Machine Learning research

School of Information and Communication Technology
Hanoi University of Science and Technology

2021

Key members

Khoat Than
SOICT, HUST,
khoattq@soict.hust.edu.vn
https://users.soict.hust.edu.vn/khoattq/

Ngo Van Linh
SOICT, HUST,
linhnv@soict.hust.edu.vn
https://users.soict.hust.edu.vn/linhnv/

- **30+** research students

Recent research directions

- Continual learning
- Generative models
- Self-supervised learning
- Representation learning

Some recent sponsors

NAFOSTED
National Foundation
for Science & Technology Development

BỘ KHOA HỌC VÀ CÔNG NGHỆ

ASIAN OFFICE OF AEROSPACE R&D
BRIDGING SCIENCE & TECHNOLOGY

AIR FORCE OFFICE OF SCIENTIFIC RESEARCH
UNITED STATES AIR FORCE

Office of Naval Research
ONR
Science & Technology

VINGROUP
Innovation Foundation

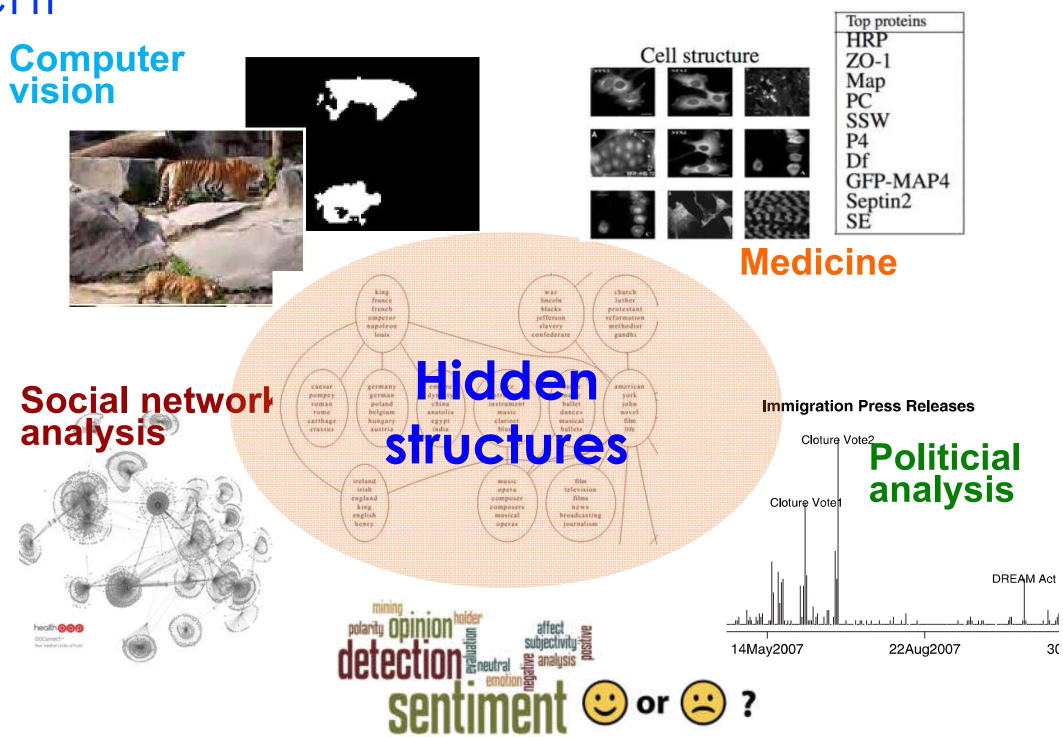
U.S. ARMY
RDECOM

Some projects

- VINIF (2019-2022, VN):
  - *Director:* Khoat Than
  - *Funding agency:* Vingroup Innovation Foundation
  - Area: Machine learning, Big data
- ONRG (2018-2020, USA):
  - *Director:* Khoat Than
  - *Funding agency:* US Navy & Air Force Office of Scientific Research
  - Area: Representation learning, Big data
- NAFOSTED (2015-2017, VN):
  - *Director:* Khoat Than
  - *Funding agency:* National Foundation for Science and Technology Development
  - Area: Machine learning, Big data
- AFOSR (2015-2017, USA):
  - *Director:* Khoat Than
  - *Funding agency:* Air Force Office of Scientific Research, and U.S. Army International Technology Center, Pacific
  - Area: Machine learning, Big data

ML: Inference & Learning

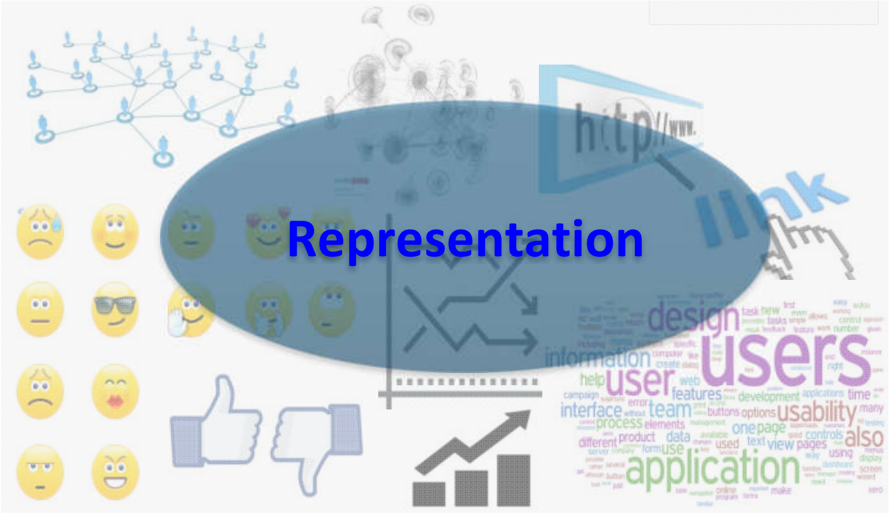
- Background: Big data are hard to interpret. Recovering **hidden semantics/structures** is beneficial, but very challenging.
- **Objective:** Develop efficient methods for analyzing the hidden structures from **big/streaming** text collections



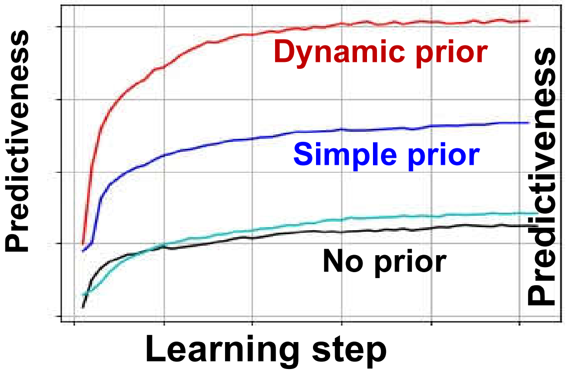
- Tools:
  - Topic models
  - Matrix factorization
  - Deep neural networks
- Research projects: NAFOSTED (VN), AFOSR (USA, 2015-2017)

