NEURAL INFORMATION PROCESSING SYSTEMS

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Knowledge-Aware Bayesian Deep Topic Model

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❖ Background And Motivation

★ Most embedded topic models(ETMs) are learned by maxizing the likelihood

- Purely data-driven, ignoring the easily accessible knowledge graph
- The learned topics sometimes are unfriendly to users

★ While several knowledge-based ETMs have recently been proposed

- Shallow topic structures
- Or ignoring the mismatch issue of the provided knowledge graph between the target corpus

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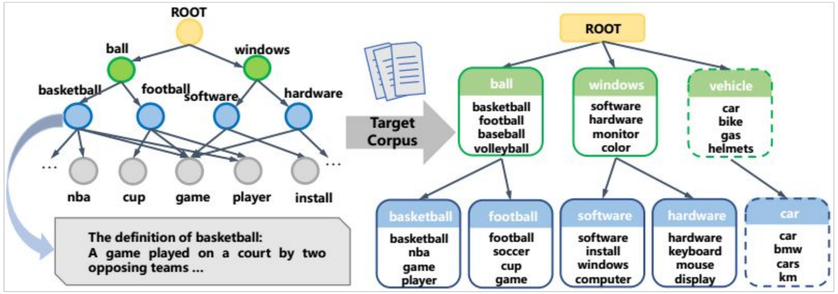
❖ Background And Motivation



★ We first propose a Bayesian generative framework (TopicKG) for incorporating domain knowledge into deep topic modeling

★ TopicKG is extended to TopicKGA that allows the given domain knowledge to-be-finetuned according to the target corpus

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❖ Topic-KG

★ The generative model of corpus x, and the knowledge graph S and C

$$\boldsymbol{\theta}_j^{(L)} \sim \mathrm{Gam}(\boldsymbol{\gamma}, 1/c_j^{(L+1)}), \quad \left\{\boldsymbol{\theta}_j^{(l)} \sim \mathrm{Gam}(\boldsymbol{\Phi}^{(l+1)}\boldsymbol{\theta}_j^{(l+1)}, 1/c_j^{(l+1)})\right\}_{l=1}^{L-1},$$

$$\boldsymbol{x}_j \sim \mathrm{Pois}(\boldsymbol{\Phi}^{(1)}\boldsymbol{\theta}_j^{(1)}) \quad \left\{\boldsymbol{\Phi}_k^{(l)} = \mathrm{Softmax}(\boldsymbol{\Psi}_k^{(l)})\right\}_{l=1}^{L}, \quad \left\{\Psi_{k_1k_2}^{(l)} = \boldsymbol{e}_{k_1}^{(l-1)^T}\boldsymbol{e}_{k_2}^{(l)},\right\}_{k_1=1,k_2=1,l=1}^{K_{l-1},K_l,L},$$

$$\left\{S_{k_1,k_2}^{(l)} \sim \mathrm{Bern}(\sigma(\boldsymbol{e}_{k_1}^{(l-1)^T}\boldsymbol{W}\boldsymbol{e}_{k_2}^{(l)})),\right\}_{k_1=1,k_2=1,l=1}^{K_{l-1},K_l,L}, \left\{C_{vk}^{(l)} \sim \mathrm{Bern}(\sigma(\boldsymbol{e}_v^{(0)^T}\boldsymbol{e}_k^{(l)})),\right\}_{v=1,k=1,l=1}^{V,K_l,L},$$

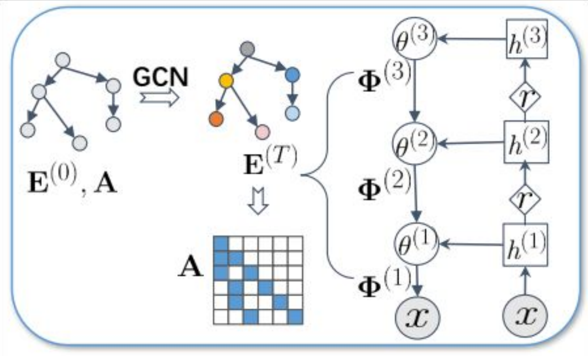

Fig1. Overview of TopicKG

★ The ELBO

$$\mathcal{L} = \sum_{j=1}^{J} \mathrm{E}_{q(\boldsymbol{\theta}|\boldsymbol{x}_j)}[\log p(\boldsymbol{x}_j|\boldsymbol{\Phi}^{(1)}, \boldsymbol{\theta}_j^{(1)})] + \beta \sum_{l=1}^{L}\sum_{k_2=1}^{K_l}(\sum_{k_1=1}^{K_{l-1}} \log p(S_{k_1k_2}^{(l)})|\boldsymbol{e}_{k_1}^{(l-1)}, \boldsymbol{e}_{k_2}^{(l)})$$

