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Neural Topic Modeling with Continual Lifelong Learning

(TLDR: Improving Unsupervised document-topic modeling within transfer learning and lifelong learning paradigm)

Presenter: **Dr. Pankaj Gupta** | ICML 2020 July, 12-18

Affiliation(s): Lead Research Scientist (ML for NLP), Siemens AG Munich Germany

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Content

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Motivation: Lifelong Neural Topic Modeling

Background: Neural Topic Model (DocNADE) for Text Documents

Methodology: Lifelong Learning in Neural Topic Modeling over Streaming Documents

- ❑ **Topic Regularization** with TopicPool (TR)
- ❑ **Transfer Learning** with WordPool (EmbTF)
- ❑ **Selective-Data Augmentation Learning** (SAL) with Distillation and Co-training

Experiments and Analysis on Future Tasks in Sparse settings

- ❑ Document Representation via Information Retrieval (IR)
- ❑ Topic Quality via Coherence (COH)

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Lifelong Machine Learning (LML)

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Build computational learning systems that can:

- ❑ Continually **acquire** knowledge from many **tasks** from several **domains**
- ❑ **Retain** and **transfer** the acquired knowledge over **lifetime**

Processing continuous streams of information →

Key Components of LML

Knowledge Mining
Transfer Learning
Domain Adaptation
Knowledge Retention
Catastrophic Forgetting
Knowledge Accumulation

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Key Components of LML

Knowledge Mining
Transfer Learning
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Knowledge Retention
Catastrophic Forgetting
Knowledge Accumulation

Challenging: Continuous non-stationary data distributions or domain shifts

→ catastrophic forgetting or interference

This work: **Lifelong Learning in Unsupervised Document Topic Modeling**

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Lifelong Machine Learning (LML)

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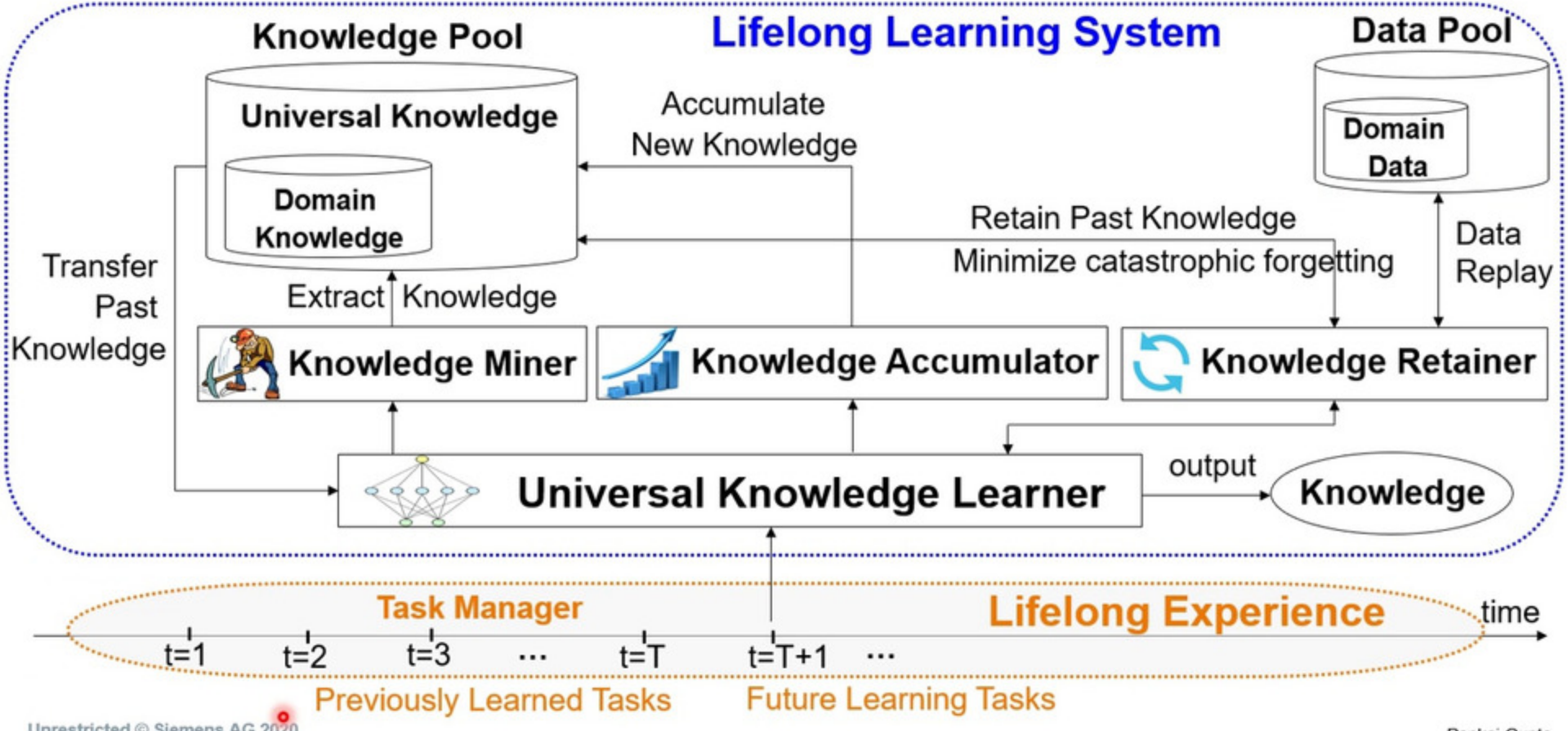

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Lifelong Neural Topic Modeling (LNTM)