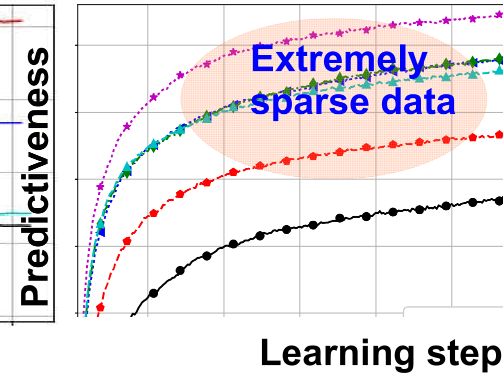
ML: Knowledge representation

- Background: **Semantic representation** is always challenging
- ***Objective:*** *Develop methods for learning efficient representations of the hidden semantics from big/streaming data*



- Tools:
  - Topic models + Neural nets (extracting hidden semantics)
  - Manifold learning (analyzing local structures)
  - Human knowledge as prior (providing supervision)



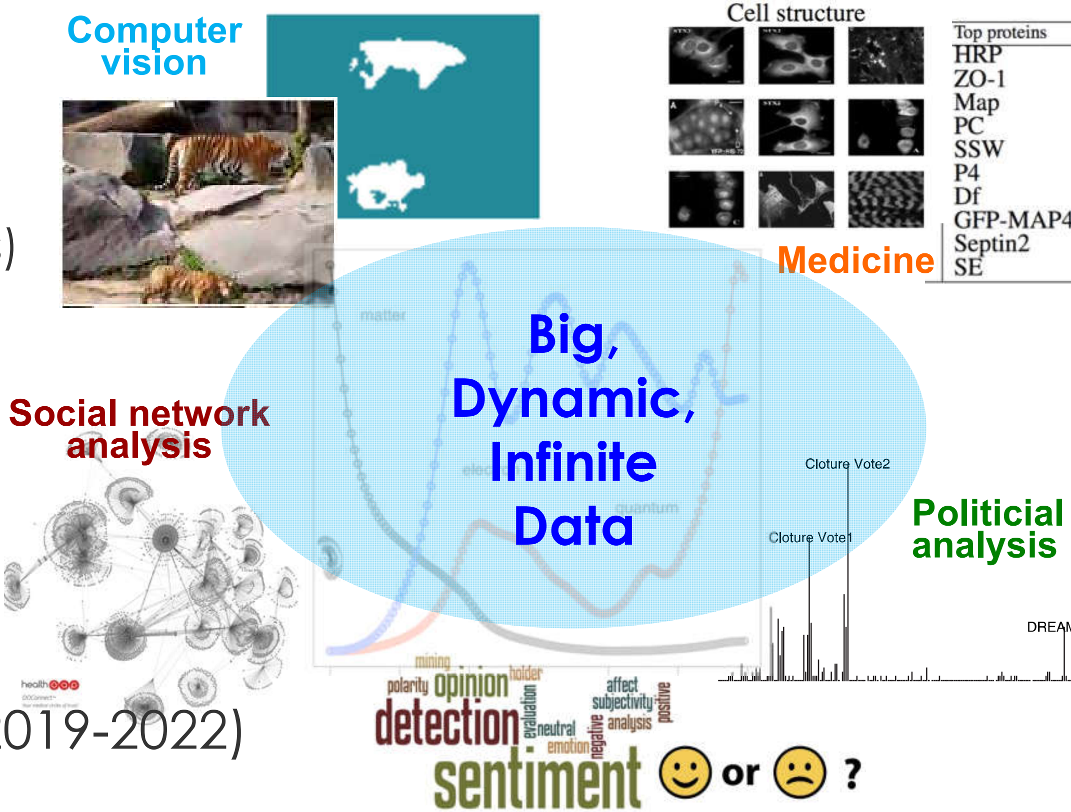


25% improvement in predictiveness

- Research projects: **ONRG** (USA, 2018-2020)

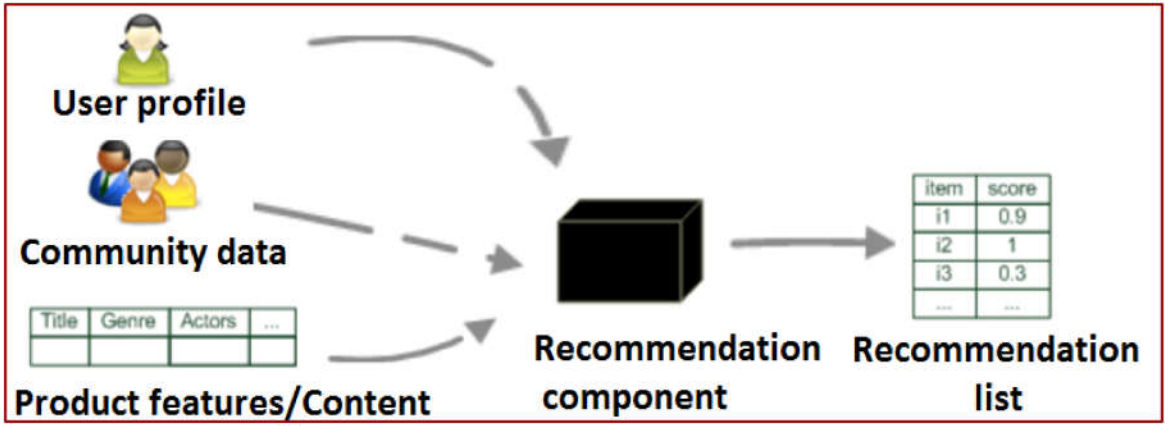
ML: Human knowledge + Learning

- Background: Integrating human knowledge into machine learning models is always beneficial but challenging.
- **Objective:** Develop efficient methods for learning from big or streaming data that can exploit human knowledge
- Tools:
  - **Topic models + Neural nets** (extracting hidden semantics)
  - **Human knowledge as prior** (providing supervision)

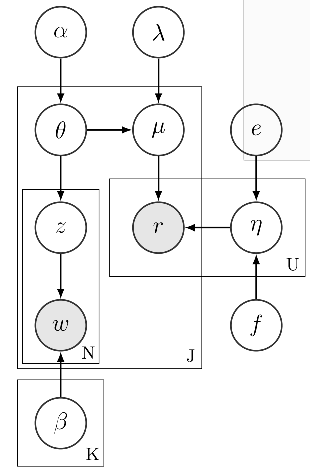


- Research projects: **VINIF** (2019-2022)

