Continual Pre-training of Language Models

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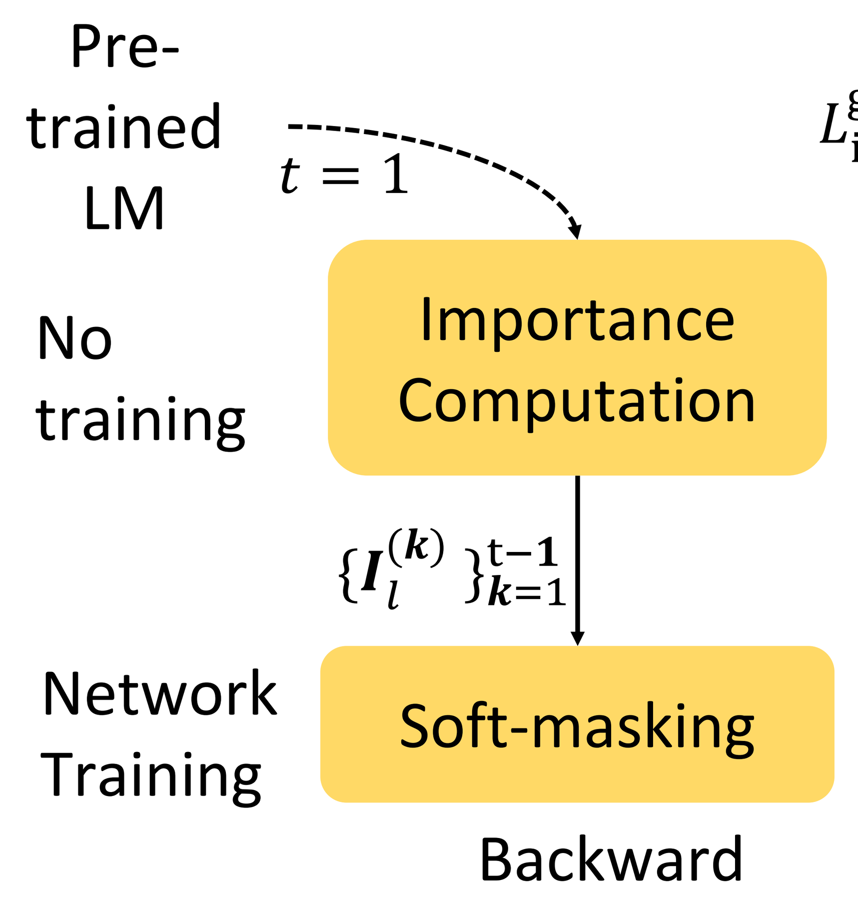
Continual **D**omain-**A**daptive pre-training of LMs with **S**oft-masking

- **Existing** language models (LMs) once trained are fixed.
- **However,** in the real world, data shifts constantly and new domains, events or topics keep emerging
- This requires LMs to be **updated** to serve the user better
- **Our focus:** Continually learning/pre-training an LM using a sequence of domain corpora, which we call **continual domain-adaptive pre-training**
- **Domain:** an emerging or specialized event or topic
- **Our goal:**
  - Catastrophic forgetting (CF) prevention
  - Knowledge Transfer (KT), including backward and forward KT

Proposed **DAS** Model: Preservation of LM general knowledge, soft-masking, and contrastive knowledge integration