$$+ \sum_{v=1}^{V} \log p(C_{vk_2}^{(l)}|\boldsymbol{e}_v^{(0)}, \boldsymbol{e}_{k_2}^{(l)})) - \sum_{j=1}^{J}\sum_{l=1}^{L} \mathrm{KL}(q(\boldsymbol{\theta}_j^{(l)})||p(\boldsymbol{\theta}_j^{(l)}|\boldsymbol{\Phi}^{(l+1)}, \boldsymbol{\theta}_j^{(l+1)})))$$

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❖ Topic-KGA

★ TopicKG requires a perfect topic tree that matches the target corpos, however, the knowledge graph may be

(1) noisy
(2) built on an ad hoc basis
(3) not closely related to the topic discovering task

★ Graph adaptive technique

$$\tilde{\boldsymbol{A}} = \tilde{\boldsymbol{A}} + \tilde{\boldsymbol{A}}^{\text{ada}}$$

$$\tilde{\boldsymbol{A}}^{\text{ada}} = \text{Softmax}(k(\boldsymbol{E}_A, \boldsymbol{E}_A))$$

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❖ Experiment

★ Topic quality

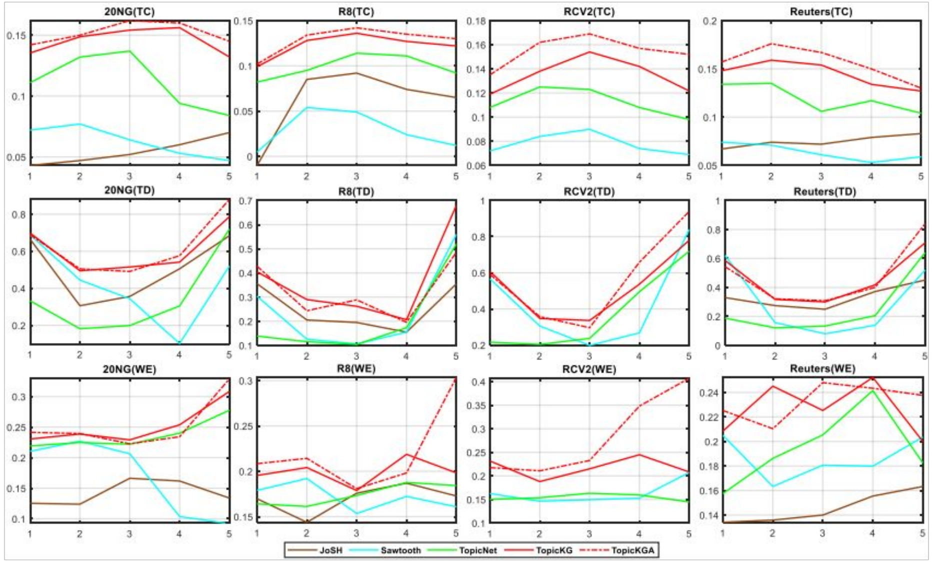

Figure 3: Topic coherence (TC, top row), topic diversity (TD, middle row), and word embedding coherence (WE, bottom row) results for various deep topic models on four datasets. In each subfigure, the horizontal axis indicates the layer index of the topics. For all metrics, higher is better.

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❖ Experiment

★ Document representation

Table 1: Micro F1 and Macro F1 score of different models on three datasets. The digits in brackets indicate the number of layers. Micro F1 /Macro F1.