Application: Recommender systems



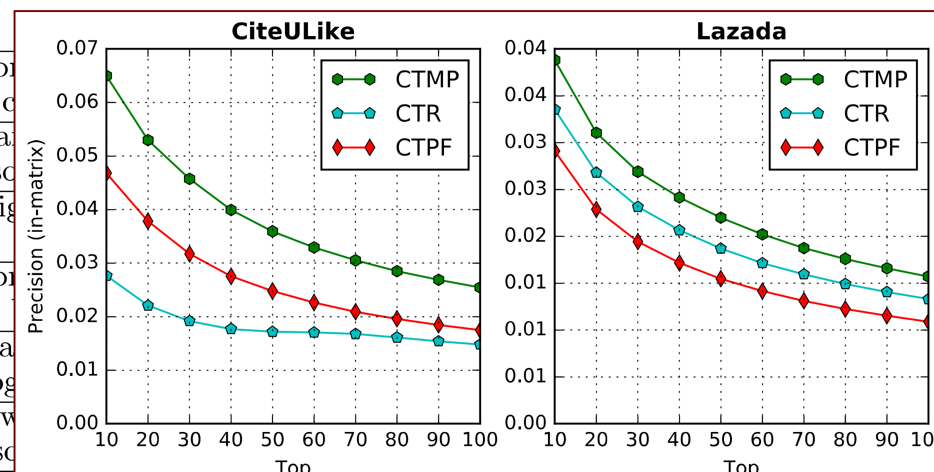
Hybrid contents and ratings/feedbacks



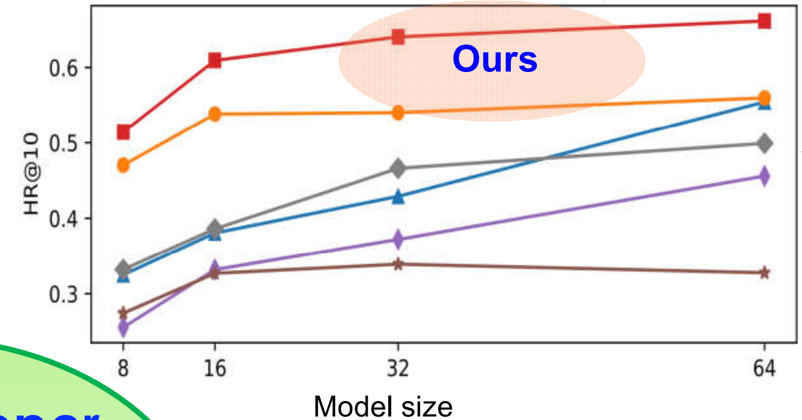
CTMP **(Our model)**

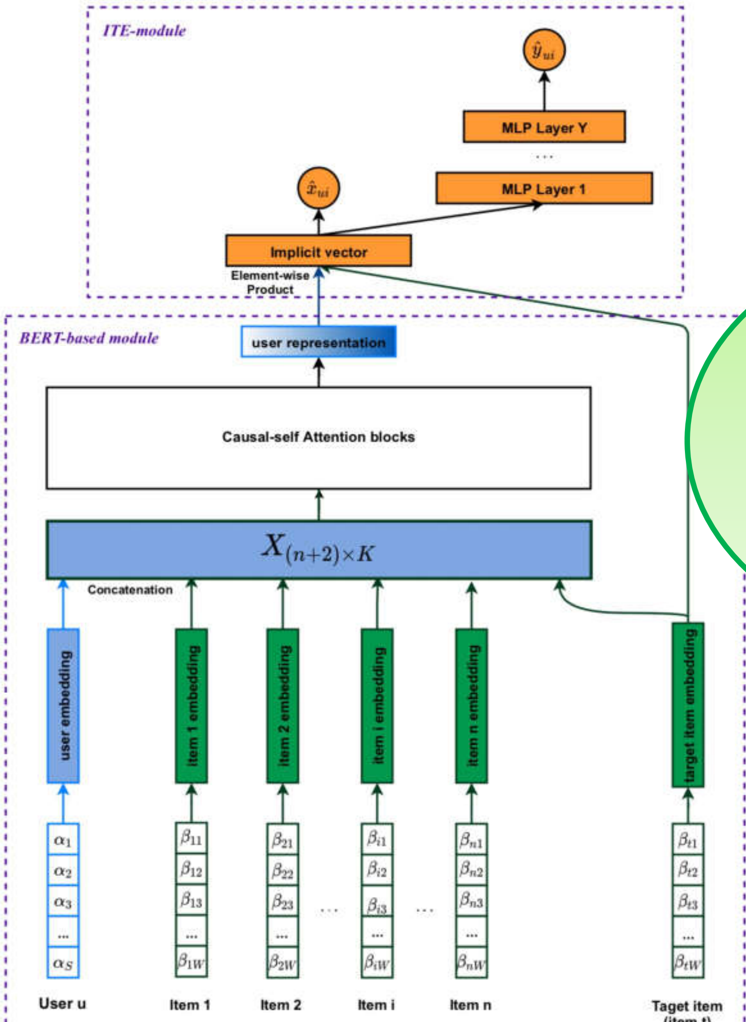
User	Profile
1	small, compact, design, charge, accessories, battery, device, pr black, sound, phone, camera, material, usage, china, laptop, c
	child, diaper, infant, tool, toy, children, hygiene, for, child, sa patch, absorptive, package, produce, pant, velcro_diaper, abso
2	wood, interior, houses, material, life, goods, room, chair, desig for, produce, vietnam, shelf, guest, sofa, bed, luxurious, size
	design, material, luxurious, fashionable, phone, usage, safe, pr goods, accessories, machine, leather, houses, black, feminine,
3	TV, LED, HD, sound, monitor, black, video, model, full, sma product, resolution, deliver ... free, inch, technolog
	machine, household_pro ... r, fridge, cold, w air_conditioner, blender ... g, produce, abso

