



Exploring Interpretable Quantum Representation for language understanding

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Done with the collaboration













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Motivation: Interpretability in end2end network

Method: Hilbert Semantic Space

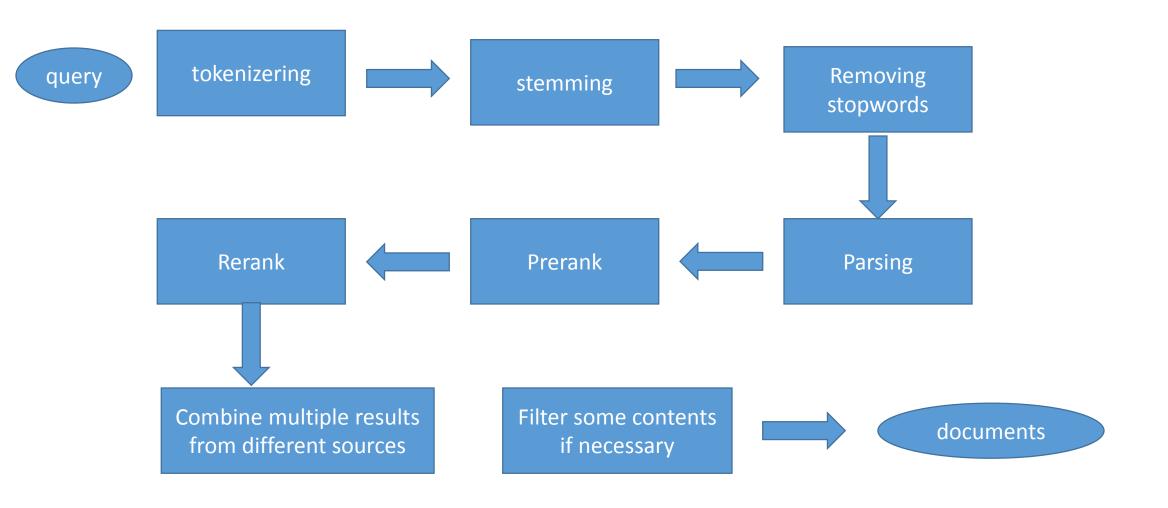
- Applications: language representation and matching
 - Text classification
 - Matching with question answering

Transparency in 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]

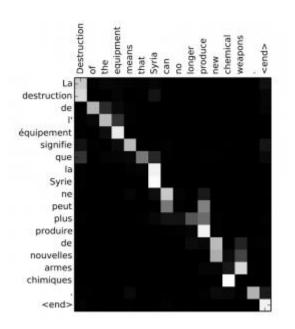
- Transparency
 - Targeting ``how does the model work?" and seeks to provide some way to understand the core mechanisms
 - E.g. Capsule Network [Hinton NIPS 2017]

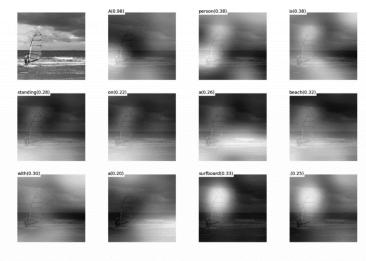
Zachary C Lipton. The mythos of model interpretability. arXiv preprint arXiv:1606.03490, 2016, ICML Workshop on Human Interpretability in Machine Learning Yanzhuo Ding, Yang Liu, Huanbo Luan, and Maosong Sun. Visualizing and understanding neural machine translation. ACL, volume 1, pages 1150–1159, 2017.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