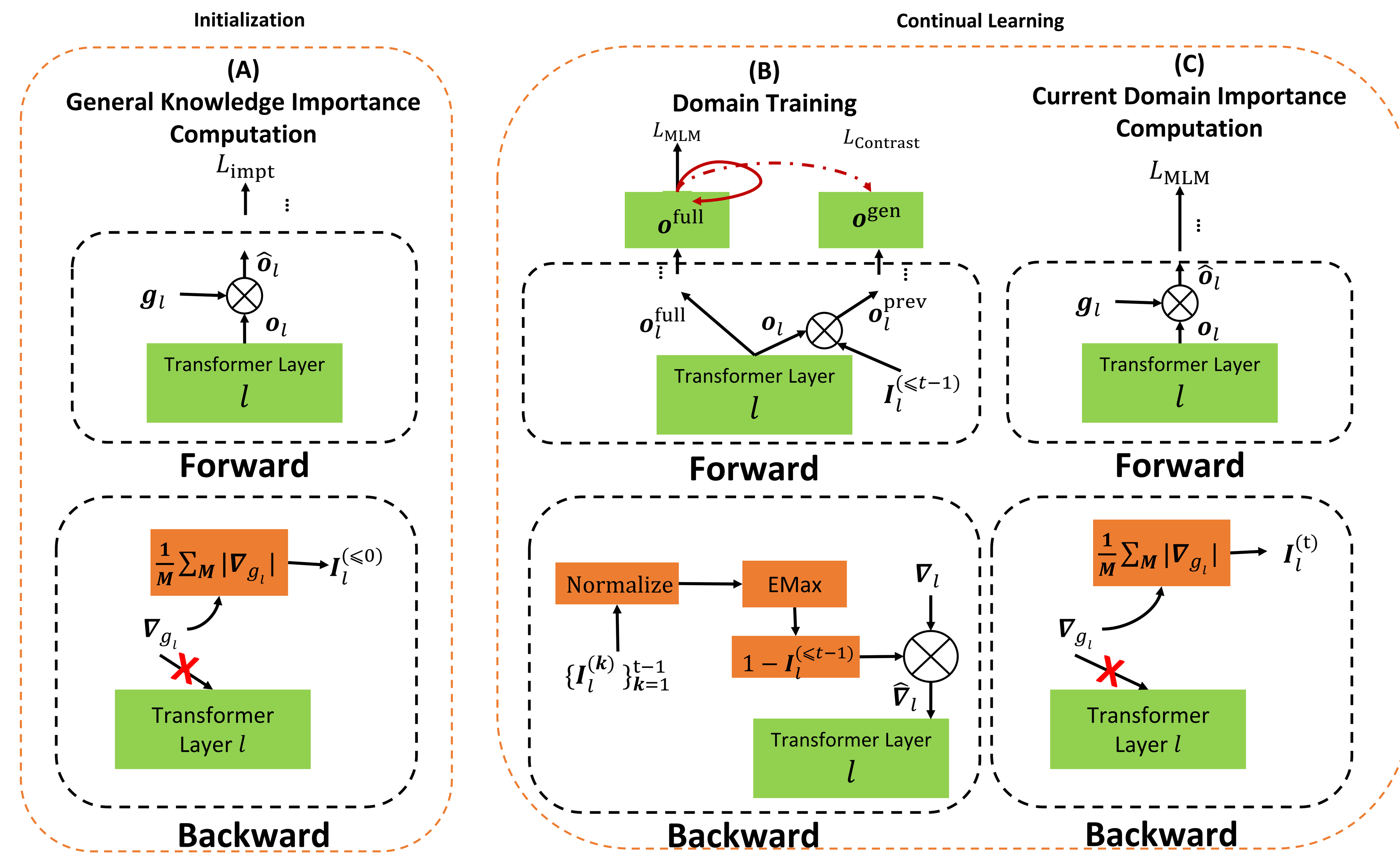
$$L_{\text{impt}}^{\text{general}} = \mathrm{KL}(f_1(x_m), f_2(x_m))$$

$$L_{\text{impt}}^{\text{domain}} = \mathrm{MLM}$$

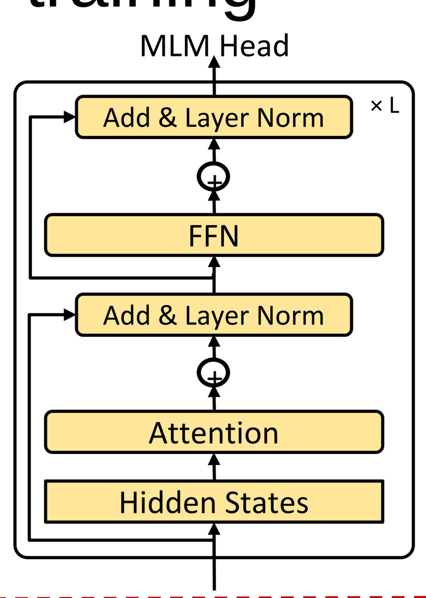
$$\nabla_{g_l}^{m} = \frac{\partial L_{\text{impt}}(x_m^{(t)}, y_m^{(t)})}{\partial g_l}$$