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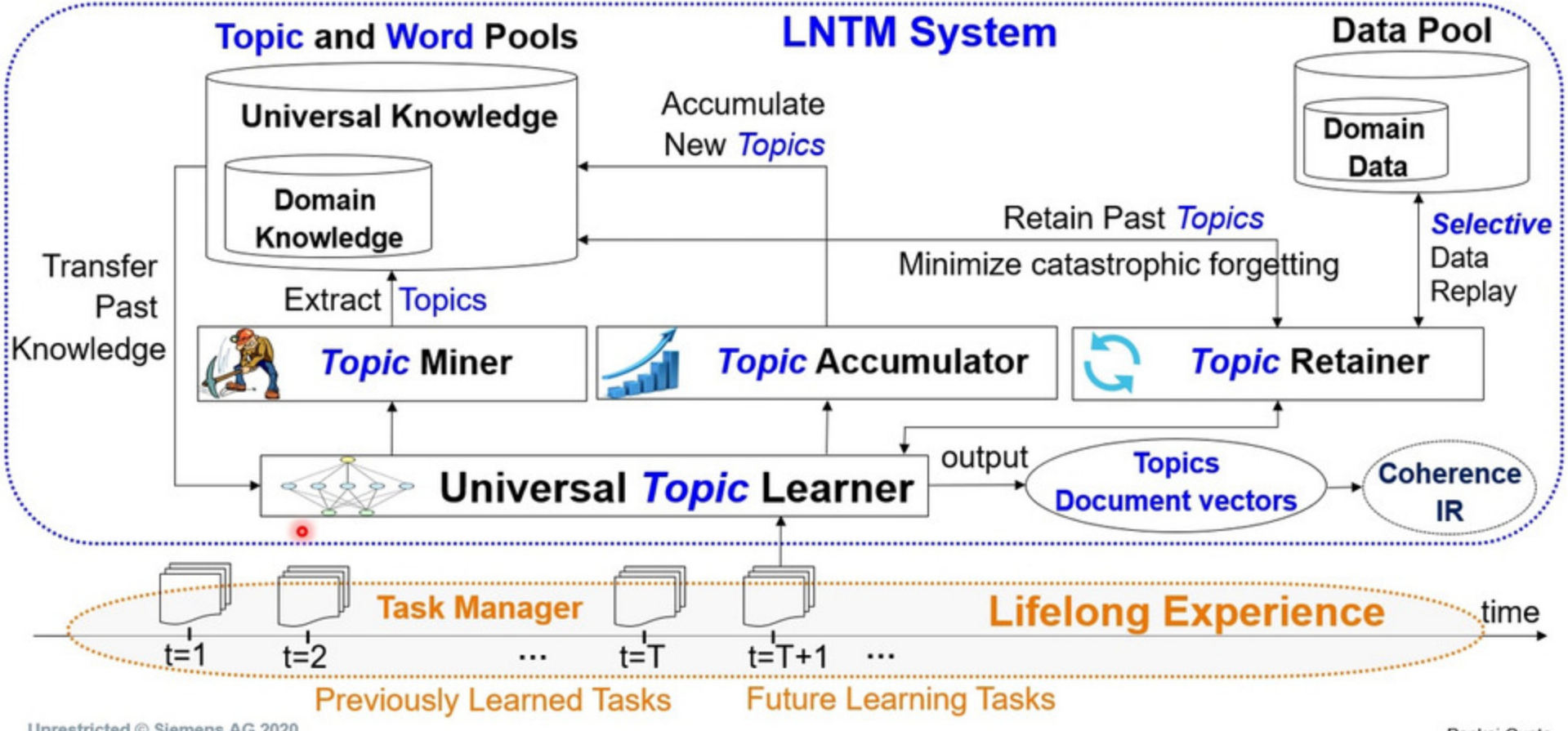

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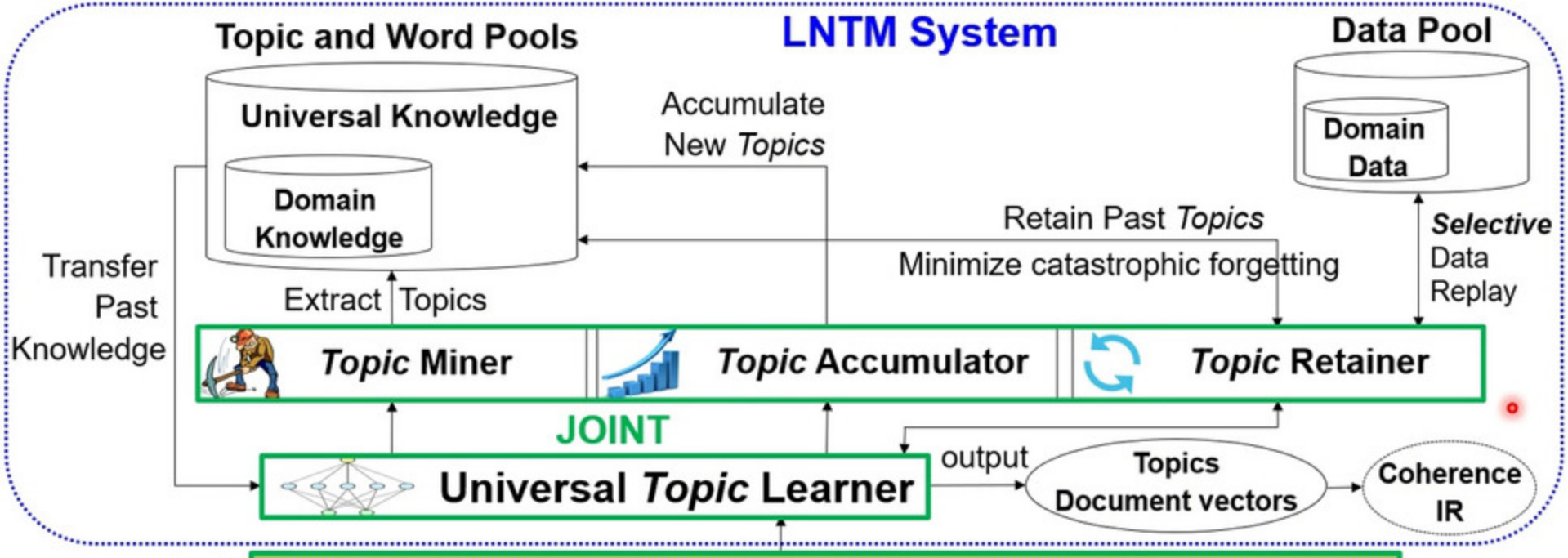

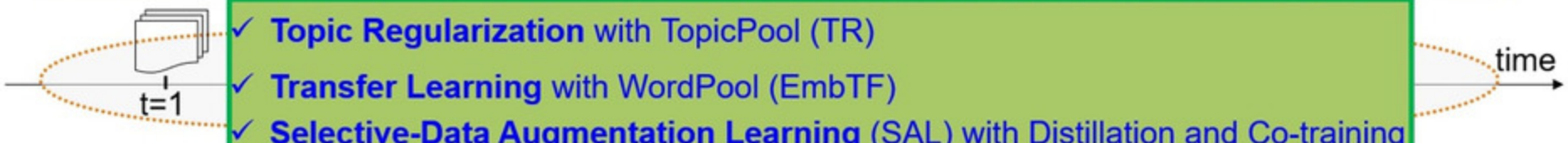

- ✓ **Topic Regularization** with TopicPool (TR)
- ✓ **Transfer Learning** with WordPool (EmbTF)
- ✓ **Selective-Data Augmentation Learning** (SAL) with Distillation and Co-training

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Why Lifelong Neural Topic Modeling?

