Graph Convolutional Networks for Text Classification

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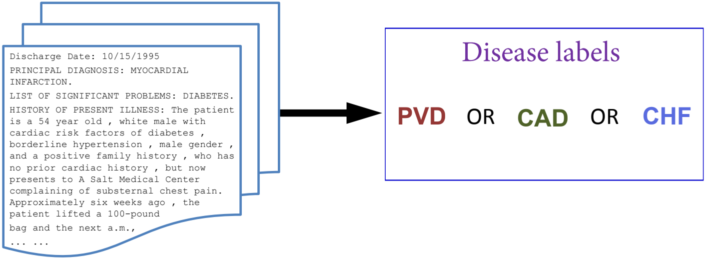
November 15, 2018

Overview

Problem

Text Classification

- A fundamental problem in Natural Language Processing (NLP)
- Many applications:
  - News filtering
  - Spam detection
  - Opinion mining
  - Computational phenotyping
- Essential Intermediate Step: Text Representation



Traditional Methods

Feature Engineering

- bag-of-words
- n-grams
- entities in ontology
- text graph feature mining
  - a textual document as a graph-of-words
  - text classification as graph classification
  - frequent subgraphs mining
  - graph-of-words as regularization

- Could not learn text representations automatically

Deep learning for Text Classification

Word embedding based methods

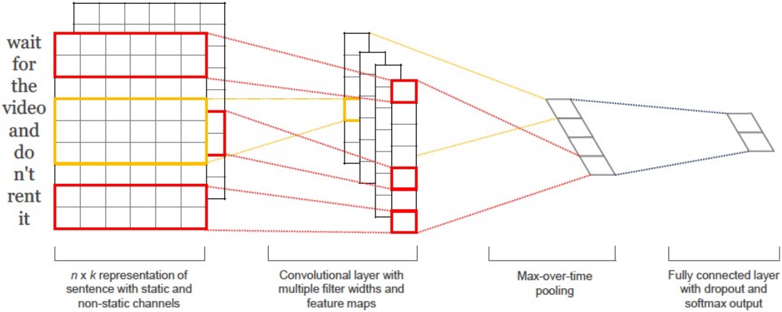
- aggregated word embeddings as document embeddings
  - PV-DBOW, PV-DM
  - fastText
  - SWEM
- jointly learned word/document and label embeddings
  - PTE
  - LEAM

Deep learning for Text Classification

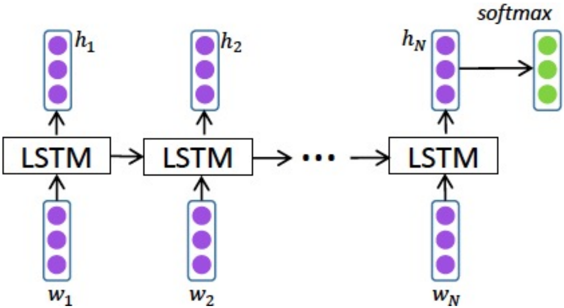
Deep neural network

- Convolutional Neural Networks (CNN)
  - Word CNN
  - Char CNN
  - Very Deep CNN
- Recurrent Neural Networks (RNN)
  - LSTM
  - Bi-LSTM
  - GRU
- Attention mechanisms
  - HAN
  - Attention-based LSTM

Word CNN


wait
for
the
video
and
do
n't
rent
it
n x k representation of sentence with static and non-static channels
Convolutional layer with multiple filter widths and feature maps
Max-over-time pooling
Fully connected layer with dropout and softmax output

LSTM

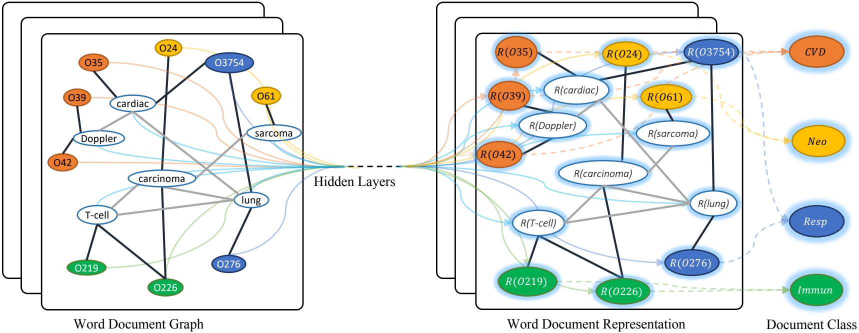


Inductive Bias

Component	Entities	Relations	Rel. inductive bias	Invariance
Fully connected	Units	All-to-all	Weak	-
Convolutional	Grid elements	Local	Locality	Spatial translation
Recurrent	Timesteps	Sequential	Sequentiality	Time translation
Graph network	Nodes	Edges	Arbitrary	Node, edge permutations

- CNN and RNN prioritize locality and sequentiality.
- They can model local consecutive word sequences well.
- They may ignore global word co-occurrence in a corpus.

