# Time is Encoded in the Weights of Finetuned Language Models

Yeajin Lee

Feb 26, 2024



### Contents

- 1. Background
- 2. Data and Finetuning
- 3. Temporal Misalignment
- 4. Temporal Adaption
- 5. Conclusion



# Background

- Temporal Variation: a fundamental characteristic of language.
  - Temporal misalignment
  - : Deviations in train and test data lead to large performance degradation across different time periods.
- Adaptation techniques for <u>customizing models to specific time periods</u> as needed
- Weight-space interpolation

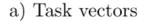
can be used to cheaply edit language model behavior over time.

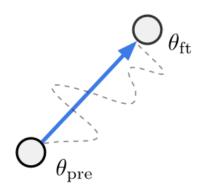


### Time vector

: simple tool to customize language models to new time periods.

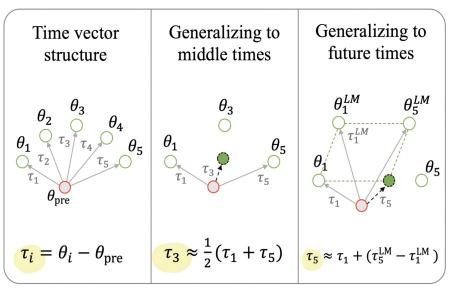
- An extension of task vectors to the time domain.
  - Task vectors: formed by taking the difference of a model finetuned on a specific time and the pre-trained model.





$$\tau = \theta_{\rm ft} - \theta_{\rm pre}$$

Editing Models with Task Arithmetic - Figure1



현재 논문 - Figure1



# **Data and Finetuning**

#### - Data -

#### 1) Language Modeling

- WMT Language Modeling(English subset of the WMT news dataset)
- Twitter Language Modeling
   (Internet Archive Twitter Stream Grab )

#### 2) Downstream Tasks

- NewsSum (ROUGE-L)
- PoliAff(macro F1).

#### - Finetuning -

- Pretrained T5
- Finetune T5- small, T5-large, and T5-3b
   on each of time
- Finetune with <u>Low-Rank Adaptation</u>
- A single epoch on LM splits and three epochs on downstream task splits



# Temporal Misalignment

Yearly Degradation is Linear

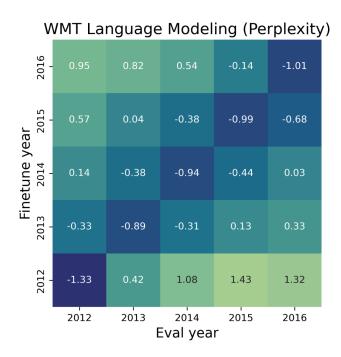


Figure 2: Model performance degrades linearly year-to-year

#### Monthly Degradation is Seasonal

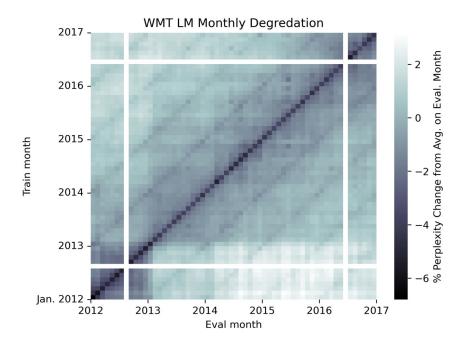


Figure 3: Monthly temporal degradation has seasonal patterns.



#### - Correlation of Time Vector Similarity and Temporal Degradation

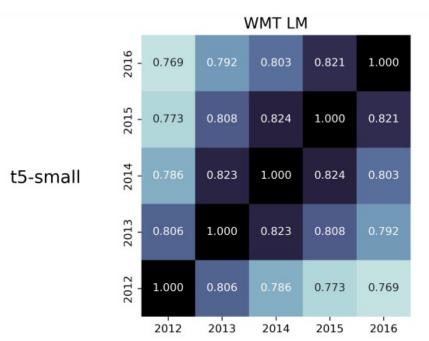


Figure 10: Cosine similarities between all pairs of year time vectors

		1 000.0010				
	T5 size	WMT LM	NewsSum	PoliAff		
•	small	-0.867	0.663	0.654		
	large	-0.737	0.628	0.672		
	3b	-0.795	0.626	0.668		

Pearson r

Table 1: The similarity between time vectors correlates with temporal degradation.