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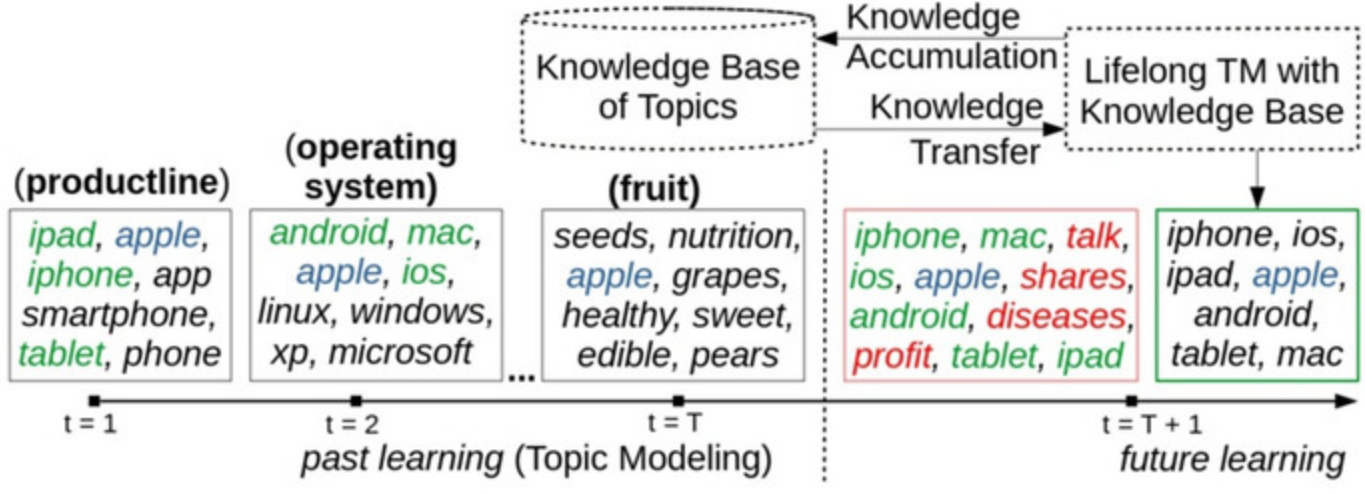
- **Continuously** analyze plethora of **unsupervised streaming texts**
- Accumulate and Build **concepts/semantics** over time
- Improve **sparse data modeling** with **knowledge-augmented** topic learning over lifetime
- Improve **topic quality** and **document representations (IR)** in **sparsity** settings



Background: Topic Modeling

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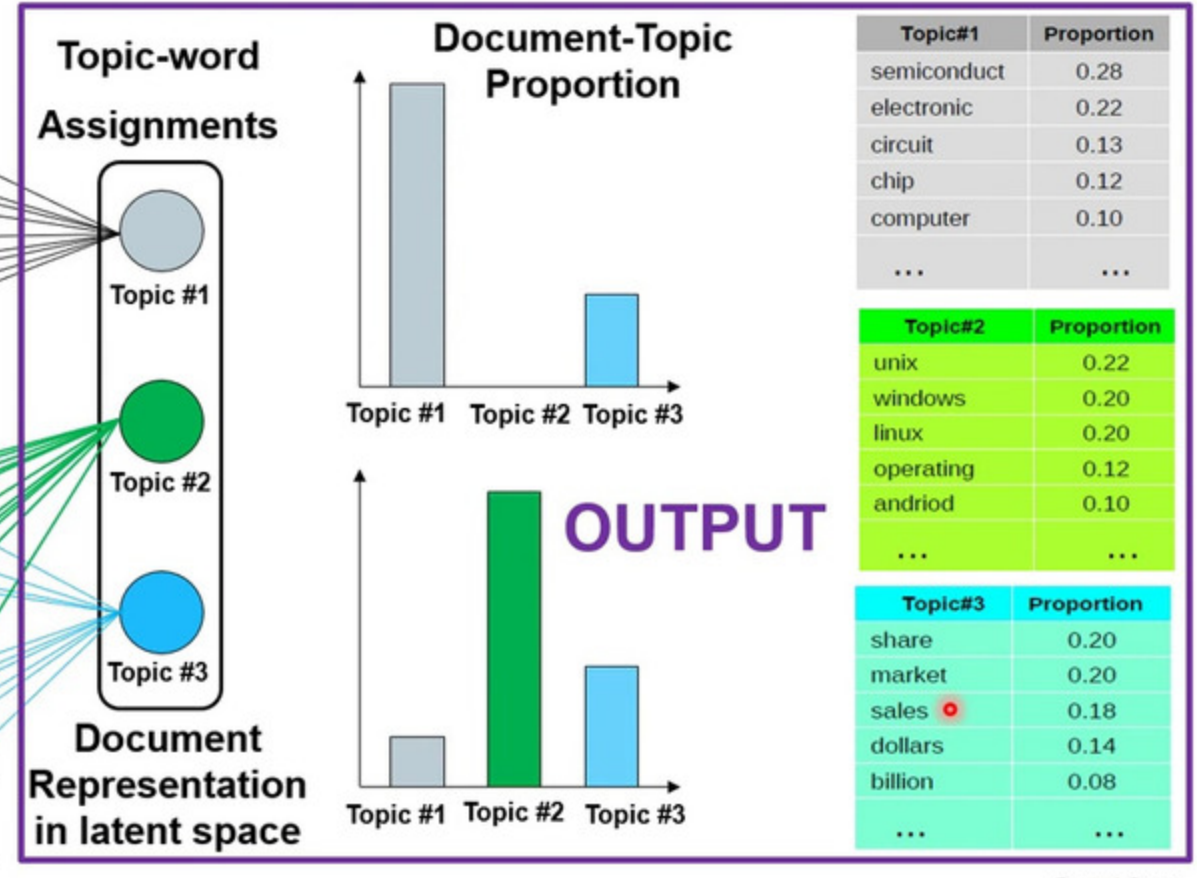
A chip is an integrated circuit, an assembly of electronic components that are used for computer processors, memory, etc. There are transistors and diodes, capacitors and resistors made of semiconductor material.

Semiconductor is a crucial component of electronic devices, e.g., computer. In 2018, the global semiconductor industry sales reached 477.94 billion dollars, where Samsung Electronics holds the largest market share.

Linux, Unix…Windows…computer operating systems. Linux…Windows, and popular a operating system for supercomputers. Android…Linux kernel…operating system…smartphones…billion dollars…financial quarter …smartphones…Android…sales… market share…



Topic#1	Proportion
semiconduct	0.28
electronic	0.22
circuit	0.13
chip	0.12
computer	0.10
…	…

Topic#2	Proportion
unix	0.22
windows	0.20
linux	0.20
operating	0.12
andriod	0.10
…	…

Topic#3	Proportion
share	0.20
market	0.20
sales	0.18
dollars	0.14
billion	0.08
…	…

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Background: Neural Autoregressive Topic Model (DocNADE)