Interpretability: Attention

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

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





by ent423, ent261 correspondent updated 9:49 pm et, thu march 19,2015 (ent261) a ent114 was killed in a parachute accident in ent45, ent85, near ent312, a ent119 official told ent261 on wednesday. he was identified thursday as special warfare operator 3rd class ent23,29, of ent187, ent265." ent23 distinguished himself consistently throughout his career. he was the epitome of the quiet professional in all facets of his life, and he leaves an inspiring legacy of natural tenacity and focused

ent119 identifies deceased sailor as ${\bf X}$,who leaves behind a wife

by ent270 ,ent223 updated 9:35 am et ,monmarch 2 ,2015 (ent223) ent63 went familial for fall at its fashion show in ent231 on sunday ,dedicating its collection to ``mamma" with nary a pair of ``momjeans "insight .ent164 and ent21, who are behind the ent196 brand ,sent models down the runway in decidedly feminine dresses and skirts adorned with roses ,lace and even embroidered doodles by the designers 'own nieces and nephews .many of the looks featured saccharine needlework phrases like ``ilove you ,

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

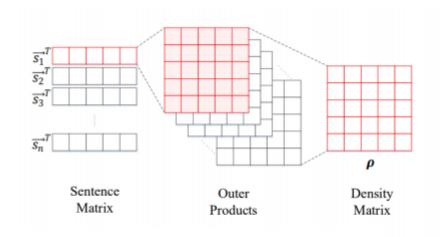
Provides more transparency as well as Post-hoc explanations

• 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]
- Hibert Semantic Space [In process]

End-2-end Language model for QA



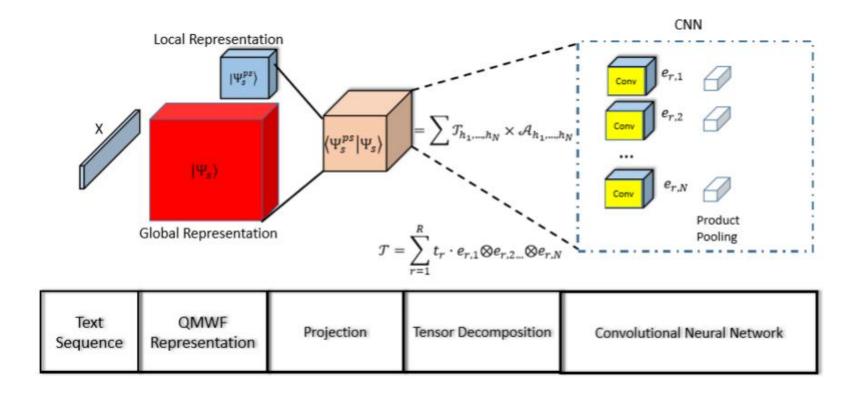
Matching with two matrices

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

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

- 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

Super-linearity superposition with phase

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

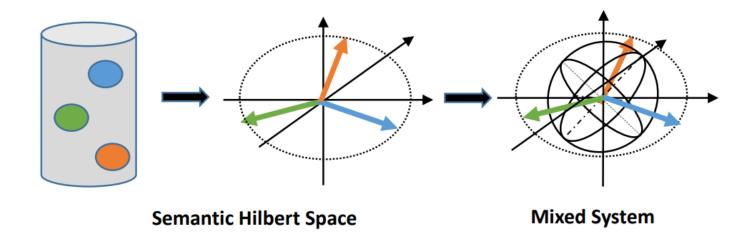
$$= \sqrt{r_1^2 + r_2^2 + 2r_1 r_2 \cos(\theta_2 - \theta_1)} \times e^{i \arctan\left(\frac{r_1 \sin(\theta_1) + r_2 \sin(\theta_2)}{r_1 \cos(\theta_1) + r_2 \cos(\theta_2)}\right)}$$

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
- Word as superstition state
- Sentence as mixed system

