hu_2020_neural_topic_modeling_with_cycle_consistent_adversarial_training

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Title

Neural Topic Modeling with Cycle-Consistent Adversarial Training

Venue

EMNLP

Topic labeling

Fully automated

Focus

Primary

Type of contribution

Novel approach

Underlying technique

Supervised Topic Modeling

Topic labeling parameters

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Label generation

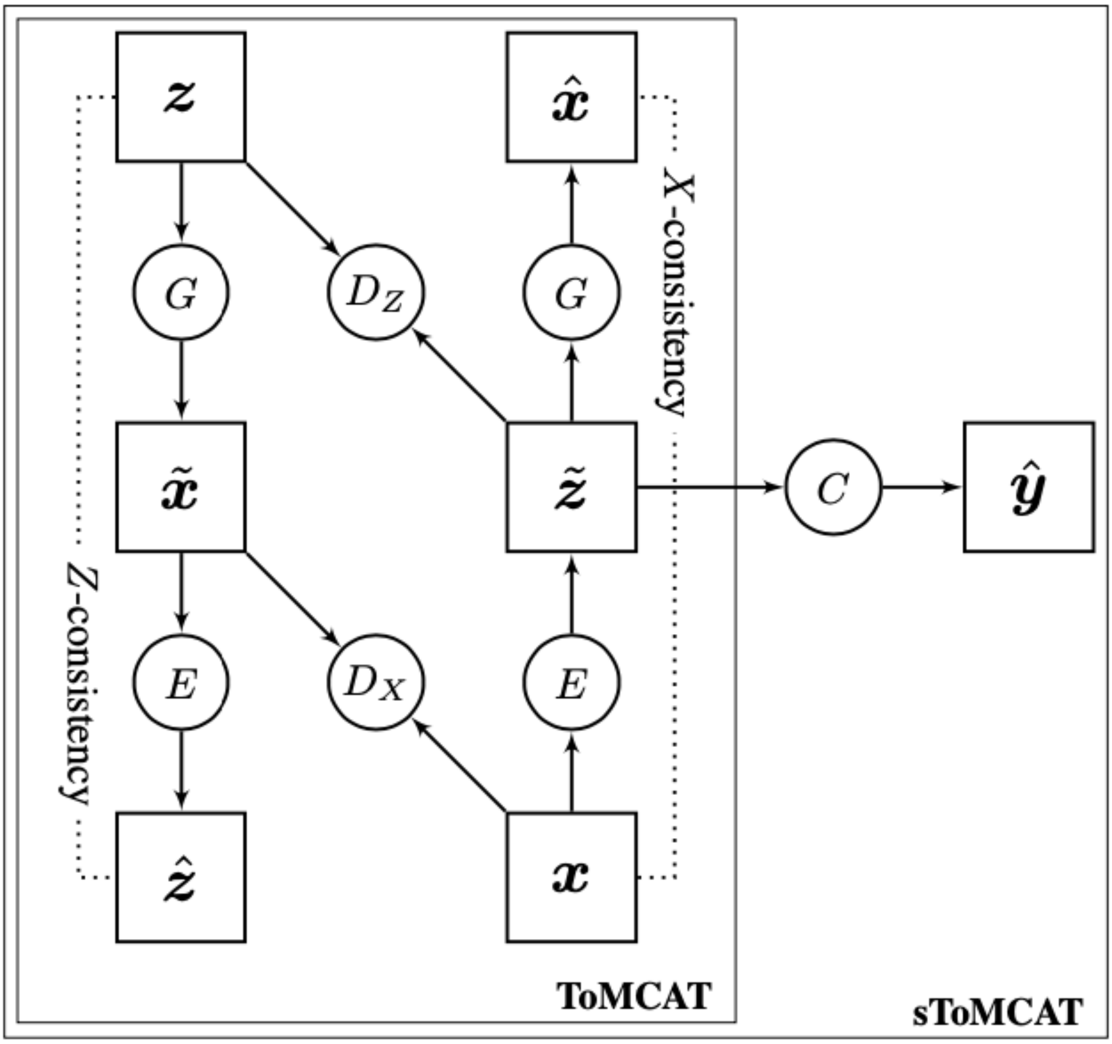

Figure 1: The framework of ToMCAT and sToMCAT. Circles are neural networks, squares are data representations, and arrows indicate the forward pass directions.