#### - Generalizing to Intervening Time periods

- Method
  - Two time vectors  $au_j$  (oldest),  $au_k$  (newest)

• 
$$\tau_j = \theta_j - \theta_{pre}$$

- Compute interpolation :  $\alpha \cdot \tau_i + (1 \alpha) \cdot \tau_k$
- With  $\alpha \in [0,1]$

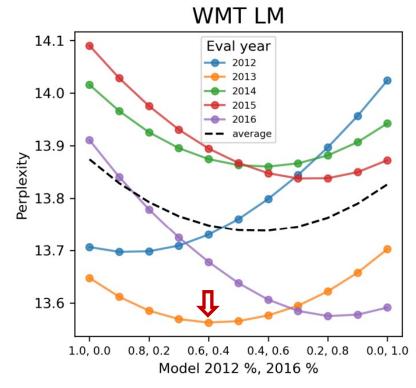


Figure 5: Interpolating between two year vectors improves performance on the years between them.



	Perplexity $(\downarrow)$	Rouge $(\uparrow)$	<i>F1</i> (†)
Method	WMT LM	NewsSum	PoliAff
Start-year finetuned $(\tau_0)$	13.92	38.56	0.6886
End-year finetuned $(\tau_n)$	13.84	35.09	0.6967
$\frac{1}{2}( au_0+ au_n)$	13.77	38.86	0.7765
Best interpolations	13.75	40.11	0.7941
Eval-year finetuned $(\tau_i)$	13.65	42.36	0.8341

Table 2: Interpolation between start and end-year finetuned models reduces temporal misalignment on intervening years.

- **Best interpolations**: Use the best performing α values for each year
- Eval-year finetuned : Performance of finetuned models for each year



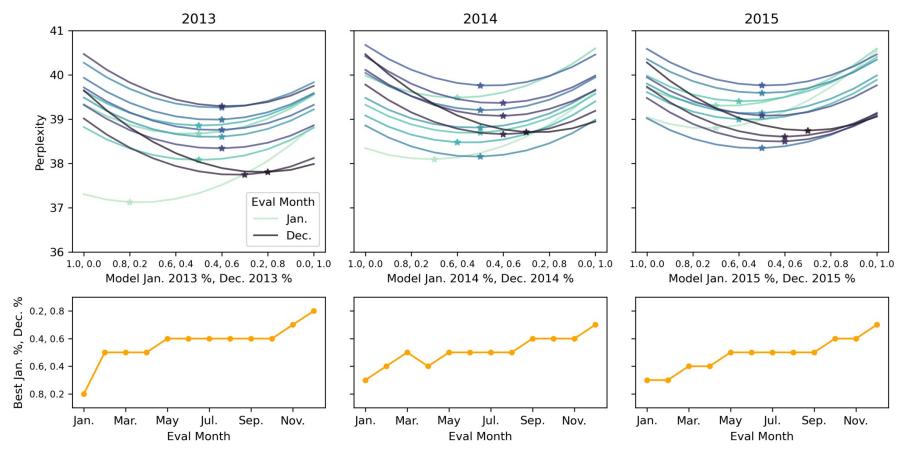


Figure 6: Interpolating between two month vectors improves performance on the months between them.



#### - Generalizing to the Future

: a new technique for updating task models <u>finetuned</u> on

#### time period j to a target time period k

with only unlabeled data from j (labeled data)

- Method
  - Given  $\theta_j$ ,  $\theta_j^{LM}$  ,  $\theta_k^{LM}$
  - Estimated  $\theta_k$
  - $\alpha_1 \in [0.6,0.8,..,2.2], \alpha_2,\alpha_3 \in [0.1,...0.6]$

$$egin{aligned} oldsymbol{ au_j} &= heta_j - heta_{pre} \ oldsymbol{ au_j^{LM}} &= heta_j^{LM} - heta_{pre} \ oldsymbol{ au_k^{LM}} &= heta_k^{LM} - heta_{pre} \end{aligned}$$

$$oldsymbol{ au_k} pprox lpha_1 \cdot oldsymbol{ au_j} + (lpha_2 \cdot oldsymbol{ au_k}^{LM} - lpha_3 \cdot oldsymbol{ au_j}^{LM})$$

$$\overline{ heta_k} = \overline{ au_k} + heta_{pre}$$



Update <u>2012 News-Sum model</u> to <u>2013–2016</u>,
 and <u>2015 PoliAff model</u> to <u>2016–2020</u>.