Users' interests



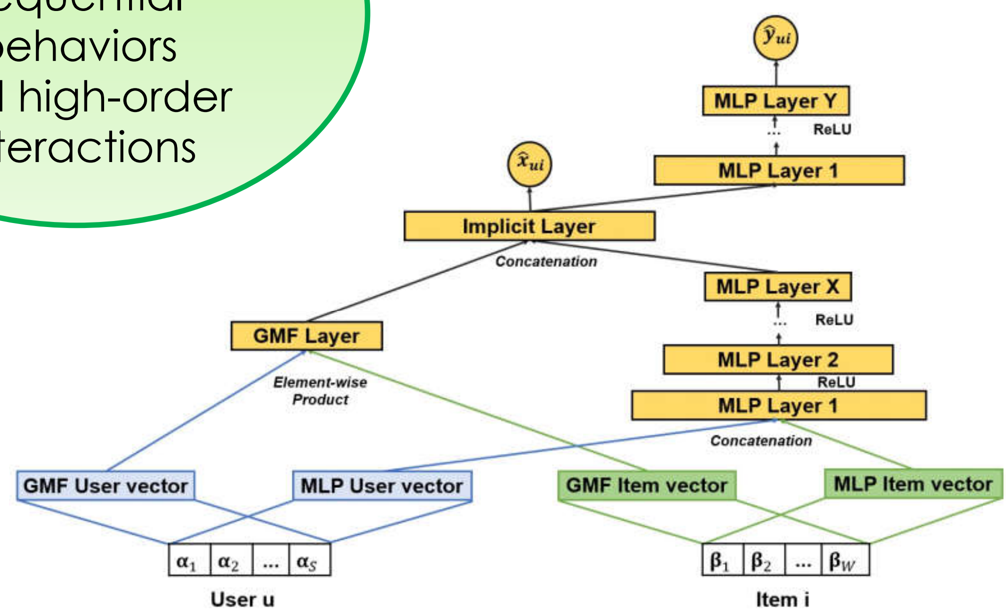
Application: Recommender systems





Going deeper

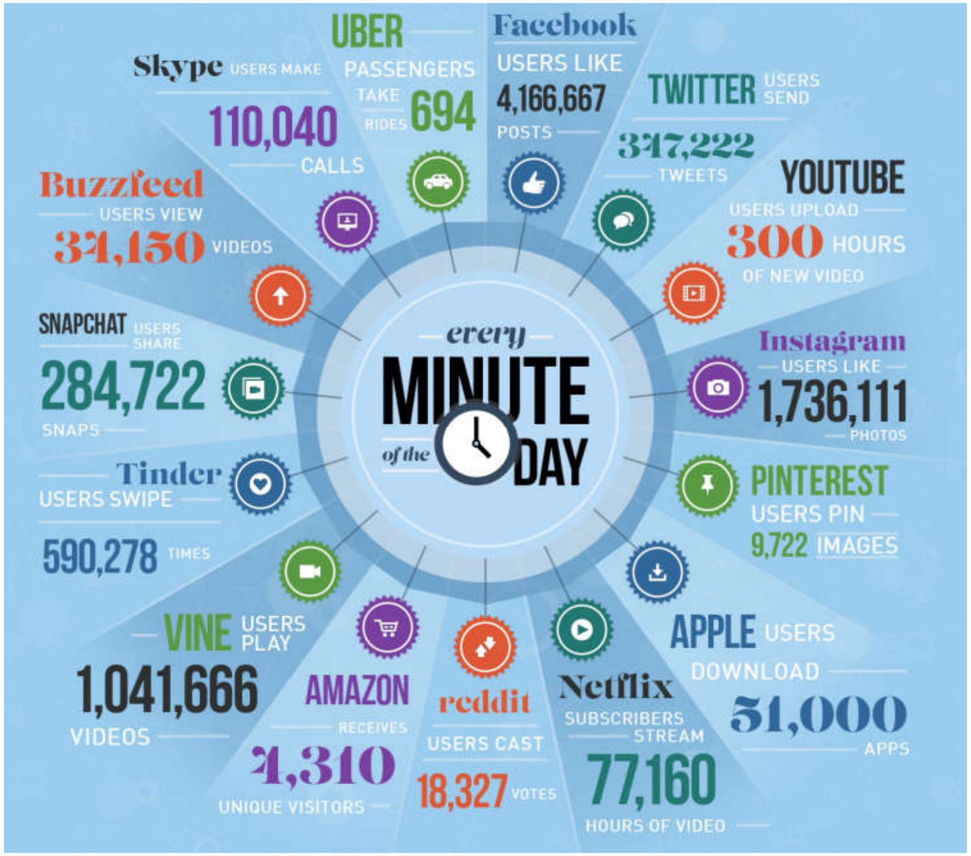
Modeling sequential behaviors and high-order interactions

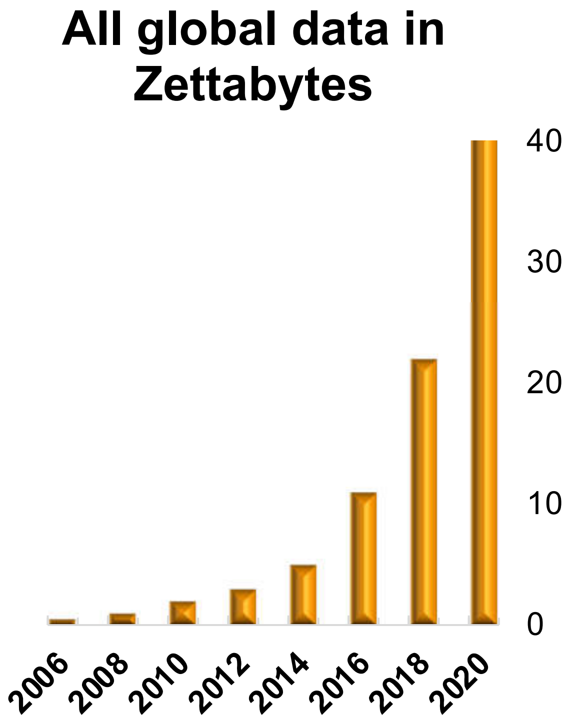


A recent research line

Question

- How to train a machine from an **infinite** sequence of data?
  - Learning from a data stream





https://www.umanis.com/lesechosdeladata/avis-dexpert/digital-listening-social-media/attachment/data-digital-social-media-3/?thc-month=201606

Applications

- Online services

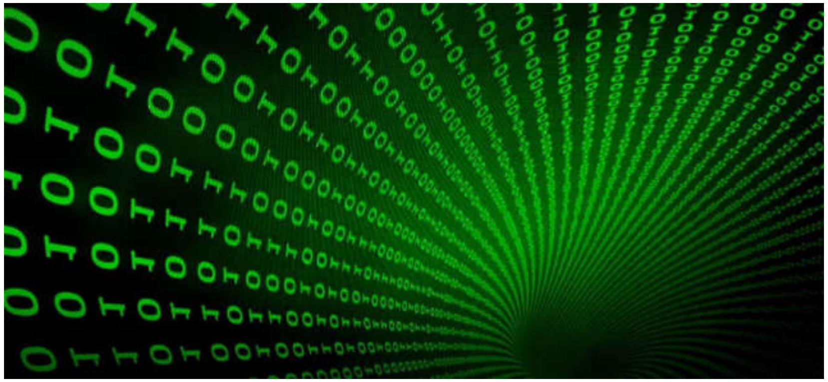
amazon

"The company reported a **29% sales increase** to \$12.83 billion during its second fiscal quarter, up from \$9.9 billion during the same time last year."
– Fortune, July 30, 2012

- Lifelong learning

Question: challenges

- Learning from infinitely many observations (data)



- The dynamic nature

- The NP-hardness of inference

- ...