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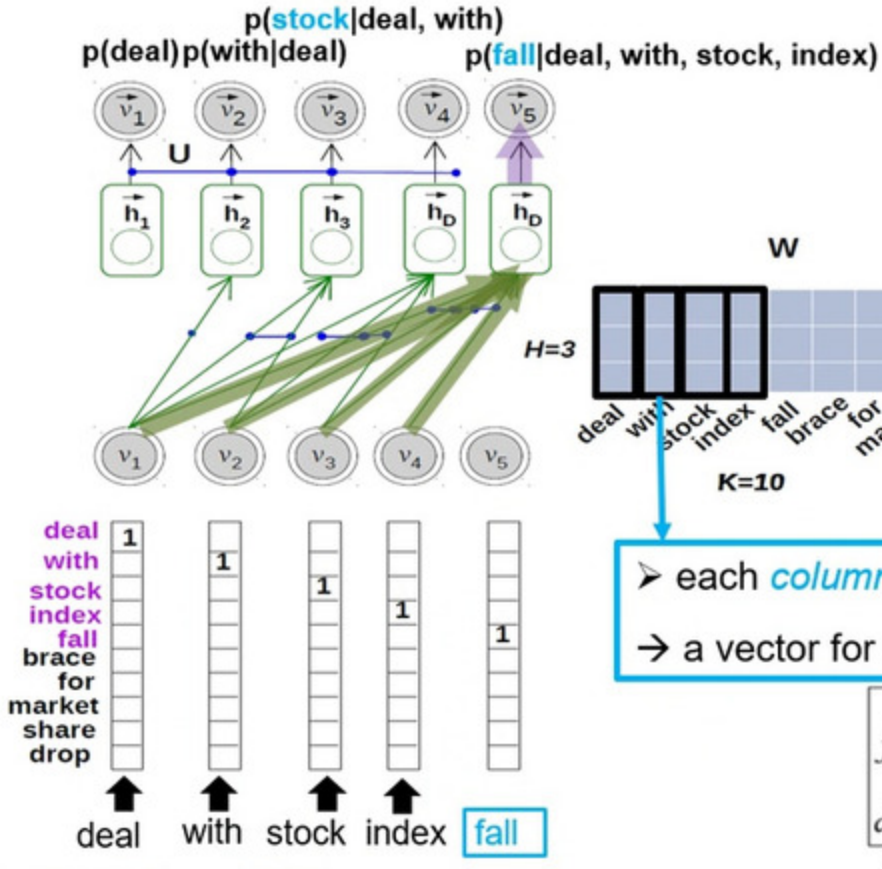
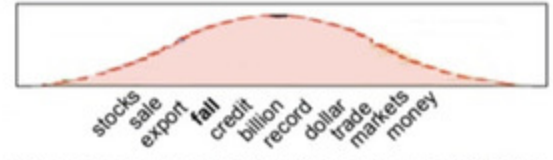


S1: ***Deal with stock index fall***
S2: *Brace for market share drop*

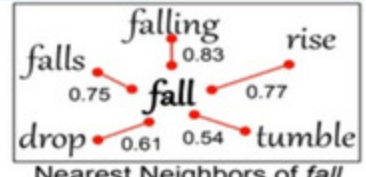
Corpus of two documents

➢ each *row-vector* $\mathbf{W}_{j,:}$
→ encodes the jth topic

➢ each *column-vector* $\mathbf{W}_{:,vi}$
→ a vector for the word at v_i index



Topic due to Word distributions *across* documents



Nearest Neighbors of *fall*

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Background: Neural Autoregressive Topic Model (DocNADE)

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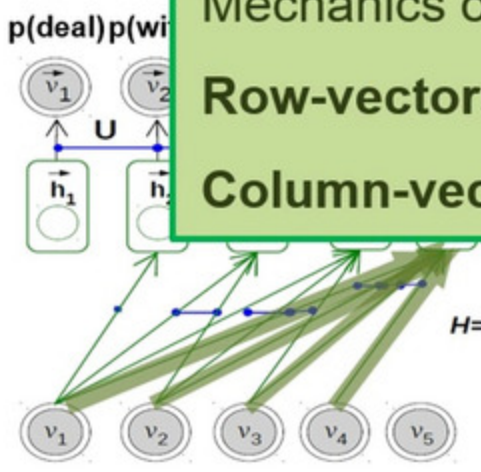
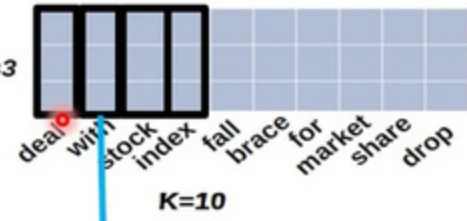
Mechanics of Knowledge Transfer via:

Row-vectors of W → Topic Embedding Transfer

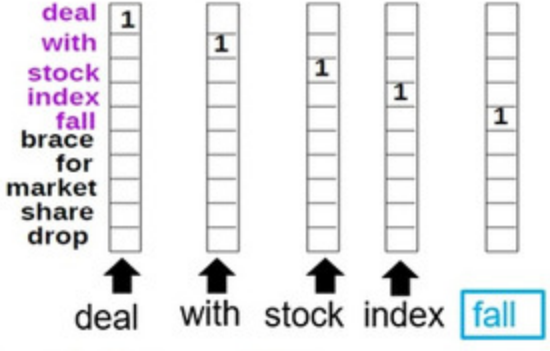
Column-vectors of W → Word Embedding Transfer





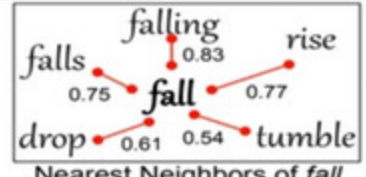
- each *row-vector* $\mathbf{W}_{j,:}$

→ encodes the jth topic



- each *column-vector* $\mathbf{W}_{:,vi}$

→ a vector for the word at v_i index



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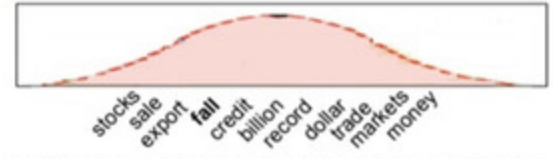

Topic due to Word distributions *across* documents

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Proposed: Lifelong Neural Topic Modeling (LNTM) framework

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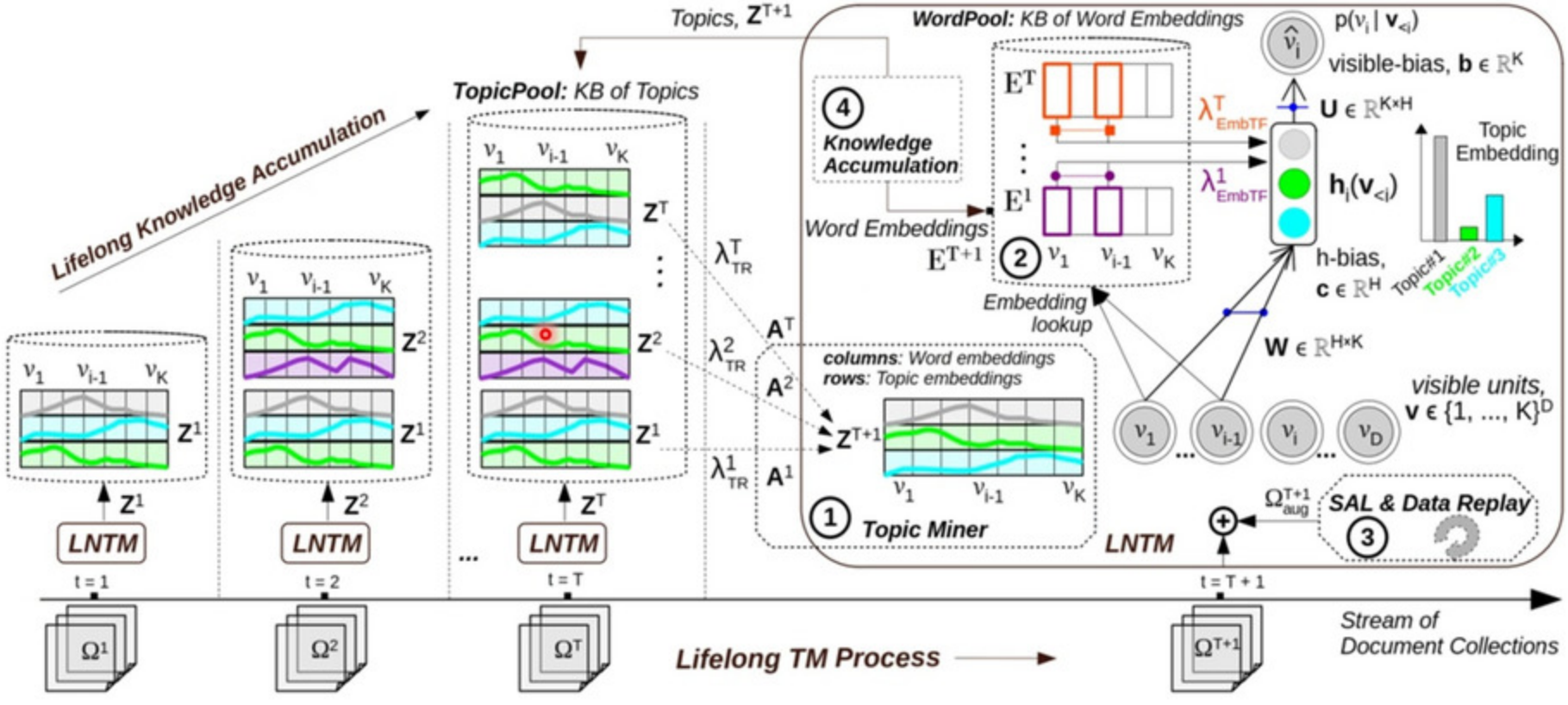

