.93** | **77.46** | **85.99** | **87.70** | 72.80 | **88.16** | **92.30** | **77.93** | **81.91** | **-1.09** | **-0.60** |

Table 2: End-task macro-F1 (MF1), accuracy and forgetting rate results for all domains *after the continual post-training of all domains*, except for CHEMPORT in the PubMed domain, for which we use micro-F1 following (Gururangan et al., 2020; Dery et al., 2021; Beltagy et al., 2019). The results are averages of 5 random seeds (the domain training order is as they appear in the first row). Due to space limits, the results for *different domain orders* and the *standard deviations* are reported in Appendix D and Appendix E, respectively). Non-CL baselines have no forgetting.

| Category | Domain | Restaurant | | ACL | | AI | | Phone | | PubMed | Camera | | Average | | Forget R. | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Model | MF1 | Acc | MF1 | Acc | MF1 | Acc | MF1 | Acc | MF1 | MF1 | Acc | MF1 | Acc | MF1 | Acc |
| Non-CL | RoBERTa | 79.81 | 87.00 | 66.11 | 71.26 | 60.98 | 71.85 | 83.75 | 86.08 | 72.38 | 78.82 | 87.03 | 73.64 | 79.27 | — | |
| | Post (RoBERTa) | 80.84 | **87.68** | 68.75 | 73.44 | 68.97 | 75.95 | 82.59 | 85.50 | 72.84 | 84.39 | 89.90 | 76.40 | 80.89 | — | |
| | Post (Adapter) | 80.19 | 87.14 | 68.87 | 72.92 | 60.55 | 71.38 | 82.71 | 85.35 | 71.68 | 83.62 | 89.23 | 74.60 | 79.62 | — | |
| | Post (Prompt) | 79.00 | 86.45 | 66.66 | 71.35 | 61.47 | 72.36 | 84.17 | 86.53 | **73.09** | 85.52 | 90.38 | 74.98 | 80.03 | — | |
| CL Post-train | CPS (w/o contrast) | 81.06 | 87.55 | **70.39** | **74.39** | 67.60 | 75.32 | 83.53 | 86.00 | 72.01 | 84.48 | 90.06 | 76.51 | 80.89 | -0.54 | -0.23 |
| | CPS (w/o softmask) | 80.48 | 87.27 | 69.92 | 74.39 | 67.73 | 75.78 | 84.00 | 86.37 | 73.03 | 87.96 | 92.08 | 77.19 | 81.48 | -0.24 | -0.12 |
| | CPS (w/o initialization) | **81.30** | 87.79 | 68.35 | 73.10 | 67.82 | 75.73 | 85.13 | 86.98 | 71.82 | 87.25 | 91.57 | 76.95 | 81.16 | 0.70 | 0.48 |
| | CPS (domain-specific) | 80.95 | **87.68** | 69.18 | 73.21 | 68.92 | 76.27 | 83.89 | 86.26 | 72.46 | 86.74 | 91.53 | 77.02 | 81.23 | -0.07 | 0.08 |
| | CPS | 80.34 | 87.16 | 69.36 | 74.01 | **70.93** | **77.46** | **85.99** | **87.70** | 72.80 | **88.16** | **92.30** | **77.93** | **81.91** | **-1.09** | **-0.60** |

Table 3: Ablation results - averages of 5 random seeds. See *standard deviations* in Appendix E.

**KD** is knowledge distillation (Hinton et al., 2015). **(11) EWC** (Buzzega et al., 2020) is a popular regularization-based method. **(12) DER++** (Buzzega et al., 2020) is a replay method based on knowledge distillation. 16.4K tokens are saved for each domain in the replay memory, which is the largest memory we can use for the system to run. **(13) HAT** (Serrà et al., 2018) is an effective *parameter-isolation* method. HAT is applied to Transformer layers (i.e., self-attention, intermediate and output layers). **(14) HAT-All** is a HAT variant using the same post-training, but all features *from the LM* are used to do end-tasks (instead of only features from its domain sub-network as in HAT). **(15) HAT (Adapter)** (Ke et al., 2021b) uses HAT within adapters. We do not include ELLE (Qin et al., 2022) as we tried to adapt it for our purpose by learning from RoBERTa, but it fails to converge.