$$I_l^{(t)} = \frac{1}{M}\sum_M |\nabla_{g_l}^{m}|$$

$$\nabla'_l = (1 - \mathrm{Tanh}(\mathrm{Norm}(I_l))) \otimes \nabla_l$$

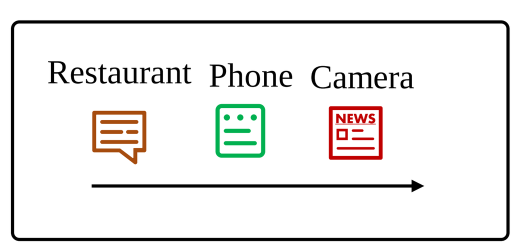


Setting: Continual Domain-adaptive Pre-training

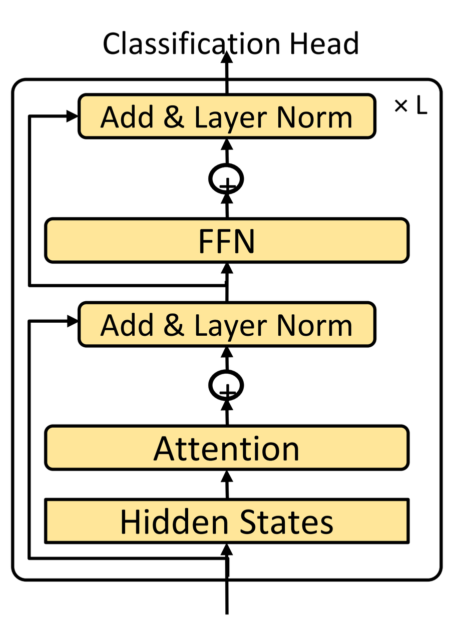


(A) Continual Domain-adaptive Pre-training

Given a pre-trained LM, continually domain-adaptive pre-train a sequence of domains



(B) Individual Fine-tuning



After continual pre-training, the performance is **evaluated** by end-tasks

Each end-task **corresponding** to one domain and has its **own** training and testing set. It is trained individually and **will not** affect the domain-adaptive pre-training

ASC-Restaurant
ASC-Phone
ASC-Camera
End-tasks

ASC: Aspect Sentiment Classification

Overall end-task performance (final performance)

Category	Domain Model	Restaurant MF1	Restaurant Acc	ACL MF1	ACL Acc	AI MF1	AI Acc	Phone MF1	Phone Acc	PubMed MF1	Camera MF1	Camera Acc	Average MF1	Average Acc	Forget R. MF1	Forget R. Acc
No pre-training	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	—	
Non-CL / Pre-training	DAPT (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	—	
	DAPT (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	—	
	DAPT (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	—	
NCL pre-training	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
SoTA pre-training	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
	DAS	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**

- ✓ w/o pre-training < pre-training < DAS
- ✓ +forgetting rate in NCL: it does suffer from forgetting
- ✓ Regularization-based methods (KD, EWC) and replay-based method (DER++) are all worse: focus on CF prevention is not enough
- ✓ Parameter-isolation method (HAT) preforms much worse: the full LM is needed for domain-adaptive pre-training
- ✓ Methods that tries to perform both KT and CF (DEMIX, BCL, CLASSIC): all weaker than DAS

KEY TAKEAWAY

- We study the problem of continual pre-training of language models
- We incrementally accumulate knowledge in the LM by
  - Computing importance of units for general and domain knowledge, with different L_{impt}
  - Soft-masking the backward propagation based on importance (help CF and KT)