Catastrophic forgetting

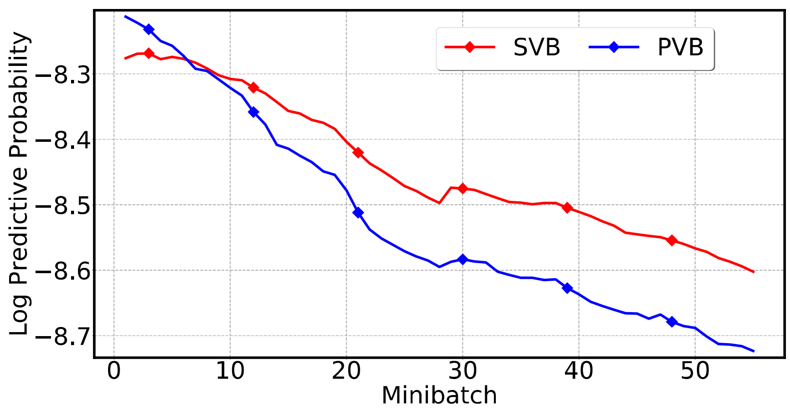
- Forget the tasks that have learned before
- This problem appears in most learning systems, but
  - Most existing focuses on neural networks [Parisi et al., 2019; French, 1999; Mermillod et al., 2013]
  - Lack of theory: forgetting rate, …
- Our finding: after training *b* minibatches

$$\|\xi_b - \xi_0\|_1 = \left\|\hat{\xi}_b + \cdots + \hat{\xi}_1\right\|_1 \geq b$$

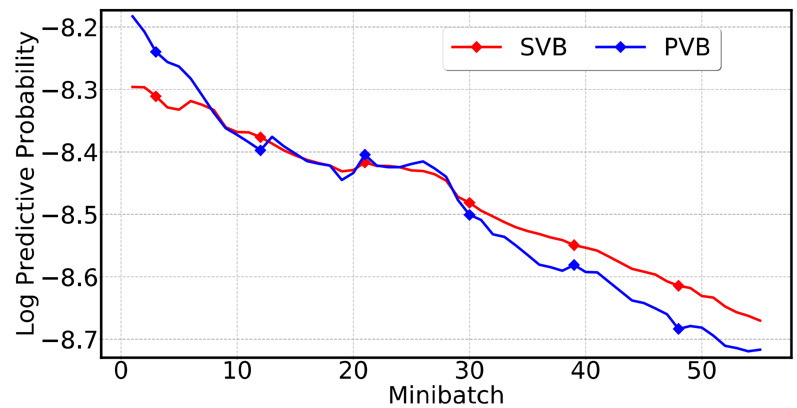
  - The knowledge ξ_0 will quickly become *negligible*
  - Forgetting rate: $\mathcal{O}(b^{-1})$ → Much faster than human: $\mathcal{O}(b^{-0.67})$

Bach, Tran Xuan, Nguyen Duc Anh, Linh Ngo Van, Khoat Than. "Dynamic transformation of prior knowledge into Bayesian models for data streams." Conditionally accepted, *IEEE Transactions on Knowledge and Data Engineering*, 2021.

Catastrophic forgetting: example



(a) Rec.autos



(b) Rec.sport.hockey

The accuracy of prediction about the first learned concept (*Rec.autos* for (a), *Rec.sport.hockey* for (b)) decreases quickly as learning from more new concepts. (Higher is better)

Stability-Plasticity dilemma

- Stability: should not forget what has been learned
- Plasticity: *quickly adapt with new changes* *[Mermillod et al., 2013]*
- **How to balance efficiently?**

Old knowledge <=> New knowledge

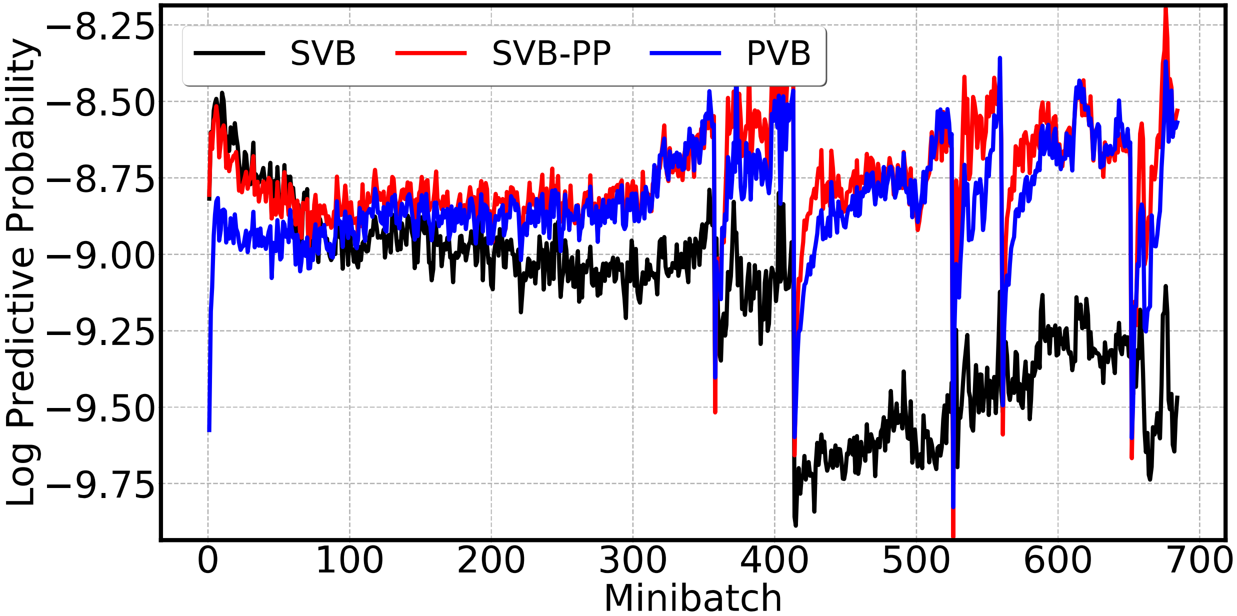
- Our finding for SVB:

$$\|\xi_b\|_1 \xrightarrow{b\to\infty} \infty \quad \xrightarrow{\text{yields}} \quad var(\xi_b) \xrightarrow{b\to\infty} 0$$

  - a model will evolve slowly (too stable)
  - could not deal well with sudden changes (Plasticity?)

Van-Son Nguyen, Duc-Tung Nguyen, Linh Ngo Van, Khoat Than, “Infinite Dropout for training Bayesian models from data streams”, IEEE Big Data, 2019.

Stability-Plasticity: concept drift



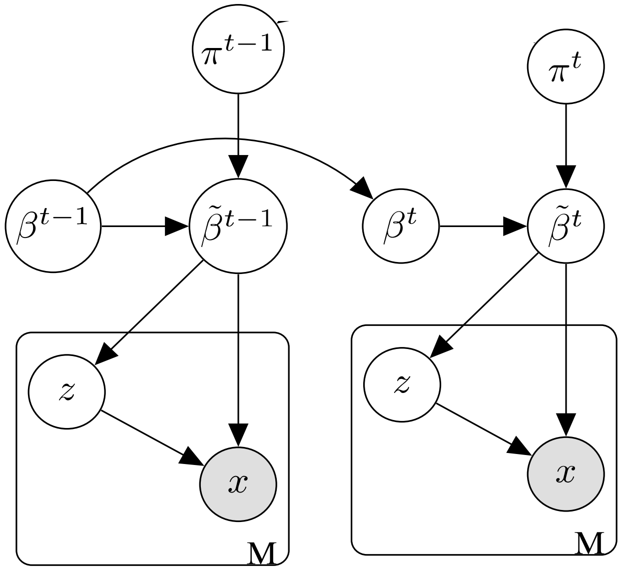
Generalization of a model when concept drifts sometimes appear over time.
(Higher is better)