### 4.2 Results Analysis and Ablation Study

Due to space limits, ***Implementation Details*** are given in Appendix A. Table 2 reports the end-task fine-tuning results of all 15 systems on the 6 datasets. We can see that the proposed CPS outperforms all baselines on average and also achieve the best knowledge transfer (negative forgetting rate).

(1). CPS achieves both forgetting prevention and knowledge transfer. Those baselines (KD, EWC, DER++) focusing only on forgetting prevention give poorer performance as they sacrifice accuracy to avoid CF. Those baselines (BCL, CLASSIC and DEMIX) perform knowledge transfer achieve better results but still poorer than CPS. DEMIX has very weak transfer. BCL, which can avoid CF while also achieving some transfer, is weaker than NCL. In general, CL baselines are all poorer than CPS as they don't have methods to encourage knowledge transfer or they have to rely on adapters.

(2). Directly learning the domains within the LM helps CPS achieve better results than adapter and prompt based methods. We believe that this is because adapters and prompts do not have sufficient trainable parameters, which are also randomly initialized and can be difficult to train.

(3). Using the full LM to learn all tasks rather than using sub-networks (of HAT-based methods) as in parameter-isolation method makes CPS more effective. HAT performs poorly, indicating that it is unsuitable for post-training as discussed in Sec. 1. It is very challenging to address the issue. Even if we use all features (not only the feature from the corresponding sub-network), we still get poor

results (HAT-All). This is because the features used in post-training (in a sub-network of the LM) are different from features used in end-task fine-tuning (features from the whole LM).

**Knowledge transfer and forgetting avoidance.** To see how the models fare on CF and knowledge transfer, we compare the forgetting rates (**forget R.**) (Liu et al., 2020a), $\frac{1}{t-1}\sum_{k=1}^{t-1} A_{k,k} - A_{t,k}$, where $A_{k,k}$ is the end-task accuracy right after its domain $k$ is post-trained, and $A_{t,k}$ is the accuracy of the end-task of domain $k$ after post-training the last domain $t$. We average over all end-tasks except the last as the last domain has no forgetting. The higher the forgetting rate is, the more forgetting it has. Negative rates indicate positive knowledge transfer. Clearly, CPS has the strongest negative forgetting rate, indicating it does well on both forgetting prevention and knowledge transfer. NCL, NCL (Adapter), DEMIX, EWC, KD and DER++ all suffer from some forgetting. HAT has no forgetting but it cannot learn well. HAT and BCL have no forgetting but are weak in transfer.

**Effectiveness of the proxy KL-divergence loss.** We use proxy KL-divergence loss in the *initialization* function (Sec. 3.1) to compute the importance of units for general knowledge. We are interested in how good the proxy is. Since we don't have the data that pre-trains RoBERTa, it is not obvious how to assess the quality of the proxy directly. Here, we provide some indirect evidences to show the effectiveness of the proxy for computing the importance of units to the general knowledge in the LM.

We conduct a separate experiment (none CL) to compare the attention heads' [9] importance score vectors after applying the proxy using the data from different domains. For each domain $i$, we compare its importance vector with the importance vector of every other domain, and then average the cosine similarities to get the value for domain $i$. We get 0.92 for Restaurant, the same 0.91 for ACL, AI, and Phone, 0.89 for PubMed and 0.92 for Camera. We see that different domains give similar importance values, indirectly showing that our proxy can identify the common general knowledge.