Text GCN


O35
O24
O3754
O39
cardiac
O61
sarcoma
Doppler
O42
carcinoma
lung
T-cell
O219
O226
O276
Word Document Graph
Hidden Layers
R(O35)
R(O24)
R(O3754)
R(O39)
R(cardiac)
R(O61)
R(Doppler)
R(sarcoma)
R(O42)
R(carcinoma)
R(lung)
R(T-cell)
R(O276)
R(O219)
R(O226)
Word Document Representation
CVD
Neo
Resp
Immun
Document Class

Datasets

Dataset	# Docs	# Training	# Test	# Words	# Nodes	# Classes	Average Length
20NG	18,846	11,314	7,532	42,757	61,603	20	221.26
R8	7,674	5,485	2,189	7,688	15,362	8	65.72
R52	9,100	6,532	2,568	8,892	17,992	52	69.82
Ohsumed	7,400	3,357	4,043	14,157	21,557	23	135.82
MR	10,662	7,108	3,554	18,764	29,426	2	20.39

Implementation Details

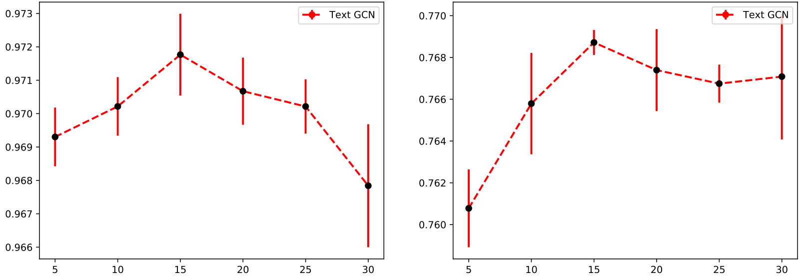
- Framework: TensorFlow.
- Parameters:
  - The number of convolution filters: 256
  - The convolution kernel size: 5
  - The dimension of hidden layer in the fully connected layer: 128
  - Dropout keep probability: 0.8
  - Learning rate: 0.001
  - Batch size: 64
  - The number of learning epochs: 30
- We also tried other parameters but do not find much difference.
- Softmax cross entropy loss as the loss function.
- Adam algorithm as the optimizer.

Results

Table 2: Test Accuracy on document classification task. We run all models 10 times and report mean $\pm$ standard deviation. Text GCN significantly outperforms baselines on 20NG, R8, R52 and Ohsumed based on student t-test ($p < 0.05$).

Model	**20NG**	**R8**	**R52**	**Ohsumed**	**MR**
TF-IDF + LR	0.8319 ± 0.0000	0.9374 ± 0.0000	0.8695 ± 0.0000	0.5466 ± 0.0000	0.7459 ± 0.0000
CNN-rand	0.7693 ± 0.0061	0.9402 ± 0.0057	0.8537 ± 0.0047	0.4387 ± 0.0100	0.7498 ± 0.0070
CNN-non-static	0.8215 ± 0.0052	0.9571 ± 0.0052	0.8759 ± 0.0048	0.5844 ± 0.0106	$\mathbf{0.7775 \pm 0.0072}$
LSTM	0.6571 ± 0.0152	0.9368 ± 0.0082	0.8554 ± 0.0113	0.4113 ± 0.0117	0.7506 ± 0.0044
LSTM (pretrain)	0.7543 ± 0.0172	0.9609 ± 0.0019	0.9048 ± 0.0086	0.5110 ± 0.0150	0.7733 ± 0.0089
Bi-LSTM	0.7318 ± 0.0185	0.9631 ± 0.0033	0.9054 ± 0.0091	0.4927 ± 0.0107	0.7768 ± 0.0086
PV-DBOW	0.7436 ± 0.0018	0.8587 ± 0.0010	0.7829 ± 0.0011	0.4665 ± 0.0019	0.6109 ± 0.0010
PV-DM	0.5114 ± 0.0022	0.5207 ± 0.0004	0.4492 ± 0.0005	0.2950 ± 0.0007	0.5947 ± 0.0038
PTE	0.7674 ± 0.0029	0.9669 ± 0.0013	0.9071 ± 0.0014	0.5358 ± 0.0029	0.7023 ± 0.0036
fastText	0.7938 ± 0.0030	0.9613 ± 0.0021	0.9281 ± 0.0009	0.5770 ± 0.0049	0.7514 ± 0.0020
fastText (bigrams)	0.7967 ± 0.0029	0.9474 ± 0.0011	0.9099 ± 0.0005	0.5569 ± 0.0039	0.7624 ± 0.0012
SWEM	0.8516 ± 0.0029	0.9532 ± 0.0026	0.9294 ± 0.0024	0.6312 ± 0.0055	0.7665 ± 0.0063
LEAM	0.8191 ± 0.0024	0.9331 ± 0.0024	0.9184 ± 0.0023	0.5858 ± 0.0079	0.7695 ± 0.0045
Graph-CNN-C	0.8142 ± 0.0032	0.9699 ± 0.0012	0.9275 ± 0.0022	0.6386 ± 0.0053	0.7722 ± 0.0027
Graph-CNN-S	–	0.9680 ± 0.0020	0.9274 ± 0.0024	0.6282 ± 0.0037	0.7699 ± 0.0014
Graph-CNN-F	–	0.9689 ± 0.0006	0.9320 ± 0.0004	0.6304 ± 0.0077	0.7674 ± 0.0021
Text GCN	$\mathbf{0.8634 \pm 0.0009}$	$\mathbf{0.9707 \pm 0.0010}$	$\mathbf{0.9356 \pm 0.0018}$	$\mathbf{0.6836 \pm 0.0056}$	0.7674 ± 0.0020