Proposed: Lifelong Neural Topic Modeling (LNTM) framework

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Phase 1: Joint Topic Mining, Transfer and Retention:

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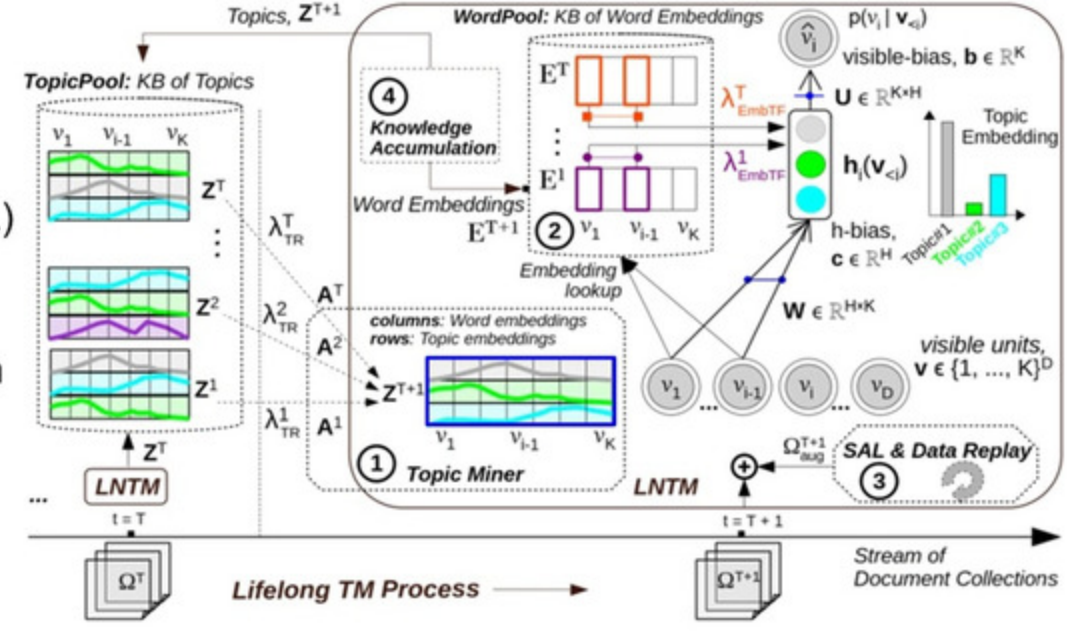
Phase 2: Lifelong Knowledge Accumulation



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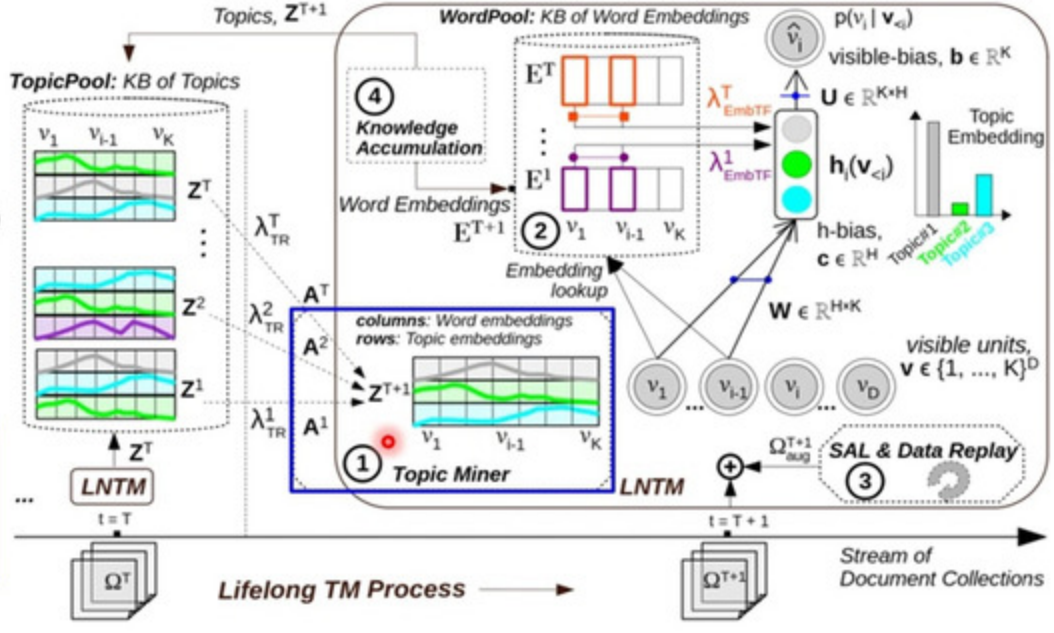
Phase 2: Lifelong Knowledge Accumulation

$$\Delta_{TR} = \sum_{t=1}^{T} \lambda_{TR}^{t} \Big(\underbrace{\|\mathbf{Z}^t - \mathbf{A}^t \mathbf{Z}^{T+1}\|_2^2}_{topic-imitation} + \underbrace{\|\mathbf{U}^t - \mathbf{P}^t \mathbf{U}\|_2^2}_{decoder-proximity} \Big)$$

$$\mathcal{L}(\Omega^{T+1}; \Theta^{T+1}) = \sum_{\mathbf{v} \in \Omega^{T+1}} \mathcal{L}(\mathbf{v}; \Theta^{T+1}) + \Delta_{TR}$$



