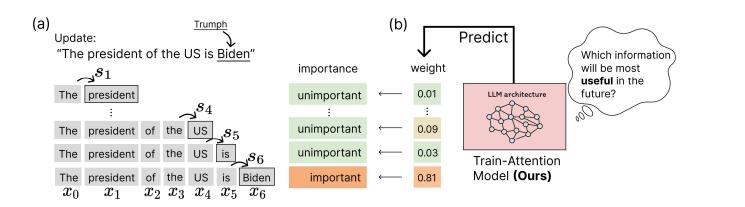
Train-Attention: Meta-Learning Where to Focus in Continual Knowledge Learning

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Background: Continual Knowledge Learning (CKL)

Ex)

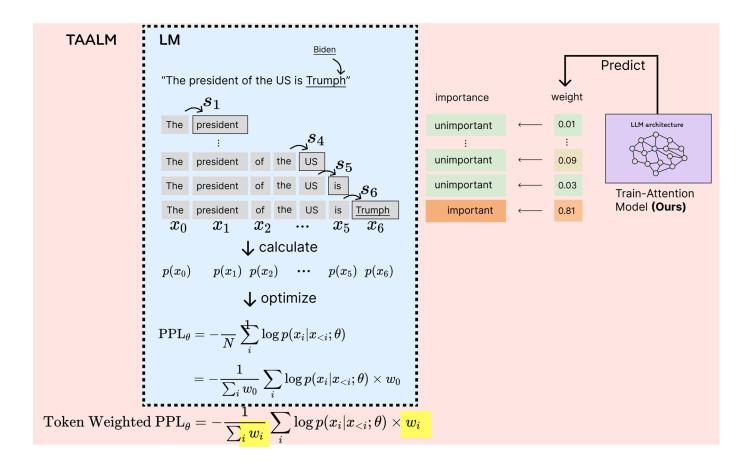
The president of the US is Biden

 \rightarrow The president of the US is <u>Trumph</u>

- CKL : Enabling LMs to constantly obtain new and updated knowledge while mitigating forgetting of previous learned
- Two dimensions of evaluating CKL
 - Plasticity : How well obtained
 - Stability : How well preserved
- Previous approach
 - 1) Adapter
 - 2) Regularization
 - 3) Review
- Our approach : Learn only important (useful) information, skip un-important.

Learning only **useful** information

Train-Attention (TA) : detecting and highlighting useful token in the document (D). **TA-augmented LM (TAALM)** : LMs learning new information with the aid of TA.



What is **importance**? : **Usefulness**

$$\mathcal{D}_{i} = \{x_0, x_1, \dots, x_i, \dots x_n\}$$

: a text data (document), that
consists of tokens (\mathcal{X}_i)

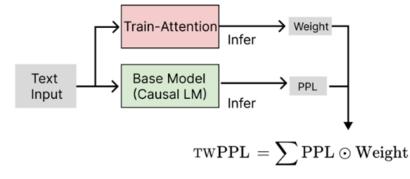
$$\mathcal{T}_{\mathcal{D}_{-}}$$
 : a task related to $_{\mathcal{D}_{-}}$

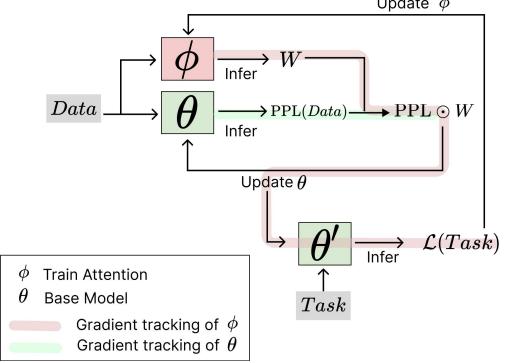


• x_i is **useful** if learning it is expected to help solving some tasks (i.e., improves the performance on tasks) in the future.

Formulate into Meta-learning problem $heta' \leftarrow heta - lpha abla_{ heta} tw \operatorname{PPL}_{ heta}(\mathcal{D}, W_{\mathcal{D}, \phi})$ $\phi \leftarrow \phi - \beta abla_{\phi} \mathcal{L}_{ heta'}(\mathcal{T}_{\mathcal{D}})$ Update ϕ $\rightarrow W$ Infer Data θ $\rightarrow \operatorname{PPL}(Data)$ - \rightarrow PPL $\odot W$ Infer

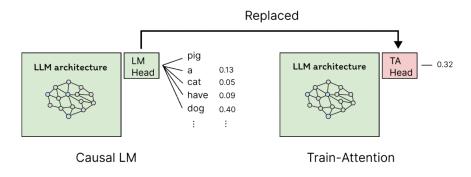
Train-Attention-Augmented Language Model



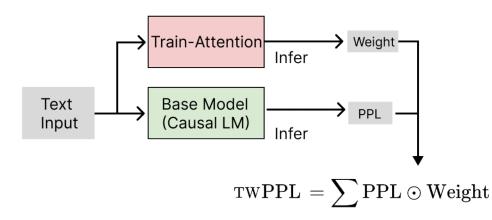


Architecture

TA : Replace decoder layer of transformer model into $hidden_{size} \times 1$ TA head.