We also compute the importance score distributions of the proxy. For each of the 6 domains, after applying the proxy, around 20% of the attention heads are heavily protected ($0.8 \leq I^{\text{gen}}_{l,i} \leq 1.0$) and another 20% moderately protected ($0.6 \leq I^{\text{gen}}_{l,i} < 0.8$), which indicate the general knowledge. While Phone, AI, Camera and Restaurant share a similar distribution, ACL and PubMed protect slightly less. This is understandable as PubMed and ACL (medical or NLP publications) are probably less common than the other domains and the general knowledge in the LM covers them less.

**Ablation.** We want to know if the proposed (1) initialization function (Sec. 3.1), (2) soft-masking mechanism, and (3) contrastive learning are helpful. To answer (1), we conduct the ablation experiment **CPS (w/o initialization)**, where we remove the initialization function and directly do the continual learning given no consideration to the general knowledge in the original LM. To answer (2), we conduct the ablation experiment **CPS (w/o softmask)**, where we remove soft masking, and only use contrastive learning based on inputting the same input twice in Eq. 11 (with the second term in the denominator removed). To answer (3), we conduct two ablations: **(i) CPS (w/o contrast)** where we remove the contrastive loss and only soft-mask the backward pass according to the importance; **(ii) CPS (domain-specific)** where we contrast domain-specific and learned knowledge (see Sec. 3.2)

Table 3 shows that the full CPS is the best on average and for most domains, indicating that every component contributes. Additional observations are: (1) CPS's gain is partially from the preserved general knowledge. We can see CPS (w/o initialization) is poorer on average; (2) Soft-masking helps as CPS (w/o softmask) is poorer than CPS. This is reasonable because soft masking can preserve learned domains; (3) Contrastive learning is effective as CPS (w/o contrast) and CPS (domain-specific) are both poorer, indicating the contrastive learning in CPS can help learn good representations.

## 5 Conclusion

This paper proposed a novel method for the continual post-training of an LM. It has two key ideas: (1) Preserving the important previous knowledge by soft-masking units according to their importance to overcome CF and to facilitate knowledge transfer. (2) Learning complementary representations for knowledge integration. A set of techniques is proposed to achieve them. Extensive experiments showed the effectiveness of the proposed method. The current proposed approach involves two functions in learning. We will study how to combine them to further improve the results in the future.

[9] We use attention heads instead of other units because they are arguably the most important component in a Transformer (Michel et al., 2019; Voita et al., 2019; McCarley et al., 2019).

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| Random Sequence Order | NCL | | CPS | |
|---|---|---|---|---|
| | MF1 | Acc | MF1 | Acc |
| Restaurant → ACL → AI → Phone → PubMed → Camera | 76.36 | 80.77 | **77.93** | **81.91** |
| Phone → AI → PubMed → Camera → Restaurant → ACL | 76.06 | 80.69 | **76.90** | **81.10** |
| PubMed → Camera → ACL → Restaurant → AI → Phone | 76.49 | 80.84 | **76.86** | **81.09** |
| Camera → ACL → Phone → Restaurant → PubMed → AI | 76.28 | 80.83 | **77.52** | **81.65** |
| AI → PubMed → Camera → Phone → ACL → Restaurant | 76.17 | 80.68 | **78.18** | **82.10** |

Table 4: CPS performance averaged over all domains after the final post-trained (averaged over 5 random seeds).

# A Implementation Details

**Architecture.** We adopt RoBERTa$_{\textbf{BASE}}$ as our backbone LM. A masked language model head is applied for post-training. The end-task fine-tuning of RoBERTa follows the standard practice. For the three ASC tasks (see Table 1), we adopt the ASC formulation in Xu et al. (2019), where the aspect (e.g., "*sound*") and review sentence (e.g., "*The sound is great*") are concatenated via </s>.

**Hyperparameters.** Unless otherwise stated, the same hyper-parameters are used in all experiments. The maximum input length is set to 164 which is sufficient for all datasets. Adam optimizer is used for both post-training and end-task fine-tuning. The max sequence length is also set to 164.