Proposed: Lifelong Neural Topic Modeling (LNTM) framework

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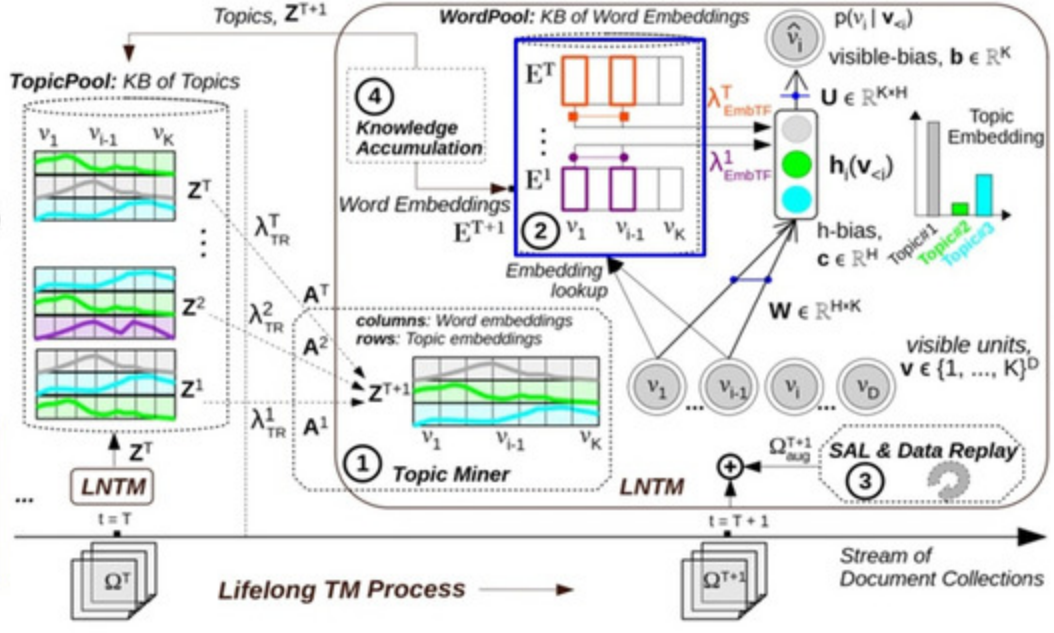
Phase 2: Lifelong Knowledge Accumulation

$$\mathbf{h}(\mathbf{v}_{<i}) = g(\mathbf{c} + \sum_{q<i} \mathbf{W}_{:,v_q} + \sum_{q<i} \sum_{t=1}^{T} \lambda^t_{EmbTF}\, \mathbf{E}^t_{:,v_q})$$



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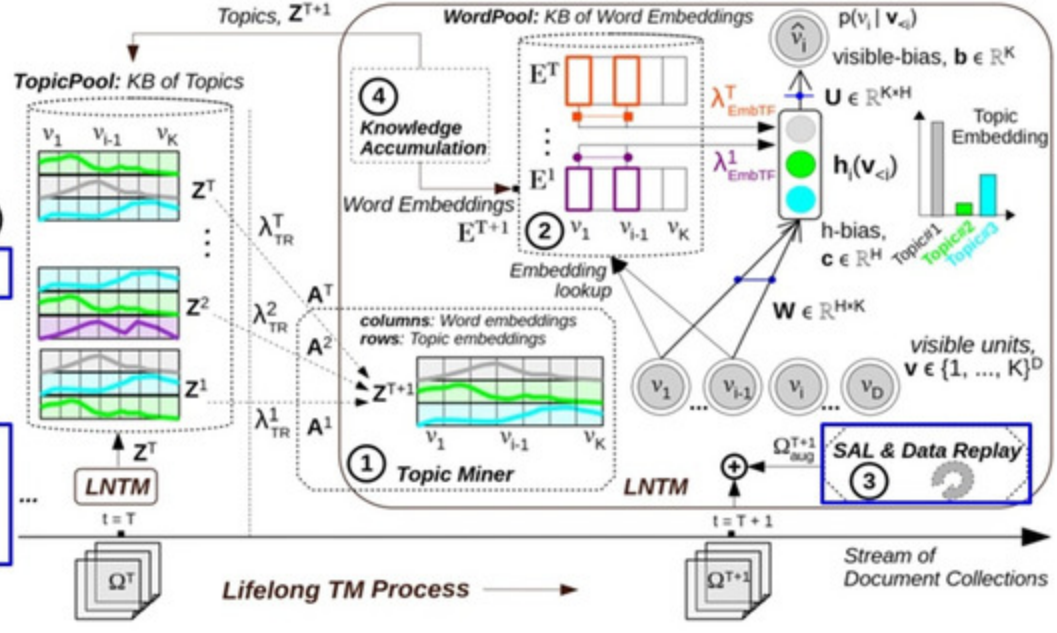
Phase 2: Lifelong Knowledge Accumulation

$$\textbf{if } \mathrm{PPL}(\mathbf{v}^t; \boldsymbol{\Theta}^{T+1}) \leq \mathrm{PPL}^{T+1} \textbf{ then}$$
$$\text{Document selected: } \Omega_{aug}^{T+1} \leftarrow \Omega_{aug}^{T+1} \cup (\mathbf{v}^t, t)$$



Proposed: Lifelong Neural Topic Modeling (LNTM) framework

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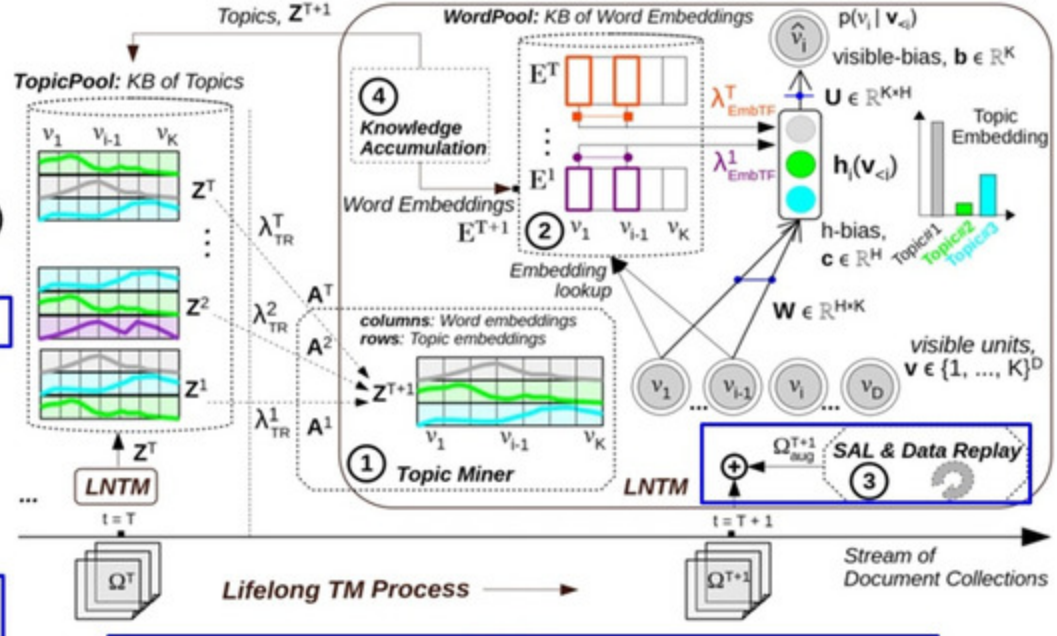
if $\mathrm{PPL}(\mathbf{v}^t; \boldsymbol{\Theta}^{T+1}) \leq \mathrm{PPL}^{T+1}$ **then**
Document selected: $\Omega_{aug}^{T+1} \leftarrow \Omega_{aug}^{T+1} \cup (\mathbf{v}^t, t)$

