Sequential Text-based Knowledge Update with Self-Supervised Learning for Generative Language Models

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Introduction

The rapid pace of change in the world means that knowledge is constantly evolving, and that existing knowledge carriers need to be updated in order to stay relevant and accurate. This work addresses the task of multi-round sequential knowledge update in a time window. We introduce a novel NLP task for text-based sequential knowledge update from dynamic news sources. Our proposed task and model framework have the potential to significantly enhance the automation of knowledge organization.

The contributions of this work are threefold as follows:

- Introduction of a new NLP task.
- Proposal of a hybrid learning architecture and a novel self-supervised training strategy.
- Development of a dataset.

Problem Formulation

$$x_t = \arg\max_y Pr(y|x_1, x_2, ..., x_{t-1}, e_t) \quad (1)$$

$$\approx \arg\max_y Pr(y|x_{t-1}, e_t) \quad (2)$$

This work focuses on updating a sequence of text-based knowledge facts (x_1, x_2, ..., x_{t-1}) with new information e_t related to an event at time t.

	Training	Validation	Test
# Clusters	4,583	556	556
# Articles	276k	43k	42k
Mean	60.3	76.8	74.9
Median	66	100	100
Period Begin	2016-8-25	2019-1-6	2019-5-8
Period End	2019-1-5	2019-5-7	2019-8-20

Table 1. Based on the statistics, each cluster has an average of 60 news events, resulting in an average sequence length of 60.

Methods

Hybrid Training Framework

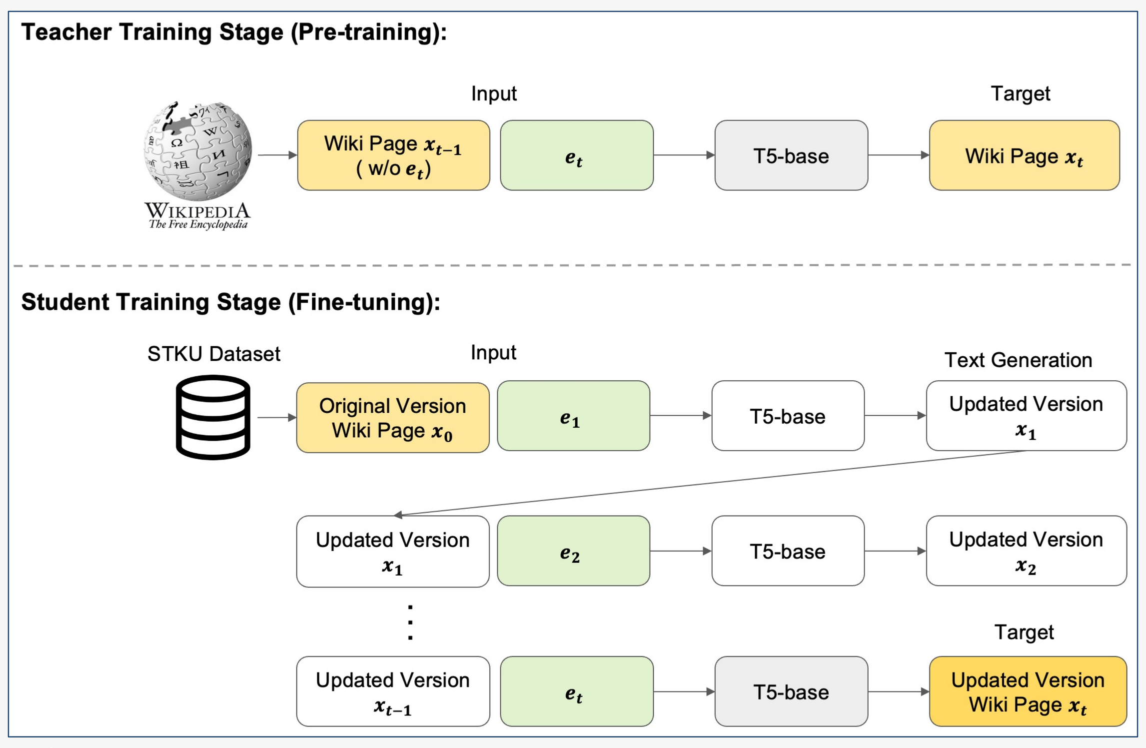

Figure 1. Our framework consists of two steps: **teacher training** and **student training**.

1. Student Training Stage

The model is fine-tuned using our dataset to iteratively update text knowledge as dynamic events (from e_1 to e_t) occur over time, ensuring that x_{t+1} includes new e_t information.