Stability-Plasticity: our solution

- Infinite Dropout: ensemble of infinite learners in streaming conditions
  - Transition from time $t-1$ to t:
$$\beta^t \sim Normal(\beta^{t-1}, \sigma I)$$
  - Drop out some of the global variable:
$$\hat{\beta}^t = f(\beta^t \otimes \pi^t)$$
$$\pi^t \sim Bernoulli(dr)$$

Balance the old & new

Room for new knowledge

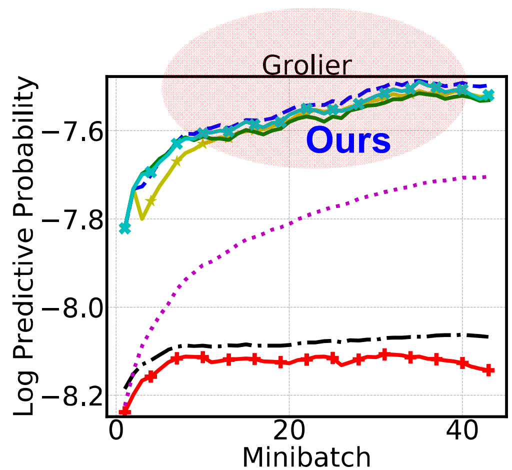


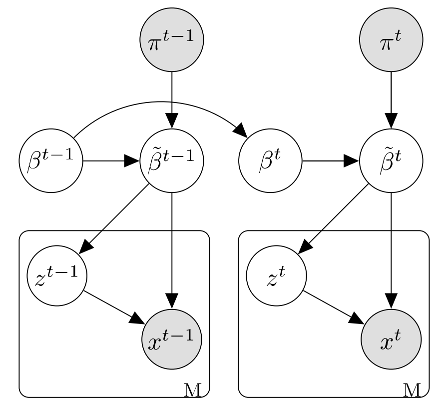
(a) iDropout for $B(\beta, z, x)$

Van-Son Nguyen, Duc-Tung Nguyen, Linh Ngo Van, Khoat Than, "Infinite Dropout for training Bayesian models from data streams", *IEEE Big Data*, 2019.

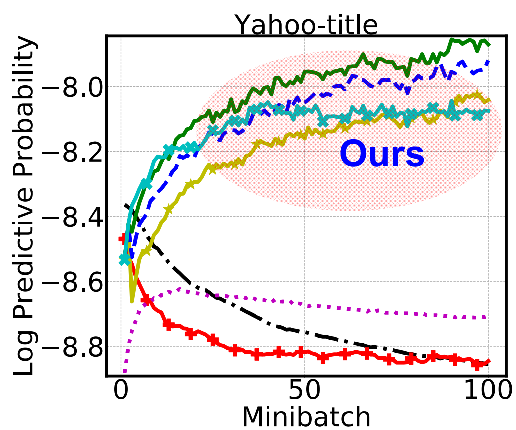
Stability-Plasticity: our solution

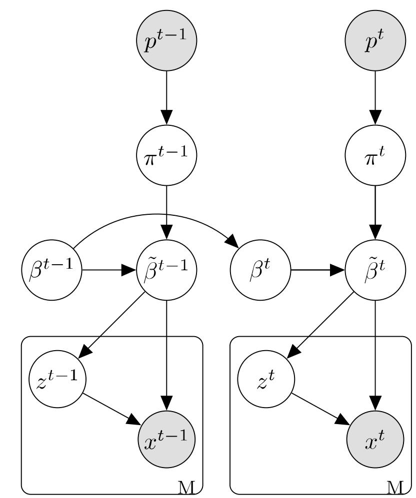
- iDropout & aiDropout
  - Adapt well with sudden changes
  - Deal well with noisy and sparse data



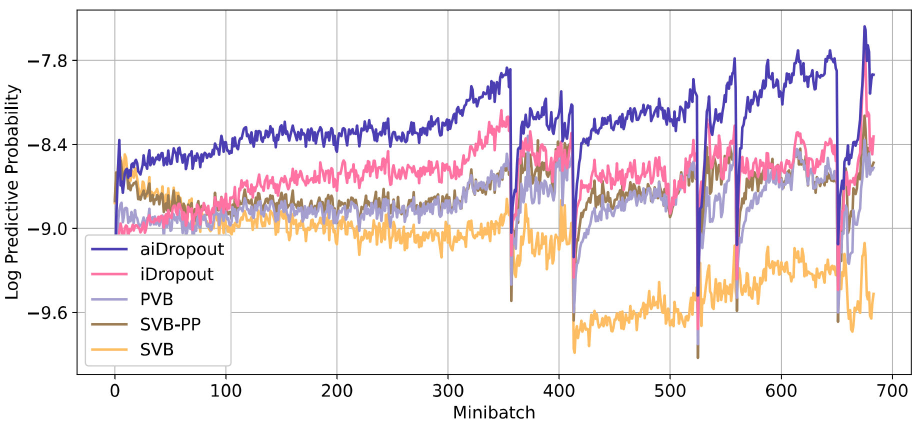


(a) iDropout for $B(\beta, z, x)$



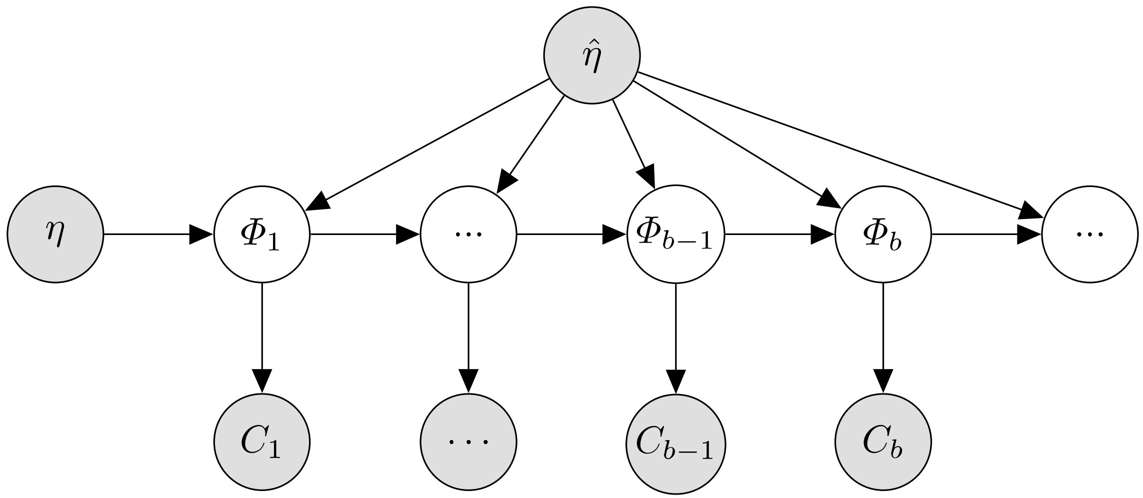


(b) aiDropout for $B(\beta, z, x)$



Ha Nguyen, Hoang Pham, Son Nguyen, Linh Ngo Van, Khoat Than. “Adaptive Infinite Dropout for Noisy and Sparse Data Streams,” Conditionally accepted, *Machine Learning journal*, 2021.