$$\Delta_{SAL} = \sum_{(\mathbf{v}^t, t) \in \Omega_{aug}^{T+1}} \lambda_{SAL}^t \, \mathcal{L}(\mathbf{v}^t; \boldsymbol{\Theta}^{T+1})$$



$$\mathcal{L}(\Omega^{T+1}; \boldsymbol{\Theta}^{T+1}) = \sum_{\mathbf{v} \in \Omega^{T+1}} \mathcal{L}(\mathbf{v}; \boldsymbol{\Theta}^{T+1}) + \Delta_{SAL}$$

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Proposed: Lifelong Neural Topic Modeling (LNTM) framework

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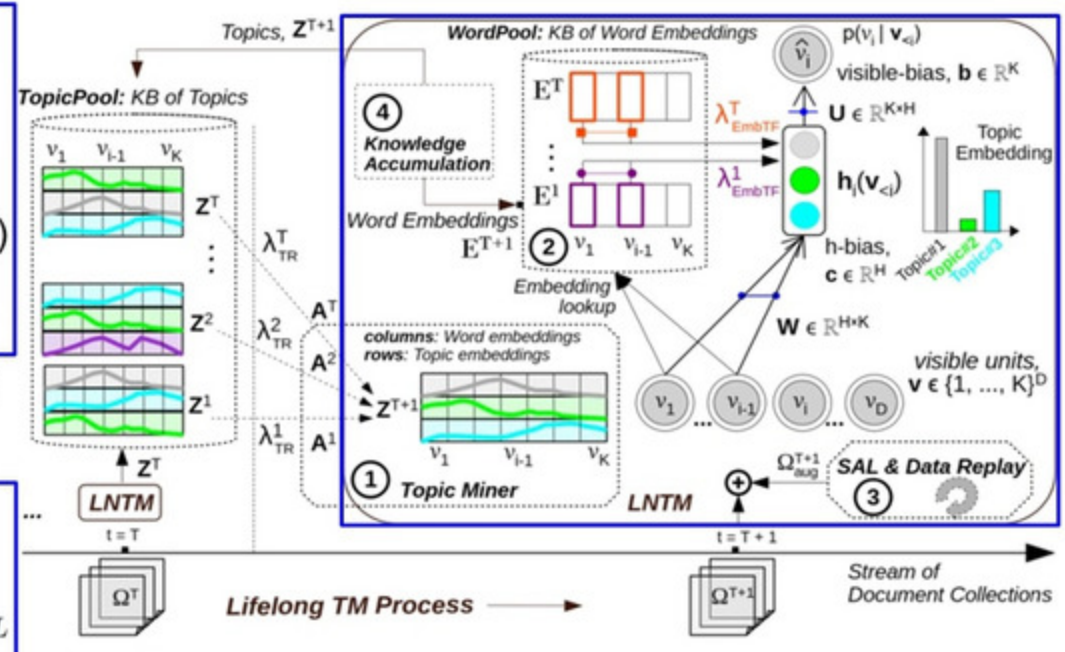

Overall loss in LNTM framework

$$\mathcal{L}(\Omega^{T+1}; \Theta^{T+1}) = \sum_{\mathbf{v} \in \Omega^{T+1}} \mathcal{L}(\mathbf{v}; \Theta^{T+1}) + \Delta_{TR} + \Delta_{SAL}$$

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Proposed: Lifelong Neural Topic Modeling (LNTM) framework

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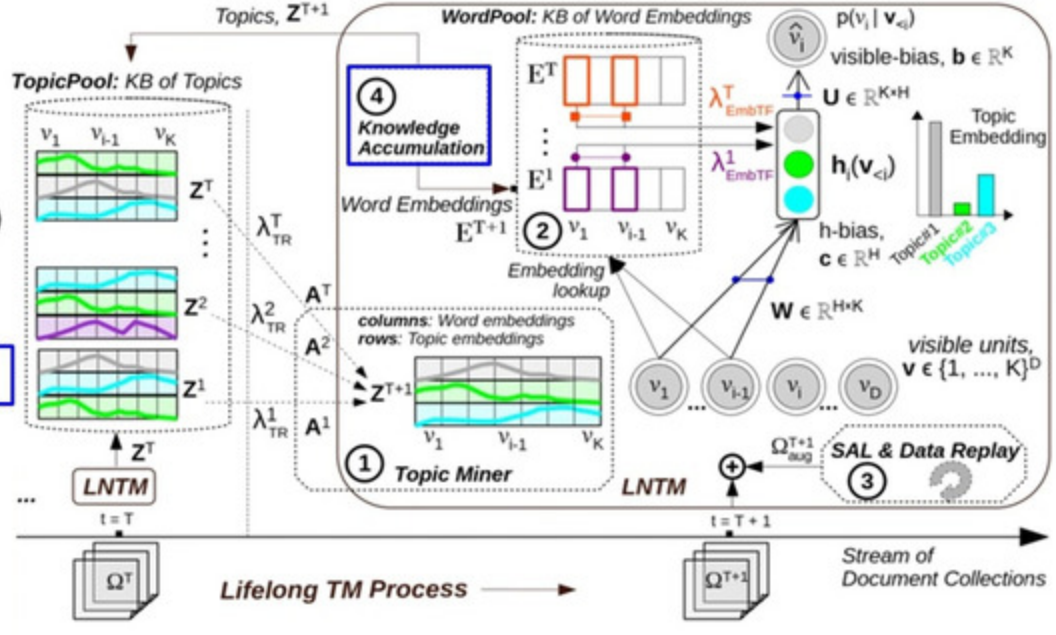

Experiments and Analysis

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Three Streams of Document Collections

Future learning tasks

S1: AGnews → TMN → R21578 → 20NS → 20NSshort
S2: AGnews → TMN → R21578 → 20NS → TMNtitle
S3: AGnews → TMN → R21578 → 20NS → R21578title

Evaluation

→ Topic Quality via Coherence (**COH**)
→ Information Retrieval via Precision@Recall (**P@R**)
→ Generalization via Perplexity (**PPL**)

Results: PPL, P@R and COH (Max. Knowledge Transfer + Min. Forgetting)

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S1: AGnews → TMN → R21578 → 20NS → 20NSshort