 Improvement increases as the target and start years become more misaligned.

Model size also affects performance.

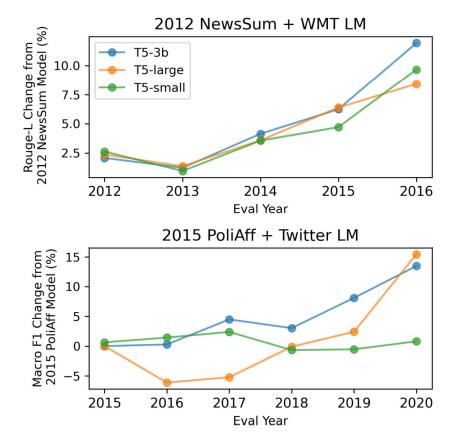


Figure 7 : Task analogies can offset downstream temporal misalignment without labeled data from the target time.



$$au_k pprox lpha_1 \cdotp au_j + (lpha_2 \cdotp au_k^{LM} - lpha_3 \cdotp au_j^{LM})$$

- Only scaling  $\alpha_1$  can also **improve** performance on future years.
- Scaling only : only scaling the base  $\tau_j$  model  $(\alpha_1 \neq 0, \alpha_2, \alpha_3 = 0)$
- Task addition : only adding the language modeling vector  $(\alpha_1, \alpha_2 \neq 0, \alpha_3 = 0)$

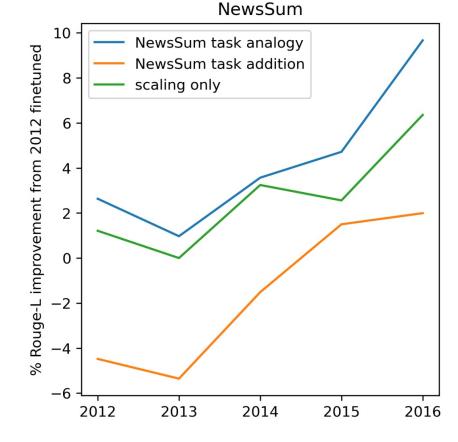


Figure 15: Time vector analogy ablations for three sizes of T5



- Generalizing to Multiple Time Periods
  - Method

Model soup technique

**Uniform soup**: A uniform weight among all constituent models in the interpolation.

$$lacksquare heta_{pre} + rac{1}{|T|} \sum_{t \in T} au_t$$

**Greedy soup**: Only includes models in the soup that improves validation performance.

Measure the average performance across all evaluation years for each task.

	Perplexity $(\downarrow)$	Rouge $(\uparrow)$	<i>F1</i> (†)
Method	WMT LM	NewsSum	PoliAff
Best single-year model	34.45	38.95	0.7101
Uniform time soup	34.70	33.05	0.6078
Greedy time soup	34.45	38.95	0.7202
Training on all years	29.17	40.07	0.7853

Table3: Interpolation does not enable generalization to multiple time periods simultaneously

- <u>Time soups</u> perform worse than <u>the model finetuned on all shuffled available data</u>.
- A model which generalizes to multiple time periods does **not lie** in a region of weight space bounded by models finetuned on single years of data.



### Conclusion

- Connect studies of <u>temporal misalignment</u> and <u>weight arithmetic</u> with time vectors.
- The similarities of weights of each different time are highly correlated to temporal misalignment at both yearly and monthly scales.
- Induce new models that perform better on intervening years by <u>interpolating between</u> adjacent time vectors.
- Use task analogies to improve downstream performance on future time periods using only unlabeled data from those times.
- ⇒ Weight arithmetic can be a simple tool for combating temporal misalignment.



### Thank you for Listening!

#### Reference:

Paper - <a href="https://arxiv.org/pdf/2312.13401.pdf">https://arxiv.org/pdf/2312.13401.pdf</a>
Task vector paper - <a href="https://arxiv.org/abs/2212.04089">https://arxiv.org/abs/2212.04089</a>
Model soup technique paper - <a href="https://arxiv.org/abs/2203.05482">https://arxiv.org/abs/2203.05482</a>