TAALM : Apply TA when training.



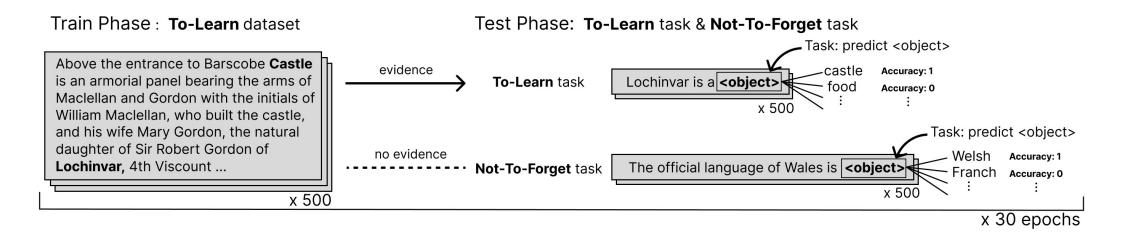
the weight map generated by the trained TA. Orange light highlight key information, such as the subject's name, occupation, or date of birth.

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	Par	agu	ay	and	Uruguay		it.	has	become	natural	ised	in	Asia	in .	Bh	ut	ari	6	China
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and	Z	imb	ab	we															

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#	James		1	have	been	volunte	ering	for	last	\s	7	years	#	Me	8	Nice		1	try
to		but	1	98. 	ve	been	working	on	the	two	Must	angs		One	15	3	8	6	8
and	the	other	is	(a)	\s	6	6	H	ert	z	clone		*	James	35	What	are	doing	with
those	two	7	4	Me		The	15	6	8	IS		daily	driver		at	least	during	the	summer
	The	Н	ert	z	clone	is	a	tra	iler	queen	4	1	4	m	too	afraid	of	pay	ing
for	on	the	road	ins	urance		15	*	James		How	long	have	you	been	doing	this	7	#
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ob	by	7	#	Me		Well	1	do	like	to	listen	to	classic	country		and	1	do	have
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	guess																		

Benchmark: LamaCKL



```
pre-test accuracy 1 -> Not-To-Forget set -> evaluate stability
pre-test accuracy 0 -> To-Learn set -> evaluate plasticity
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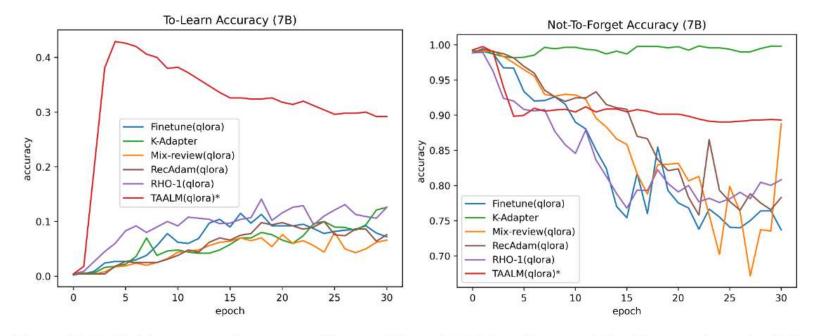


Figure 7: LAMA-CKL performance of large (Llama2-7B) baseline models. The graph on the left represents TO-LEARN task, and the graph on the right represents NOT-TO-FORGET task performance. The x-axis is the learning epoch, and the y-axis is accuracy.

	Top Acc	Epoch	NF Acc	Total Knowledge
Finetune(QLoRA)	0.1150	16	0.8174	0.9324
K-Adapter	0.1260	30	0.9980	1.1240
Mix-review(QLoRA)	0.0800	25	0.7988	0.8788
RecAdam(QLoRA)	0.1000	24	0.7933	0.8933
RHO-1(QLoRA)	<u>0.1410</u>	18	0.8223	0.9633
TAALM(QLoRA)	0.4290	4	0.8983	1.3273

Results

	TWi	ki-Probes	-0910	TWil	ki-Probes	s- <u>1011</u>	TWiki-Probes-1112			
	Un	С	Avg	Un	С	Avg	Un	С	Avg	
Finetune(QLoRA)	9.999	10.057	10.028	9.554	9.531	9.543	9.736	9.632	9.684	
Mix-review(QLoRA)	9.529	9.579	9.554	9.514	9.486	9.501	9.562	9.452	9.507	
RecAdam(QLoRA)	9.514	9.604	9.559	8.992	9.031	9.012	9.579	9.479	9.529	
RHO-1(QLoRA)	4.389	4.624	4.507	4.360	4.395	4.3775	4.471	<u>4.717</u>	4.594	
TAALM(QLoRA)	4.019	4.268	4.1435	4.030	4.154	4.092	4.036	4.357	4.197	