	Scores on historical data incurring Catastrophic Forgetting								Scores with Lifelong Knowledge Transfer					
	PPL	P@0.02	PPL	P@0.02	PPL	P@0.02	PPL	P@0.02	PPL	P@5	P@10	P@0.02	COH	r-time (second)
LNTM + EmbTF + TR + SAL	471	0.786	696	0.647	380	0.724	541	0.248	**641**	**0.418**	**0.375**	**0.324**	**0.735**	50.1
LNTM + EmbTF + TR	469	0.786	698	0.649	382	0.724	541	0.247	672	0.376	0.341	0.297	0.728	2.80
LNTM + TR	466	0.786	690	0.649	382	0.724	538	0.249	655	0.380	0.345	0.306	0.719	2.76
LNTM + EmbTF	468	0.786	696	0.649	383	0.724	540	0.247	647	0.386	0.348	0.310	0.670	2.37
NTM without Lifelong Learning	454	0.785	584	0.651	311	0.726	470	0.268	646	0.375	0.335	0.290	0.667	1.98

AGnews ***TMN*** ***R21578*** ***20NS*** ***20NSshort*** (Sparse Data)

Lifelong Neural Topic Modeling over a stream of document collections →

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Results: PPL, P@R and COH (Max. Knowledge Transfer + Min. Forgetting)

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S2: AGnews → TMN → R21578 → 20NS → TMNtitle

	Scores on historical data incurring Catastrophic Forgetting								Scores with Lifelong Knowledge Transfer					
	PPL	P@0.02	PPL	P@0.02	PPL	P@0.02	PPL	P@0.02	PPL	P@5	P@10	P@0.02	COH	r-time (second)
LNTM + EmbTF + TR + SAL	493	0.786	698	0.650	390	0.720	535	0.249	707	**0.689**	**0.662**	**0.562**	0.745	852
LNTM + EmbTF + TR	484	0.786	701	0.650	390	0.720	534	0.249	723	0.679	0.656	0.556	**0.750**	29.38
LNTM + TR	483	0.784	700	0.650	389	0.725	534	0.249	736	0.676	0.652	0.554	0.743	29.75
LNTM + EmbTF	485	0.784	700	0.650	390	0.722	534	0.249	**666**	0.675	0.649	0.548	0.726	23.21
NTM without Lifelong Learning	454	0.785	584	0.651	311	0.726	470	0.268	706	0.665	0.634	0.521	0.709	22.23

AGnews *TMN* *R21578* *20NS* *TMNtitle* (Sparse Data)

Lifelong Neural Topic Modeling over a stream of document collections

See scores for R21578title data in the paper

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IR Analysis: P@R Curve (Max. Knowledge Transfer + Min. Forgetting)

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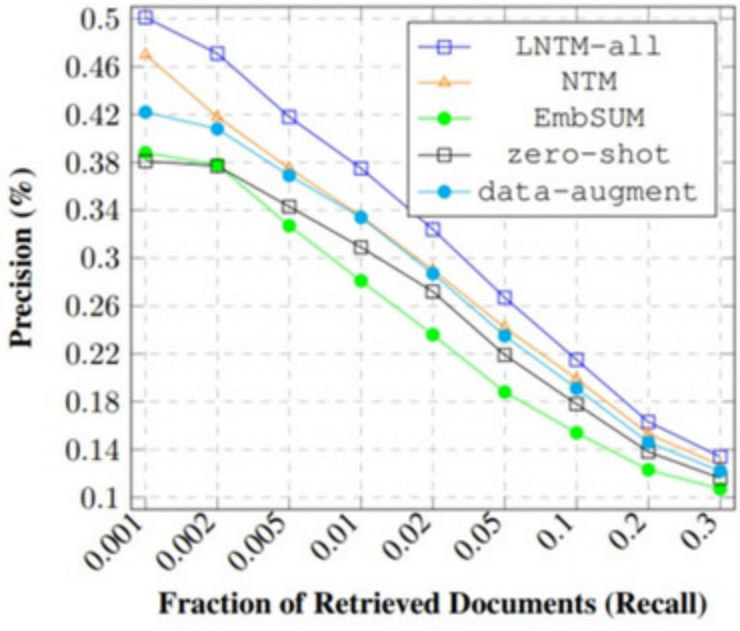
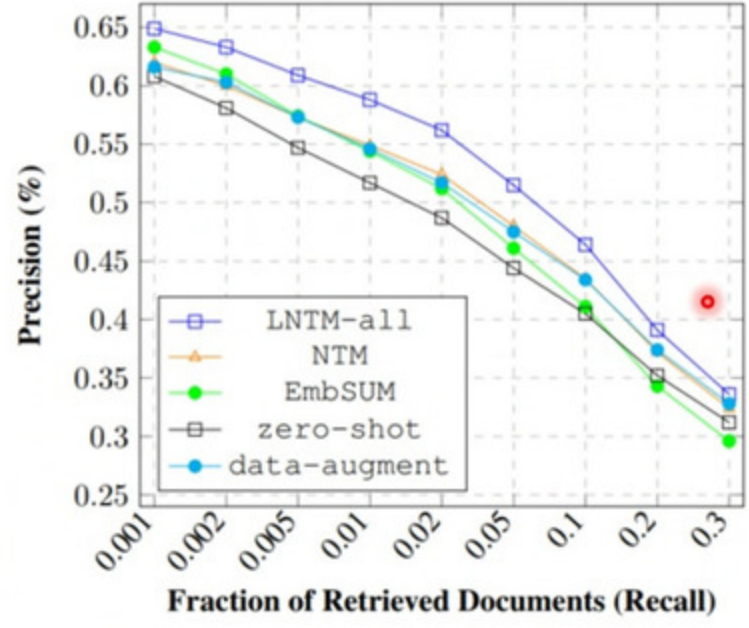


(a) **IR:** 20NSshort



(b) **IR:** TMNtitle

See IR plot for R21578title data in the paper

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Topic Analysis: Qualitative (Max. Knowledge Transfer + Min. Forgetting)

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Model	Topic-words (Top 5)
NTM	T1: nuclear, break, jobs, afghanistan, ipad T2: gulf, bruins, japanese, michigan, radiation
LNTM + TR	T1: arts, android, iphone, tablet, ipad T2: rail, medicare, wildfire, radioactive, recession
LNTM-all	T1: linkedin, android, tablet, ipad, iphone T2: tornadoes, fukushima, radioactive, radiation, medicare

Analysis: Qualitative topics of TMNtitle

See ablation studies in the paper

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Conclusion

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Novel **Lifelong Neural Topic Modeling** framework over Streaming Document Collections

- *Transfer Learning and Domain Adaptation:*
  - **Topic Regularization** with TopicPool (TR)
  - **Transfer Learning** with WordPool (EmbTF)
- *Knowledge Retention/Minimizing Catastrophic Forgetting:*
  - **Topic Regularization** with TopicPool (TR)
  - **Selective-Data Augmentation Learning** (SAL) with Distillation and Co-training
- **Joint** Topic Mining, Knowledge Transfer, Domain Adaptation and Knowledge Retention
- State-of the-art results (**PPL/IR/Topic Coherence**) in modeling **sparse** data sets

Code: https://github.com/pgcool/Lifelong-Neural-Topic-Modeling

Webpage: https://sites.google.com/view/gupta-pankaj
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Conclusion

Thanks!!!

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Wish You

A Happy

LIFELONG LEARNING!!!

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