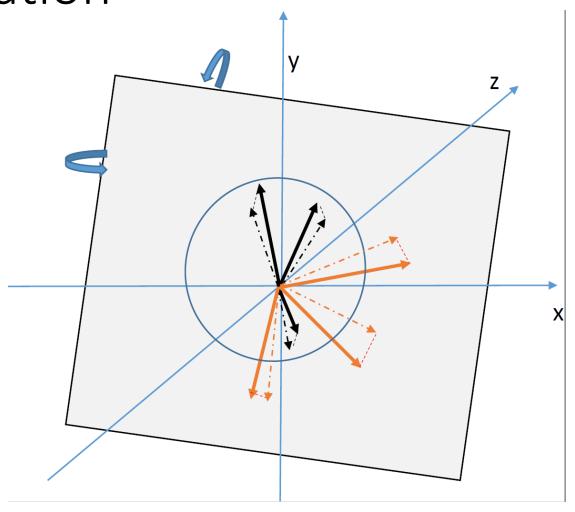


Complex word embedding

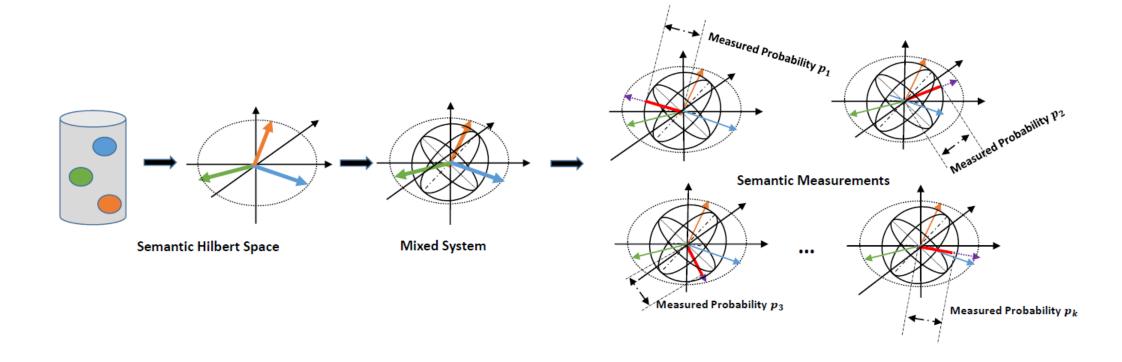
- Dimension: the number of
- Length: weight
- Amplitude part: meaning
- Phase part: polarity?

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

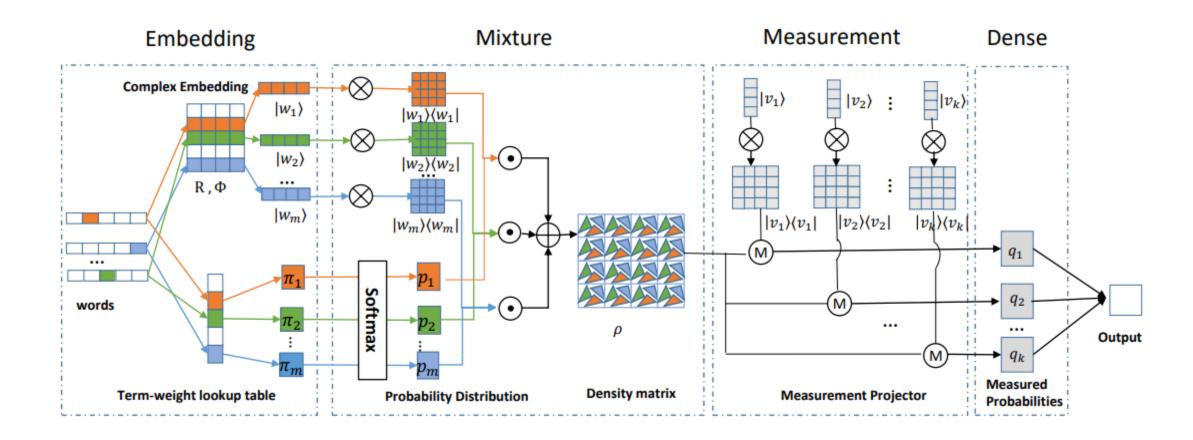
Trainable Measurements for sentence classification