Model	20NG	R8	RCV2
ETM	50.25 ±0.42 / 47.44 ±0.21	88.10 ±0.45 / 59.67 ±0.24	68.63 ±0.15 / 24.40 ±0.11
CombinedTM	56.43 ±0.14 / 54.95 ±0.11	93.69 ±0.09 /84.14 ±0.10	84.85 ±0.11 / 51.47 ±0.21
Sawtooth(3)	52.41 ±0.08 / 51.53 ±0.10	90.04 ±0.15 / 78.84 ±0.21	82.54 ±0.11 / 49.25 ±0.10
TopicNet(3)	55.16 ±0.22 / 54.78 ±0.34	89.95 ±0.17 / 64.15 ±0.16	84.15 ±0.25 / 50.37 ±0.22
TopicKG(3)	55.73 ±0.15 / 54.48 ±0.08	93.6 ±0.05 / 83.32 ±0.07	84.75 ±0.16 / 50.51 ±0.41
TopicKGA(3)	**58.63** ±0.15 / **57.90** ±0.10	**93.70** ±0.52 / **84.50** ±0.11	**85.34** ±0.14 / **52.35** ±1.10
ETM	47.79 ±0.12 / 44.19 ±1.01	86.54 ±0.84 / 59.88 ±1.11	63.77 ±0.14 / 21.44 ±1.04
CombinedTM	58.16 ±0.15 / 58.10 ±0.10	93.50 ±0.13 /84.84 pm0.11	82.91 ±0.11 / 48.17 ±0.05
Sawtooth(7)	53.71 ±0.11 / 53.02 ±0.47	92.86 ±0.07 / 82.54 ±0.41	82.46 ±0.15 / 49.34 ±0.34
TopicNet(7)	56.13 ±0.19 / 55.41 ±0.39	90.65 ±0.00 / 66.57 ±0.00	82.81 ±0.00 / 49.44 ±0.00
TopicKG(7)	56.32 ±0.12 / 57.35 ±0.04	94.04 ±0.12 / 85.04 ±0.11	82.48 ±0.11 / 48.24 ±0.09
TopicKGA(7)	**60.04** ±0.34 / **59.12** ±0.13	**94.10** ±0.08 / **85.50** ±0.10	**83.08** ±0.23 / **50.50** ±0.08

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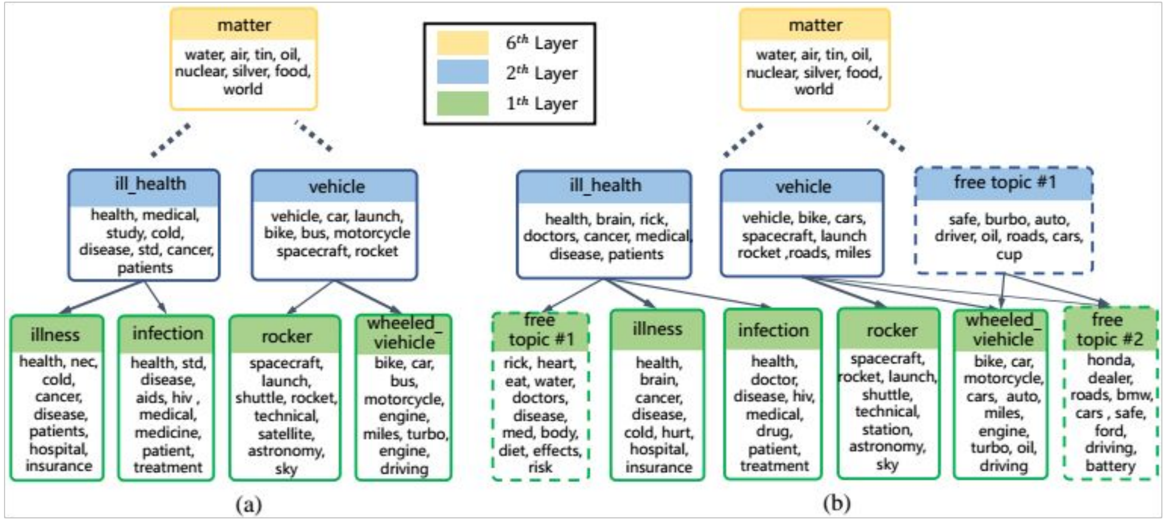
- ❖ Experiment
  - ★ The learned topic hierarchies



Thank you for listening