**Post-training.** The learning rate is set to 1e-4 and batch size to 256. We train 2.5K steps for each domain, roughly a full pass through the domain data, following Gururangan et al. (2020); Xu et al. (2019). The subset of data $\{\boldsymbol{x}_m^{\text{sub}}\}$ for computing $\mathcal{L}^{\text{impt}}$ to determine head importance in Secs. 3.1 and 3.3 is set to 1.64 Million tokens, which is sufficient in our experiments. $\lambda$ in Eq. 12 is set to 1 and $\tau$ in Eq. 11 is set to 0.05.

**End-task fine-tuning.** The learning rate is set to 1e-5 and batch size to 16. We train on end-task fine-tuning datasets for 5 epochs for Restaurant; 10 epochs for ACL, AI and PubMed; and 15 epochs for Phone and Camera. We simply take the results for the last epoch, assuming no validation sets. We empirically found that the above number of epochs gives us stable and convergence results.

# B Datasets Details

Table 1 in the main paper has already showed the number of examples in each dataset. Here we provide additional details about the 4 types of end-tasks.

(1) **(Phone, Camera and Restaurant) Aspect Sentiment Classification (ASC)** is defined as follows: given an aspect or product feature (e.g., *picture quality* in a camera review) and a review sentence containing the aspect in a domain or product category (e.g., camera), classify if the sentence expresses a positive, negative, or neutral (no opinion) sentiment or polarity about the aspect (for the Phone and Camera datasets, there are only negative and positive polarities in the data).

(2) **(ACL) Citation intent classification** is defined as follows: given a citing sentence (a sentence contains a citation), classify if the sentence expresses a citation function among "background", "motivation", "uses", "extension" and "comparison or contrast future".

(3) **(AI) Relation classification** is defined as follows: given a within-sentence word sequence span containing a pair of entities, classify if the span expresses a relation among "feature of", "conjunction", "evaluate for", "hyponym of", "used for", "part of" and "compare".

(4) **(PubMed) Chemical-protein interaction classification** is defined as follows: given a span containing a pair of chemical and protein, classify if the span expresses a chemical-protein interaction among "downregulator", "substrate", "indirect-upregulator", "indirect-downregulator", "agnonist", "activator", "product of", "agonist-activator", "inhibitor", "upregulator", "substrate product of", "agonist-inhibitor"and "antagonist".