Framework



Implements



Physical meaning for our models

Table 3: Physical meaning and constraint for each component

Components	Traditional DNN	NNQLM [56]	QPDN
Input embedding	arbitrary real vector	arbitrary real vector	unit complex vector, corresponding to superposition state
input embedding	$(-\infty, \infty)$	$(-\infty, \infty)$	$\{w w\in C^n, w _2=1\}$
Low-level representation	arbitrary real vector	fake, real-valued density matrix	density matrix, corresponding to mixed state
Low-level representation	$(-\infty, \infty)$	$\{\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	$(-\infty, \infty)$	$(-\infty, \infty)$	$\{w w\in C^n, w _2=1\}$
High lovel representation	arbitrary real vector	arbitrary real vector	real-valued probability, corresponding to measurement result
High-level representation	(−∞, ∞)	(−∞, ∞)	(0, 1)

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

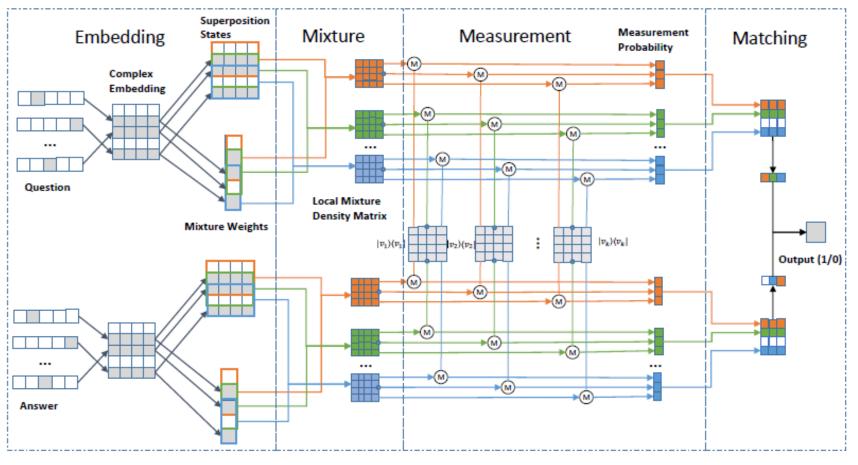
Case study for our measurement

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

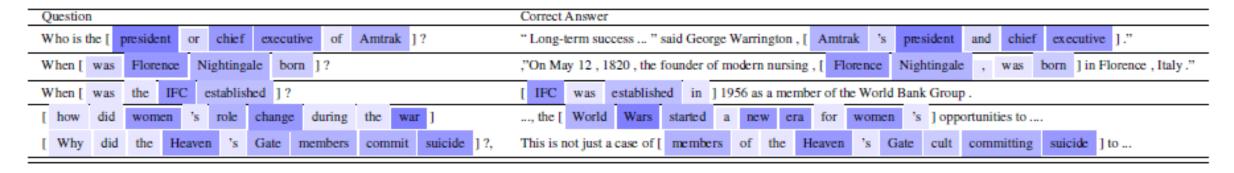
Figure 1: Architecture of Complex-valued Network for Matching. M means a measurement operation according to Eq. 2.



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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.



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.

Setting	MAP	MRR
FastText-MaxPool	0.6659 (0.10421)	0.7152 (0.14391)
CNM-Real	$0.7112 (0.0589 \downarrow)$	$0.7922 (0.0659 \downarrow)$
CNM-Global-Mixture	$0.6968 (0.0733 \downarrow)$	$0.7829 (0.0762 \downarrow)$
CNM-trace-inner-product	$0.6952 (0.0749 \downarrow)$	$0.7688 (0.0903 \downarrow)$
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 with this topic

- Explore high-dimension tensor network with Quantum representation
- Capsule Network with Quantum insights
- Incorporating more knowledge (e.g. word Polarity) in phase part
- Multi-task setting to transfer learned measurement to similar tasks
- Exploring the language generating task (unitary transform)
- Cross-language entanglement
- Exploring position-aware quantum representation for image