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Interpretable Neural network driven by quantum probability theory

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Done with the collaboration













Contents

- Motivation: Interpretability in end2end network
- Method: Hilbert Semantic Space
- Applications: language representation and matching
 - Text classification
 - Matching with question answering

End-to-end Paradigm



https://www.youtube.com/watch?v=TYpBJ71VW9g

An Pipeline example for text processing



End to end mechanism

- ✓ Less accumulating error
- ✓ Less involvement with Human beings
- Improve performance with shared features of the downstream tasks and upstream tasks

Hard to adjust
Hard to transfer
Hard to understand

We need End to End mechanism, but in a fine-grained way

What is **Interpretability**

- Post-hoc explanations
 - Take a learned model and draw some kind of useful insights
 - E.g. Visualization in machine translation [Liu Yang & Maosong Sun ACL 2017]
- Transparency
 - Targeting ``how does the model work?" and seeks to provide some way to understand the core mechanisms
 - E.g. Capsule Network [Hinton NIPS 2017]

Zachary C Lipton. The mythos of model interpretability. arXiv preprint arXiv:1606.03490, 2016, **ICML** Workshop on Human Interpretability in Machine Learning Yanzhuo Ding, Yang Liu, Huanbo Luan, and Maosong Sun. Visualizing and understanding neural machine translation. **ACL**, volume 1, pages 1150–1159, 2017. Sabour S, Frosst N, Hinton G E. Dynamic routing between capsules[C]//**NIPS . 2017**: 3856-3866.

Interpretability: Attention

For a given vector \vec{w} , we normalize it with **softmax** thus guarantee their sum equals to 0

$$\vec{w}' = softmax(\vec{w}), \ w_i = \frac{e^{w_i}}{\sum e^{w_i}}$$





by ent423, ent261 correspondent updated 9:49 pm et, thu	by ent270, ent223 updated 9:35 am et, mon march 2, 2015
march 19,2015 (ent261) a ent114 was killed in a parachute	(ent223) ent63 went familial for fall at its fashion show in
accident in ent45, ent85, near ent312, a ent119 official told	ent231 on sunday , dedicating its collection to `` mamma"
ent261 on wednesday .he was identified thursday as	with nary a pair of `` mom jeans " in sight .ent164 and ent21
special warfare operator 3rd class ent23,29, of ent187,	who are behind the ent196 brand, sent models down the
ent265 . `` ent23 distinguished himself consistently	runway in decidedly feminine dresses and skirts adorned
throughout his career . he was the epitome of the quiet	with roses , lace and even embroidered doodles by the
professional in all facets of his life , and he leaves an	designers 'own nieces and nephews . many of the looks
inspiring legacy of natural tenacity and focused	featured saccharine needlework phrases like `` i love you ,
ent119 identifies deceased sailor as X, who leaves behind a wife	X dedicated their fall fashion show to moms

(b) A person is standing on a beach with a surfboard.

Design each subcomponents in the End-2-end architecture with a good background of the task

• Both language understanding and artificial intelligence require being able to understand bigger things from knowing about smaller parts

Christopher Manning 2017

Motivations

- Design self-*explainable* subcomponents in end2end network
- Provides more transparency as well as Post-hoc explanations
- Theoretically-sound network

Related works

- End to End language model for QA [AAAI 2018]
- Quantum Many body function for language model in QA [CIKM 2018]
- Quantum-inspired word Embedding [ACL REP4NLP 2018]
- Hilbert Semantic Space [In process without peer review]
 - Text Representation
 - Text Matching

End-2-end Language model for QA



Matching with two matrices

- $tr(\rho_1\rho_2)$
- CNN over $\rho_1 \rho_2$

Zhang Peng, Niu Jiabing, Su Zhan, **Wang Benyou** et al. <u>End-to-End Quantum-like Language Models with Application to</u> <u>Question Answering</u> AAAI 2018

Metric/similarity for $\rho_q \rho_a$ [e.g. tr($\rho_q \rho_a$) or $f_{cnn}(\rho_q \rho_a)$]

- Not theoretically-sound
 - $tr(\rho_q \rho_a)$ can not obtain the maximum value if $\rho_q \neq \rho_a$
 - Can not guarantee $tr(\rho_q \rho_x) + tr(\rho_x \rho_a) > tr(\rho_q \rho_a)$
- Ignoring the mathematical property of density matrix (probability distribution)
- Others
 - Real-valued based instead of **complex-valued**
 - Can not guarantee the unity length of density matrix.