| Category | Domain | Restaurant | | ACL | | AI | | Phone | | PubMed | Camera | | Average | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Model | MF1 | Acc | MF1 | Acc | MF1 | Acc | MF1 | Acc | MF1 | MF1 | Acc | MF1 | Acc |
| Non-CL | RoBERTa | ±0.0117 | ±0.0049 | ±0.0192 | ±0.0096 | ±0.0646 | ±0.0347 | ±0.0210 | ±0.0154 | ±0.0071 | ±0.0403 | ±0.0179 | ±0.0119 | ±0.0070 |
| | Post (RoBERTa) | ±0.0096 | ±0.0056 | ±0.0218 | ±0.0118 | ±0.0117 | ±0.0086 | ±0.0165 | ±0.0103 | ±0.0035 | ±0.0479 | ±0.0298 | ±0.0118 | ±0.0075 |
| | Post (Adapter) | ±0.0102 | ±0.0068 | ±0.0142 | ±0.0099 | ±0.0551 | ±0.0288 | ±0.0265 | ±0.0181 | ±0.0055 | ±0.0165 | ±0.0110 | ±0.0132 | ±0.0087 |
| | Post (Prompt) | ±0.0060 | ±0.0035 | ±0.0068 | ±0.0108 | ±0.0301 | ±0.0124 | ±0.0126 | ±0.0087 | ±0.0028 | ±0.0243 | ±0.0138 | ±0.0049 | ±0.0019 |
| CL Post-train | NCL | ±0.0064 | ±0.0035 | ±0.0168 | ±0.0084 | ±0.0164 | ±0.0099 | ±0.0126 | ±0.0104 | ±0.0073 | ±0.0449 | ±0.0247 | ±0.0116 | ±0.0073 |
| | NCL (Adapter) | ±0.0090 | ±0.0060 | ±0.0063 | ±0.0065 | ±0.0835 | ±0.0405 | ±0.0196 | ±0.0124 | ±0.0086 | ±0.0312 | ±0.0152 | ±0.0117 | ±0.0058 |
| | DEMIX | ±0.0065 | ±0.0029 | ±0.0118 | ±0.0094 | ±0.0376 | ±0.0218 | ±0.0731 | ±0.0428 | ±0.0069 | ±0.0099 | ±0.0071 | ±0.0121 | ±0.0064 |
| | BCL | ±0.0106 | ±0.0059 | ±0.0050 | ±0.0054 | ±0.0433 | ±0.0229 | ±0.0191 | ±0.0130 | ±0.0069 | ±0.0290 | ±0.0164 | ±0.0097 | ±0.0055 |
| | CLAASSIC | ±0.0071 | ±0.0039 | ±0.0337 | ±0.0171 | ±0.0227 | ±0.0084 | ±0.0187 | ±0.0124 | ±0.0085 | ±0.0140 | ±0.0094 | ±0.0114 | ±0.0065 |
| | KD | ±0.0352 | ±0.0197 | ±0.0096 | ±0.0107 | ±0.0164 | ±0.0088 | ±0.0149 | ±0.0115 | ±0.0075 | ±0.0277 | ±0.0128 | ±0.0072 | ±0.0042 |
| | EWC | ±0.0161 | ±0.0085 | ±0.0136 | ±0.0076 | ±0.0178 | ±0.0089 | ±0.0205 | ±0.0140 | ±0.0069 | ±0.0725 | ±0.0424 | ±0.0172 | ±0.0098 |
| | DER++ | ±0.0081 | ±0.0042 | ±0.0156 | ±0.0089 | ±0.0355 | ±0.0160 | ±0.0402 | ±0.0272 | ±0.0090 | ±0.0367 | ±0.0215 | ±0.0158 | ±0.0088 |
| | HAT | ±0.0182 | ±0.0091 | ±0.0271 | ±0.0206 | ±0.0369 | ±0.0126 | ±0.0834 | ±0.0474 | ±0.0038 | ±0.1082 | ±0.0408 | ±0.0323 | ±0.0155 |
| | HAT-All | ±0.0257 | ±0.0140 | ±0.0643 | ±0.0273 | ±0.1355 | ±0.0991 | ±0.0428 | ±0.0217 | ±0.0125 | ±0.0526 | ±0.0163 | ±0.0175 | ±0.0145 |
| | HAT (Adapter) | ±0.0093 | ±0.0061 | ±0.0048 | ±0.0053 | ±0.0289 | ±0.0168 | ±0.0277 | ±0.0195 | ±0.0037 | ±0.0760 | ±0.0370 | ±0.0129 | ±0.0074 |
| | CPS | ±0.0090 | ±0.0063 | ±0.0186 | ±0.0103 | ±0.0142 | ±0.0086 | ±0.0160 | ±0.0135 | ±0.0067 | ±0.0289 | ±0.0154 | ±0.0099 | ±0.0060 |

Table 5: Standard deviations of the corresponding metrics of the proposed CPS model and the baselines