For labeled documents we extend ToMCAT with a classifier C to allow the incorporation of label information

For a word distribution x and its one-hot label y, x is first encoded by the encoder E into the topic distribution z, and then z is fed to the classifier C to predict the probability of y. The predictive objective is defined as:

$$\mathcal{L}_{\text{cls}}(E, C) = -\mathbb{E}_{(\boldsymbol{x},\boldsymbol{y})\sim p_{\text{data}}(\boldsymbol{x},\boldsymbol{y})}[\boldsymbol{y} \log C(E(\boldsymbol{x}))],$$

where L is the dimension of y.

We employ an MLP classifier: [Linear(K, H) → LeakyReLU(0.1) → BN → Linear(H, L) → Softmax].

For sToMCAT, the topic model and the classifier are trained jointly, and its overall objective is defined as:

$$\mathcal{L}\text{sup}(G, E, D_X, D_Z, C) = \mathcal{L}(G, E, D_X, D_Z) + \lambda_3 \mathcal{L}_{\text{cls}}(E, C).$$

Motivation

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Topic modeling

Supervised neural topic model (with cycle-consistent adversarial training and MLP classifier, sToMCAT)

Baselines: sLDA (Mcauliffe and Blei, 2008), Scholar (Card et al., 2018)

Topic modeling parameters

Nr of topics: {20, 30, 50, 75, 100}
Optimizer: Adam
learning rate: 0.0001 (for G, E, D_X) , 0.001 (for C)
momentum term β_1: 0.5 (for G, E, D_X) , 0.9 (for C)
Hidden unit nr: 100
Weight clipping: 0.01
λ^1: 2
λ^2: 0.2
λ^3: 1

Nr. of topics

Results examined on 20, 30, 50, 75, 100

Label

One of 14 or 20 categories from the DBpedia and 20 Newsgroups datasets respectively

Label selection

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Label quality evaluation

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Assessors

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Domain

Domain (paper): Neural topic modeling
Domain (corpus): News, miscellaneous (Wikipedia)

Problem statement

Advances on deep generative models have attracted significant research interest in neual topic modeling.
The recently proposed Adversarial-neural Topic Model models topics with an adversarially trained generator network and employs Dirichlet prior to capture the semantic patterns in latent topics.
It is effective in discovering coherent topics but unable to infer topic distributions for given documents or utilize available document labels.

To overcome such limitations, we propose Topic Modeling with Cycle-consistent Adversarial Training (ToMCAT) and its supervised version sToMCAT.
ToMCAT employs a generator network to interpret topics and an encoder network to infer document topics.
Adversarial training and cycle-consistent constraints are used to encourage the generator and the encoder to produce realistic samples that coordinate with each other.
sToMCAT extends ToMCAT by incorporating document labels into the topic modeling process to help discover more coherent topics.

Corpus

Origin: Various news sources

Nr. of documents: 18.750

Details:

- 20 Newsgroups

Origin: Wikipedia

Nr. of documents: 169.984

Details:

- DBPedia (Ontology)

Dataset	#Train	#Test	Vocab Size	#Class
NYT	99,992	-	12,604	-
GRL	29,762	-	15,276	-
DBP	99,991	69,993	9,005	14
20NG	11,258	7,492	2,000	20

Table 1: Dataset statistics.

Document

Pre-processing

- tokenization
- lemmatization
- removal of stopwords, and low-frequency words

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research interest in neural topic modeling. The recently proposed Adversarial-
neural Topic Model models topics with an adversarially trained generator
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topics. It is effective in discovering coherent topics but unable to infer
topic distributions for given documents or utilize available document labels.
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document topics. Adversarial training and cycle-consistent constraints are used
to encourage the generator and the encoder to produce realistic samples that
coordinate with each other. sToMCAT extends ToMCAT by incorporating document
labels into the topic modeling process to help discover more coherent topics.
The effectiveness of the proposed models is evaluated on unsupervised/
supervised topic modeling and text classification. The experimental results
show that our models can produce both coherent and informative topics,
outperforming a number of competitive baselines.",
}
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#Thesis/Papers/Initial