Quantum many-body function for LM



Use CNN to approximate Tensor Decomposition in the projection of Quantum Many-Body Language Function

Peng Zhang, Zhan Su, Lipeng Zhang, **Benyou Wang**, Dawei Song. 2018. A Quantum Many-body Wave Function Inspired Language Modeling Approach, **CIKM 2018**

Complex word-embedding

superposition with phase

$$z^* = z_1 + z_2 = r_1 e^{i\theta_1} + r_2 e^{i\theta_2}$$

= $\sqrt{r_1^2 + r_2^2 + 2r_1 r_2 \cos(\theta_2 - \theta_1)} \times e^{i \arctan\left(\frac{r_1 \sin(\theta_1) + r_2 \sin(\theta_2)}{r_1 \cos(\theta_1) + r_2 \cos(\theta_2)}\right)}$

Li Qiuchi, Uprety Sagar, **Wang Benyou**, Song Dawei <u>Quantum-inspired Complex Word Embedding</u>, ACL 2018 3rd <u>Workshop on Representation Learning for NLP</u>, ACL 2018 RepL4NLP

Hilbert Semantic Space

- Unify these four things in a complex-valued space
 - Sememes
 - Word
 - Phrase/Sentence/Documents
 - Topic as measurements

Definition

- Sememes as basic state
 - { $|e_1\rangle$, $|e_2\rangle$, ..., $|e_n\rangle$ }
- Word as superstition state
 - $|w\rangle = \sum \alpha_i |e_i\rangle$
- Sentence as mixed system



Complex word embedding

- Dimension: the number of
- Length : weight
- Amplitude part: meaning
- Phase part: polarity ?

- How to infer the overall polarity from the polarity of each words?
 - Is there any quantum phenomena here ?

Trainable Measurements for sentence classification



Framework



Implements



https://github.com/wabyking/qnn.git

Physical meaning for our models

Components	Traditional DNN	NNQLM [56]	QPDN
Input embedding	arbitrary real vector	arbitrary real vector	unit complex vector, corresponding to superposition state
input embedding	(-∞, ∞)	(−∞, ∞)	$\{w w \in C^n, w _2 = 1\}$
Low lovel representation	arbitrary real vector	fake, real-valued density matrix	density matrix, corresponding to mixed state
Low-level representation	(-∞, ∞)	$\{\rho \rho \in \mathcal{R}^{n*n}\},\$	$\{\rho \rho = \rho^*, tr(\rho) = 1, \mu \rho \mu^T > 0 \forall \mu \neq \overrightarrow{0}, \rho \in C^{n*n}\},\$
Abstraction	CNN/RNN/Attention	CNN	measurement vector, corresponding to measurement
Abstraction	(-∞, ∞)	(−∞, ∞)	$\{w w \in C^n, w _2 = 1\}$
High-level representation	arbitrary real vector	arbitrary real vector	real-valued probability, corresponding to measurement result
righ-level representation	(-∞, ∞)	(−∞, ∞)	(0, 1)

Table 3: Physical meaning and constraint for each component

Experiments

Table 2: Experiment Results in percentage(%). The best performed value (except for CNN/LSTM) for each dataset is in bold.

Model	CR	MPQA	MR	SST	SUBJ	TREC
Uni-TFIDF	79.2	82.4	73.7	-	90.3	85.0
Word2vec	79.8	88.3	77.7	79.7	90.9	83.6
FastText [28]	78.9	87.4	76.5	78.8	91.6	81.8
Sent2Vec [42]	79.1	87.2	76.3	80.2	91.2	85.8
CaptionRep [21]	69.3	70.8	61.9	-	77.4	72.2
DictRep [22]	78.7	87.2	76.7	-	90.7	81.0
Ours: QPDN	81.0	87.0	80.1	83.9	92.7	88.2
CNN [29]	81.5	89.4	81.1	88.1	93.6	92.4
BiLSTM [16]	81.3	88.7	77.5	80.7	89.6	85.2

Case study for our measurement

Table 7: The learned measurement for dataset MR. They are selected according to nearest words for a measurement vector in Semantic Hibert Space

Measurement	Selected neighborhood words
1	change, months, upscale, recently, aftermath
2	compelled, promised, conspire, convince, trusting
3	goo, vez, errol, esperanza, ana
4	ice, heal, blessedly, sustains, make
5	continue, warned, preposterousness, adding, falseness

Implements for matching

Figure 1: Architecture of Complex-valued Network for Matching. M means a measurement operation according to Eq. 2.



https://github.com/wabyking/qnn.git

Case study

Table 7: The matching patterns for specific sentence pairs in TREC QA. The darker the color, the bigger weight the word is. The [and] denotes the possible border of the current sliding windows.