| Category | Domain | Restaurant | | ACL | | AI | | Phone | | PubMed | Camera | | Average | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Model | MF1 | Acc | MF1 | Acc | MF1 | Acc | MF1 | Acc | MF1 | MF1 | Acc | MF1 | Acc |
| Non-CL | RoBERTa | ±0.0117 | ±0.0049 | ±0.0192 | ±0.0096 | ±0.0646 | ±0.0347 | ±0.0210 | ±0.0154 | ±0.0071 | ±0.0403 | ±0.0179 | ±0.0119 | ±0.0070 |
| | Post (RoBERTa) | ±0.0096 | ±0.0056 | ±0.0218 | ±0.0118 | ±0.0117 | ±0.0086 | ±0.0165 | ±0.0103 | ±0.0035 | ±0.0479 | ±0.0298 | ±0.0118 | ±0.0075 |
| | Post (Adapter) | ±0.0102 | ±0.0068 | ±0.0142 | ±0.0099 | ±0.0551 | ±0.0288 | ±0.0265 | ±0.0181 | ±0.0055 | ±0.0165 | ±0.0110 | ±0.0132 | ±0.0087 |
| | Post (Prompt) | ±0.0060 | ±0.0035 | ±0.0068 | ±0.0108 | ±0.0301 | ±0.0124 | ±0.0126 | ±0.0087 | ±0.0028 | ±0.0243 | ±0.0138 | ±0.0049 | ±0.0019 |
| CL Post-train | CPS (w/o contrast) | ±0.0104 | ±0.0055 | ±0.0090 | ±0.0063 | ±0.0205 | ±0.0124 | ±0.0321 | ±0.0216 | ±0.0037 | ±0.0527 | ±0.0286 | ±0.0119 | ±0.0073 |
| | CPS (w/o softmask) | ±0.0064 | ±0.0046 | ±0.0121 | ±0.0088 | ±0.0193 | ±0.0113 | ±0.0245 | ±0.0175 | ±0.0096 | ±0.0322 | ±0.0183 | ±0.0104 | ±0.0059 |
| | CPS (w/o initialization) | ±0.0124 | ±0.0075 | ±0.0054 | ±0.0048 | ±0.0134 | ±0.0078 | ±0.0135 | ±0.0104 | ±0.0118 | ±0.0460 | ±0.0261 | ±0.0093 | ±0.0058 |
| | CPS (domain-specific) | ±0.0067 | ±0.0045 | ±0.0151 | ±0.0127 | ±0.0192 | ±0.0129 | ±0.0277 | ±0.0182 | ±0.0061 | ±0.0419 | ±0.0226 | ±0.0120 | ±0.0077 |
| | CPS | ±0.0090 | ±0.0063 | ±0.0186 | ±0.0103 | ±0.0142 | ±0.0086 | ±0.0160 | ±0.0135 | ±0.0067 | ±0.0289 | ±0.0154 | ±0.0099 | ±0.0060 |

Table 6: Standard deviations of the corresponding metrics of the proposed CPS model and the ablation

## C BASELINE DETAILS

**Non-Continual Learning Baselines**: Each of these baselines builds a separate model for each task independently. It thus has no knowledge transfer or CF.

(1) **Non-post-training (RoBERTa)** Liu et al. (2019b) uses the original RoBERTa for the end-task fine-tuning without any post-training. This is the only one without any post-training. All the following baselines use the masked language model loss (MLM) for post-training.

(2) **Post-training using masked language model loss (Post (RoBERTa))** is the existing post-training method in Gururangan et al. (2020). To our knowledge, the existing post-training systems are all based on the MLM loss.

(3) **Post-training using adapter-tuning** Madotto et al. (2020); Houlsby et al. (2019) adds small adapter layers between layers of Transformer for post-training. We follow the adapter design in Madotto et al. (2020); Houlsby et al. (2019): An adapter is simply a 2 layers of fully connected network. During post-training, the Transformer is fixed, only the added adapters are trainable. The bottleneck size (adapter size) is set to 128. During end-task fine-tuning, both RoBERTa and the adapters are trainable to ensure fair comparison.

(4) **Post-training using prompt-tuning** Lester et al. (2021) adds a sequence of real vector tokens (called virtual tokens or prompt tokens) to the end of the original sequence. In post-training, RoBERTa (the LM) is fixed and only the prompt tokens are trained. In end-task fine-tuning, both LM and the trained prompt are trainable. We initialize 100 tokens and set the learning rate of the prompt token to 0.3 in post-training, following the setting in Lester et al. (2021).

**Continual Learning (CL) Baselines.**

(5) **Naive continual learning (NCL)** is a naive extension of Gururangan et al. (2020), which continually/incrementally post-trains the LM to learn all domains using MLM loss with no mechanism to deal with CF.