Catastrophic forgetting: our solution



- We propose a simple framework (**BPS**) to keep human knowledge at every step

$$p(\Phi|C_1, \dots, C_b, \eta) \propto p(\Phi|\hat{\eta}_b)p(C_b|\Phi, \eta)p(\Phi|C_1, \dots, C_{b-1}, \eta)$$

- *So, learning = boosted prior + (current + past) statistics*

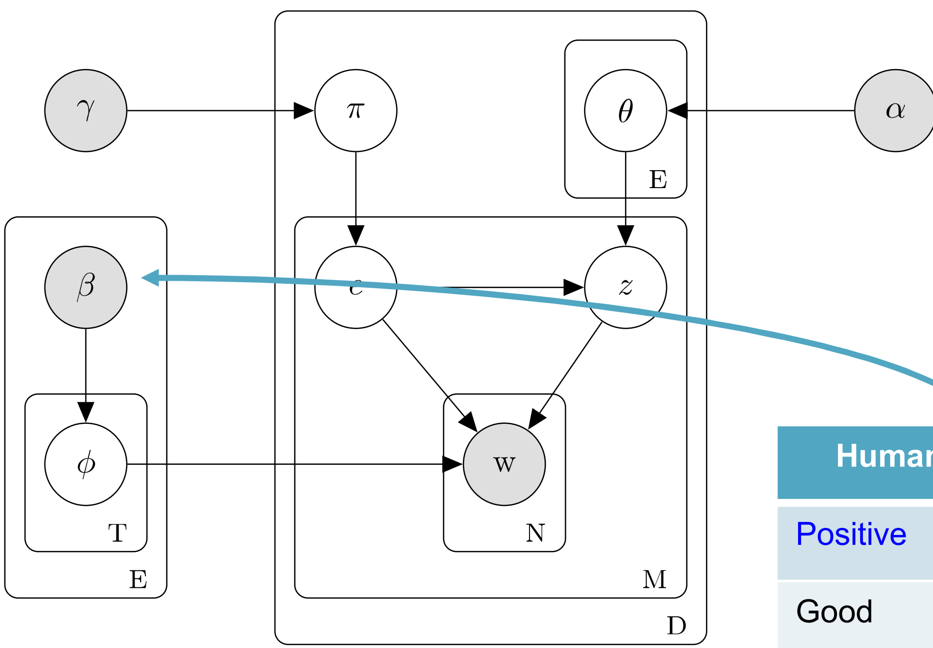
$$\boldsymbol{\xi_b = \xi_0^b + \hat{\xi}_b + \xi_{b-1}}$$

- Where ξ_0^b is the knowledge to be preserved

Anh Nguyen, Ngo Van Linh, Anh Nguyen Kim, Canh Hao Nguyen, and Khoat Than. "Boosting Priors in streaming Bayesian learning." *Neurocomputing*, vol. 424, 2021.

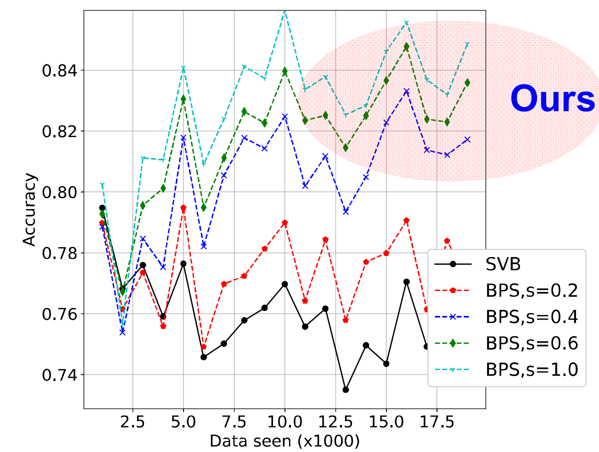
Our BPS: sentiment analysis

- Unsupervised Sentiment analysis
  - BPS mostly outperforms SVB [Nguyen et al., 2021]

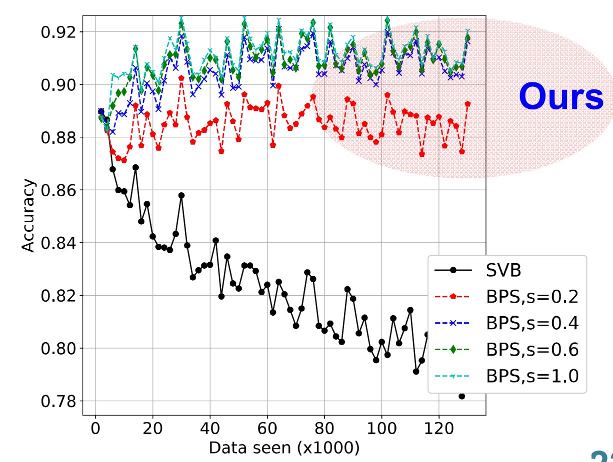


Aspect-sentiment unification model
[Jo & Oh, 2011]

Human knowledge	
Positive	Negative
Good	Bad
Awesome	Sad
Excellent	Boring



(b) Yelp.



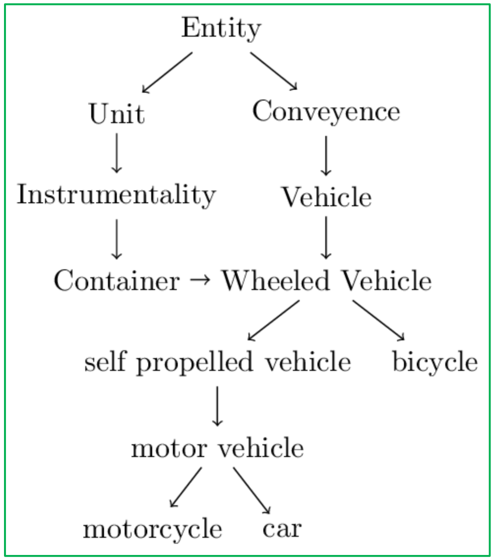
(d) Music.