Question	Correct Answer
Who is the [president or chief executive of Amtrak]?	"Long-term success " said George Warrington , [Amtrak 's president and chief executive] ."
When [was Florence Nightingale born]?	,"On May 12 , 1820 , the founder of modern nursing , [Florence Nightingale , was born] in Florence , Italy ."
When [was the IFC established]?	[IFC was established in] 1956 as a member of the World Bank Group.
[how did women 's role change during the war]	, the [World Wars started a new era for women 's] opportunities to
[Why did the Heaven 's Gate members commit suicide]?,	This is not just a case of [members of the Heaven 's Gate cult committing suicide] to

Experiments

Table 3: Experiment Results on TREC QA Dataset. The best performed values are in bold.

Model	MAP	MRR
Bigram-CNN	0.5476	0.6437
LSTM-3L-BM25	0.7134	0.7913
LSTM-CNN-attn	0.7279	0.8322
aNMM	0.7495	0.8109
MP-CNN	0.7770	0.8360
CNTN	0.7278	0.7831
PWIM	0.7588	0.8219
QLM	0.6780	0.7260
NNQLM-I	0.6791	0.7529
NNQLM-II	0.7589	0.8254
CNM	0.7701	0.8591
Over NNQLM-II	1.48%↑	4.08% ↑

Table 4: Experiment Results on Yahoo QA Dataset. The best performed values are in bold.

Model	P@1	MRR
Okapi BM-25	0.2250	0.4927
LSTM	0.4875	0.6829
CNN	0.4125	0.6323
CNTN	0.4654	0.6687
QLM	0.3950	0.6040
NNQLM-I	0.4290	0.6340
NNQLM-II	0.4660	0.6730
CNM	0.4880	0.6845
Over NNQLM-II	4.72% ↑	1.45% ↑

Table 5: Experiment Results on WikiQA Dataset. The best performed values for each dataset are in bold.

Model	MAP	MRR
Bigram-CNN	0.6190	0.6281
BILSTM	0.6557	0.6695
LSTM-attn	0.6639	0.6828
CNN	0.6701	0.6822
QLM	0.5120	0.5150
NNQLM-I	0.5462	0.5574
NNQLM-II	0.6496	0.6594
CNM	0.6548	0.6664
Over NNQLM-II	1.01% ↑	1.01% ↑

Weights

Table 6: Selected learned important words in TREC QA. All words are lower.

	Selected words
Important	studio, president, women, philosophy scandinavian, washingtonian, berliner, championship defiance, reporting, adjusted, jarred
Unimportant	71.2, 5.5, 4m, 296036, 3.5 may, be, all, born movements, economists, revenues, computers

Learned measurements

Table 8: Selected learned measurements for TREC QA. They were selected according to nearest words for a measurement vector in Semantic Hilbert Space. All the words are lower.

	Selected neighborhood words for a measurement vector
1	andes, nagoya, inter-american, low-caste, kazakhstan
2	cools, injection, boiling, adrift
3	andrews, paul, manson, bair
4	historically, 19th-century, genetic, hatchback, shipbuilding
5	missile, exile, rebellion, darkness

Ablation Test

Table 9: Ablation Test. The values in parenthesis are the performance difference between the model and CNM.

FastText-MaxPool 0.6659 (0.1) CNM-Real 0.7112 (0.0)	
CNM-Real 0.7112 (0.0	$0.7922(0.0659\downarrow)$
	• /
CNM-Global-Mixture 0.6968 (0.0	0733↓) 0.7829 (0.0762↓)
CNM-trace-inner-product 0.6952 (0.0	0749↓) 0.7688 (0.0903↓)
CNM 0.7701	0.8591

Conclusion

- More concrete physical meaning
- Self-explainable subcomponents
- More constrain for the subcomponents
- Guided by Quantum probability theory

Future works

- Current extension:
 - Incorporating more knowledge (e.g. word Polarity) in phase part
 - Multi-task setting to transfer learned measurement to similar tasks
- New insights
 - Explore high-dimension tensor network with Quantum representation
 - **Capsule** Network with Quantum insights
- New tasks:
 - Exploring generating language model with unitary transform
 - Quantum-inspired toy model for **reading comprehension**
 - Exploring position-aware quantum representation for **image**
 - Using complex-valued features for multimodal dataset
- New phenomenon:
 - Word entanglement for generating a better embedding
 - Cross-language entanglement
- Others:
 - Extending our code to some open-source project
 - Reconsidering embedding and supervised learning for IR