(6) **Continual learning with adapter (NCL (Adapter))** Houlsby et al. (2019) is similar to the adapter based system. The only difference is that the same set of adapters is shared across all domains, rather than using a new adapter for each new domain.

(7) **DEMIX (DEMIX)** Gururangan et al. (2021) is a recent model to adapt pre-trained LM with new domains. It adds a new adapter once a new domain arrives (network expansion is needed) and

initializes the new adapter with the parameters of the previous trained adapter nearest to the new domain data. They use the perplexity on a held-out sample to choose the most probable adapter. For fair comparison, we use the same size as $\{\boldsymbol{x}_m^{\text{sub}}\}$ as the held-out samples.

(8) **Hard attention to overcome forgetting (HAT (Adapter))** Ke et al. (2021b) is derived from HAT Serrà et al. (2018), the state-of-the-art parameter-isolation based method with almost no forgetting. However, HAT requires task id information in end-task fine-tuning (CPS works in *domain-agnostic* manner and does not need the task id information; see Sec. 1). HAT also needs to train an addition task embedding to mask each layer of the network which makes the post-training inefficient.

(9) **Continual learning plugin with capsule(BCL)** Ke et al. (2021b) is a continual learning model that can avoid forgetting and encourage knowledge transfer. It is similar to NCL (Adapter). The difference is that its adapters consist of two modules, one is a capsule network (a new capsule is added once a new domain arrives) to encourage transfer and the other one is similar to HAT to avoid forgetting. Similar to HAT, task/domain information is needed in end-task fine-tuning. We replace the backbone network from BERT with RoBERTa for fair comparison.

(10) **Continual learning plugin with contrastive transfer (CLASSIC)** Ke et al. (2021a) is a continual learning model that can avoid forgetting and encourage knowledge transfer via contrasting loss. It is similar to HAT. but 3 additional contrastive loss are used for distillation, knowledge transfer and supervised contrast. Since CPS is working on unsupervised data, we remove the supervised contrastive loss. Similar to HAT, task information is needed in end-task fine-tuning. We replace the backbone network from BERT with RoBERTa for fair comparison.

(11) **Knowledge distillation (KD)** Hinton et al. (2015) minimizes the representational deviation between the learned representation and the new representation in post-training. We compute the KL divergence between the representations (the output before the masked language model prediction head) of each token of the previous post-trained LM and current LM as the distillation loss.

(12) **EWC** Buzzega et al. (2020) is a popular regularization-based method which adopts elastic weights consolidation to add $L_2$ regularization to parameter changes.

(13) **DER++** Buzzega et al. (2020) is a recent replay method using distillation to regularize the new task training. We store 16.4K tokens for each learned domain as the memory, which is the largest memory we can use for the system to run.

(14) **HAT** Serrà et al. (2018) is used in the Transformer layers (including self-attention, intermediate and output layers) rather than the added adapter layers. Additional task embedding and task information for end-task fine-tuning are needed.

## D POST-TRAINING IN DIFFERENT ORDERS

Table 2 in the main paper reported the results for the order `Restaurant` → `ACL` → `AI` → `Phone` → `PubMed` → `Camera`. We now look at how the order affects the results. Due to the computation intensive nature of post-training, we only report the best baseline (NCL) and CPS results with different domain orders. Table 4 shows NCL and CPS's results of 5 different orders. We can see CPS is always better than NCL, demonstrating the effectiveness of CPS.

## E STANDARD DEVIATIONS

Table 5 reports the standard deviations of the corresponding results in Table 2 (in the main paper) of CPS and the considered baselines over 5 runs with random seeds. We can see the results of CPS are stable. Some baselines (e.g., RoBERTa in AI, Post (RoBERTa) in Camera) can have quite large standard deviations.

Table 6 reports the standard deviations of the corresponding results in Table 3 (in the main paper) of CPS and the considered baselines over 5 runs with random seeds. We can see the results of CPS and its variants are stable.