Results



(a) R8 (b) MR

Figure 2: Test accuracy with different sliding window sizes.

Results

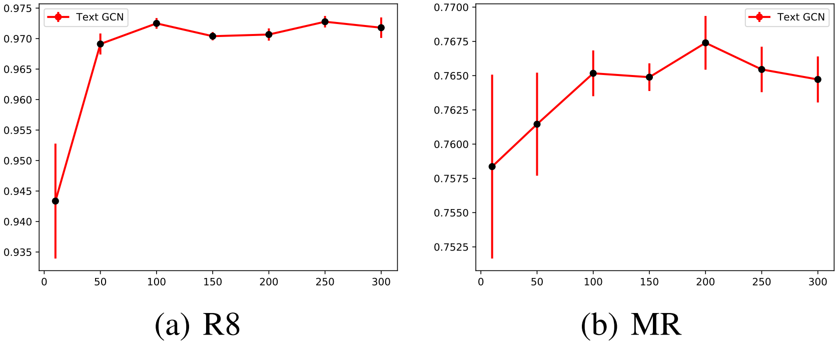


Figure 3: Test accuracy by varying embedding dimensions.

Results

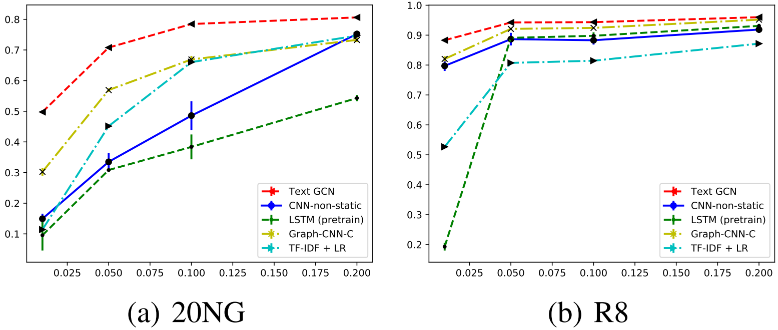
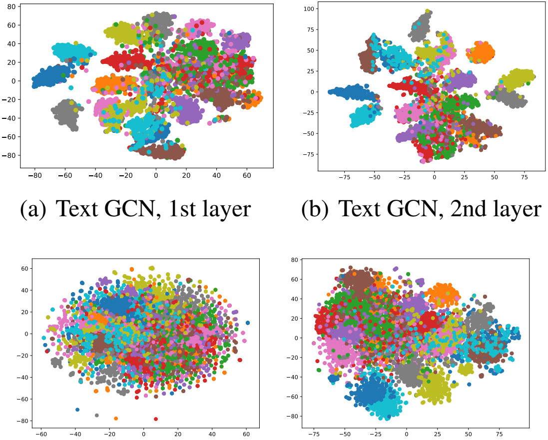


Figure 4: Test accuracy by varying training data proportions.

Results



(a) Text GCN, 1st layer (b) Text GCN, 2nd layer

(c) PV-DBOW (d) PTE

Figure 5: The t-SNE visualization of test set document embeddings in 20NG.

Results

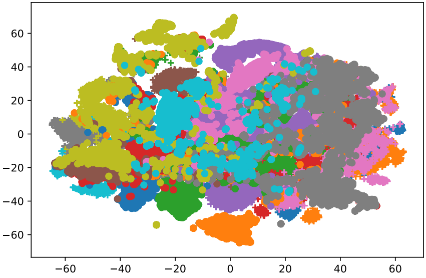


Figure 6: The t-SNE visualization of the second layer word embeddings (20 dimensional) learned from 20NG. We set the dimension with the largest value as a word's label.

Results

Table 3: Words with highest values for several classes in 20NG. Second layer word embeddings are used. We show top 10 words for each class.

comp.graphics	sci.space	sci.med	rec.autos
jpeg	space	candida	car
graphics	orbit	geb	cars
image	shuttle	disease	v12
gif	launch	patients	callison
3d	moon	yeast	engine
images	prb	msg	toyota
rayshade	spacecraft	vitamin	nissan
polygon	solar	syndrome	v8
pov	mission	infection	mustang
viewer	alaska	gordon	eliot

Results

- We released our implementation.
- `https://github.com/yao8839836/text_gcn`

Thank You!