2. Teacher Training Stage - self-supervised training strategy

Facing data scarcity, the task of textual knowledge updating is similar to reconstructing text from a corrupted one in a way. In this process, the first paragraph of a Wikipedia page is chosen as x_t , from which 15% of the sentences are randomly extracted to create new information e_t , while eliminating any duplicated sentences in x_t to produce x_{t-1}.

Perturbation Strategy	Scenario in text reconstruction
Original (No Perturbation)	To update x_{t-1} (Wiki Content) with the event e_t (original news article)
Sentence-Shuffle (SS)	To update x_{t-1} with event e_t that is randomly shuffled
Noise-Injection (NI)	To update x_{t-1} with event e_t that is injected with noise from irrelevant Wiki content
Masked-Noise-Injection (MNI)	To update masked x_{t-1} with event e_t that is injected with noise from irrelevant Wiki content
Noise-Generation (NG)	To update x_{t-1} with event e_t that is augmented with noise generation
Masked-Noise-Generation (MNG)	To update masked x_{t-1} with event e_t that is augmented with noise generation

Table 2. Perturbation strategies for self-supervised data in text reconstruction.

Examples of self-supervised training strategies :

- **Noise-Injection (NI)**
  x_{t-1}: wiki content(w/o trigger), e_t: trigger+noise(irrelevant)
- **Noise-Generation(NG)**
  x_{t-1}: wiki content(w/o trigger), e_t: trigger+noise(relevant)
- **Masked-Noise-Generation (MNG)**
  x_{t-1}: wiki content(w/o trigger)+[mask], e_t: trigger+noise(relevant)

Results

We evaluate our hybrid framework with a variety of self-supervised pre-training strategies.

- The hybrid approach outperforms the traditional supervised learning student model and improves knowledge updating.
- Our model outperforms four LLMs in all metrics.
- Models with four LLMs often generate lengthy and redundant results.
- In contrast, our model produces more precise and topical outputs.
- Fine-tuning with LoRA resulted in improvements in all LLMs, highlighting the efficacy of our training strategy.

Method	ROUGE-1	ROUGE-2	ROUGE-L	BLEU-1	BLEU-2	BLEU-3	BLEU-4	METEOR	BERTScore
Student Mode	15.14	7.61	12.26	3.67	2.31	1.98	1.83	7.50	57.68
Hybrid (Original)	67.94	63.50	65.63	52.22	49.65	48.46	47.53	57.53	84.95
Hybrid (Original+SS)	74.02	70.46	72.05	63.22	61.05	59.82	58.85	66.93	87.85
Hybrid (Original+NI)	85.19	81.81	83.23	77.15	74.69	73.25	72.13	79.76	92.94
Hybrid (Original+MNI)	78.61	74.63	76.56	68.52	66.06	64.66	63.56	71.21	90.04
Hybrid (Original+NG)	83.32	79.86	81.39	74.97	72.50	71.09	69.95	77.71	92.03
Hybrid (Original+MNG)	84.45	80.88	82.38	76.64	74.07	72.73	71.70	79.31	92.62
Hybrid (Original/NI+MNG)	**86.44**	**83.02**	**84.46**	**79.63**	**77.08**	**75.65**	**74.54**	**82.16**	**93.49**
GPT-3.5-turbo (Zero-shot)	49.35	34.98	40.41	39.79	31.71	30.07	29.59	41.00	72.75
Falcon-7B (Zero-shot)	15.96	2.08	10.14	8.16	0.99	0.13	0.02	8.36	42.42
LLaMA-13B (Zero-shot)	16.60	9.28	13.40	9.53	7.57	7.31	7.26	10.77	47.25
Vicuna-13B (Zero-shot)	43.94	28.68	35.67	36.18	26.75	25.17	24.89	35.97	68.16
Falcon-7B (Fine-Tuned)	21.20	4.66	12.32	10.79	2.19	0.53	0.18	11.13	55.38
LLaMA-13B (Fine-Tuned)	32.53	22.55	27.66	24.01	17.72	16.32	15.66	30.19	60.00
Vicuna-13B (Fine-Tuned)	48.00	36.25	41.76	42.00	34.28	33.22	33.04	42.55	68.98

Table 3. Experimental results. The "+" symbol represents a mixture of data from multiple strategies, while the "/" symbol represents a phased training of data from multiple strategies.

Conclusions

This work addresses the challenge of sequential text-based knowledge update in a time window. The aim is to extract relevant information from constantly updating news sources to keep the knowledge updated. The study proposes a hybrid learning architecture and a novel self-supervised training strategy for LLMs to consolidate knowledge in a way similar to humans. The proposed task and model framework have the potential to significantly improve the automation of knowledge organization.