Human knowledge: TPS

- Prior knowledge is exploited as learning from a stream
  - The knowledge is transformed into the global variable:

$$\beta^t = f(\pi^t \eta)$$

  - The transformation (π) is **dynamic**



Human knowledge	
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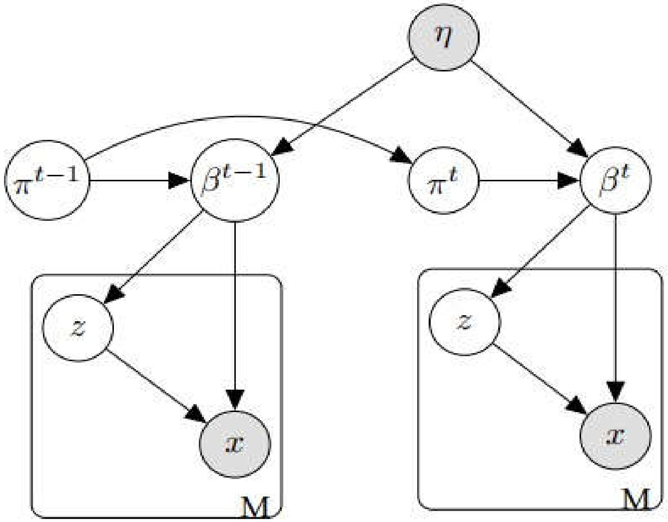
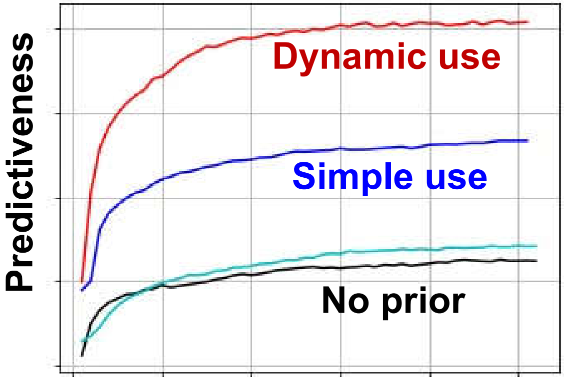
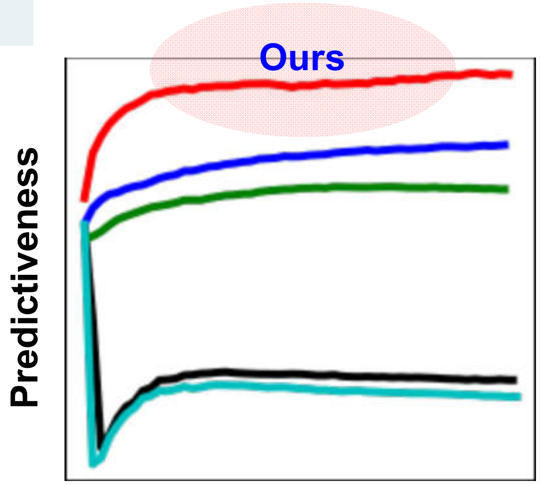
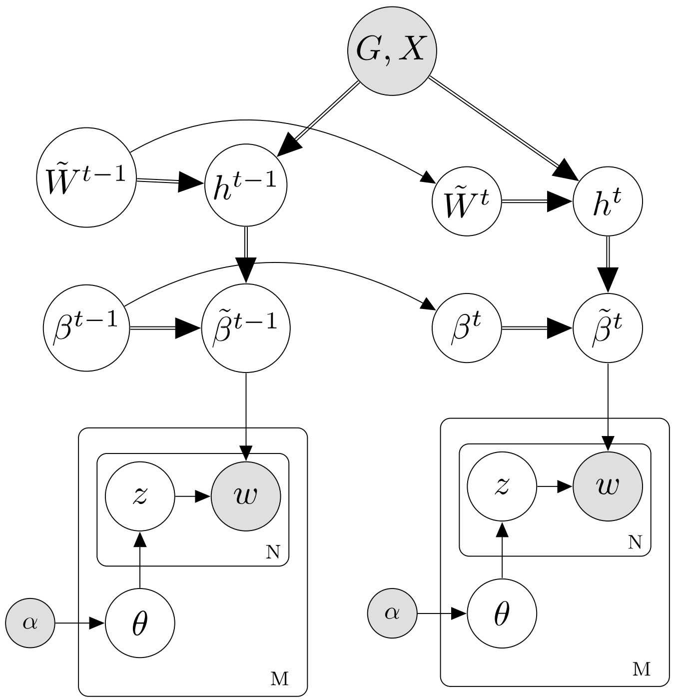






Bach, Tran Xuan, Nguyen Duc Anh, Linh Ngo Van, Khoat Than. “Dynamic transformation of prior knowledge into Bayesian models for data streams.” Conditionally accepted, *IEEE Transactions on Knowledge and Data Engineering*, 2021.

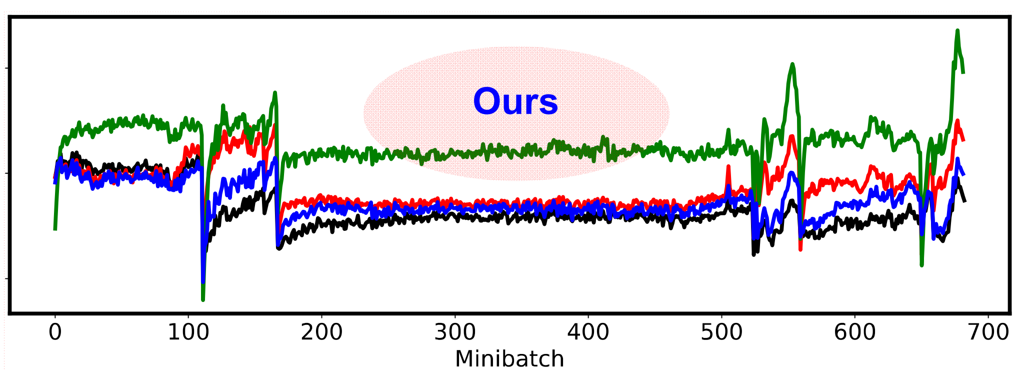
Knowledge graph: GCTM

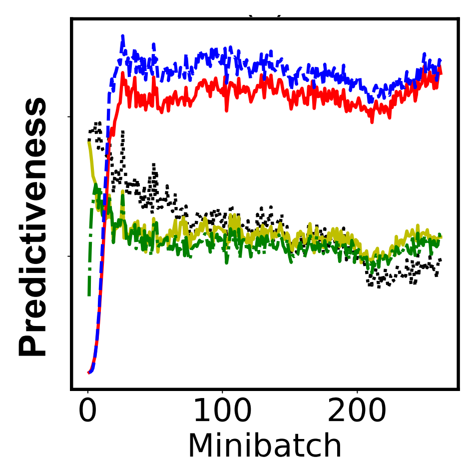


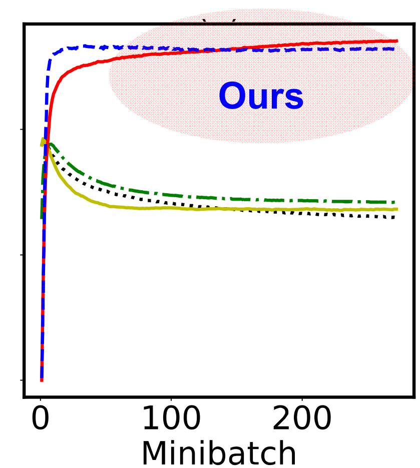
- Many sources of valuable knowledge are graphs
- **GCTM** = Graph convolutional nets + Topic models + Knowledge graph

$$h^t = GCN(G, X; W^t)$$

  - Analyzing hidden topics from text streams







Linh Ngo, Bach Tran, Khoat Than. “Graph Convolutional Topic Model for Data Streams.” Cond. accepted, *Neurocomputing*, 2021.