A Short Overview On Sentiment Analysis

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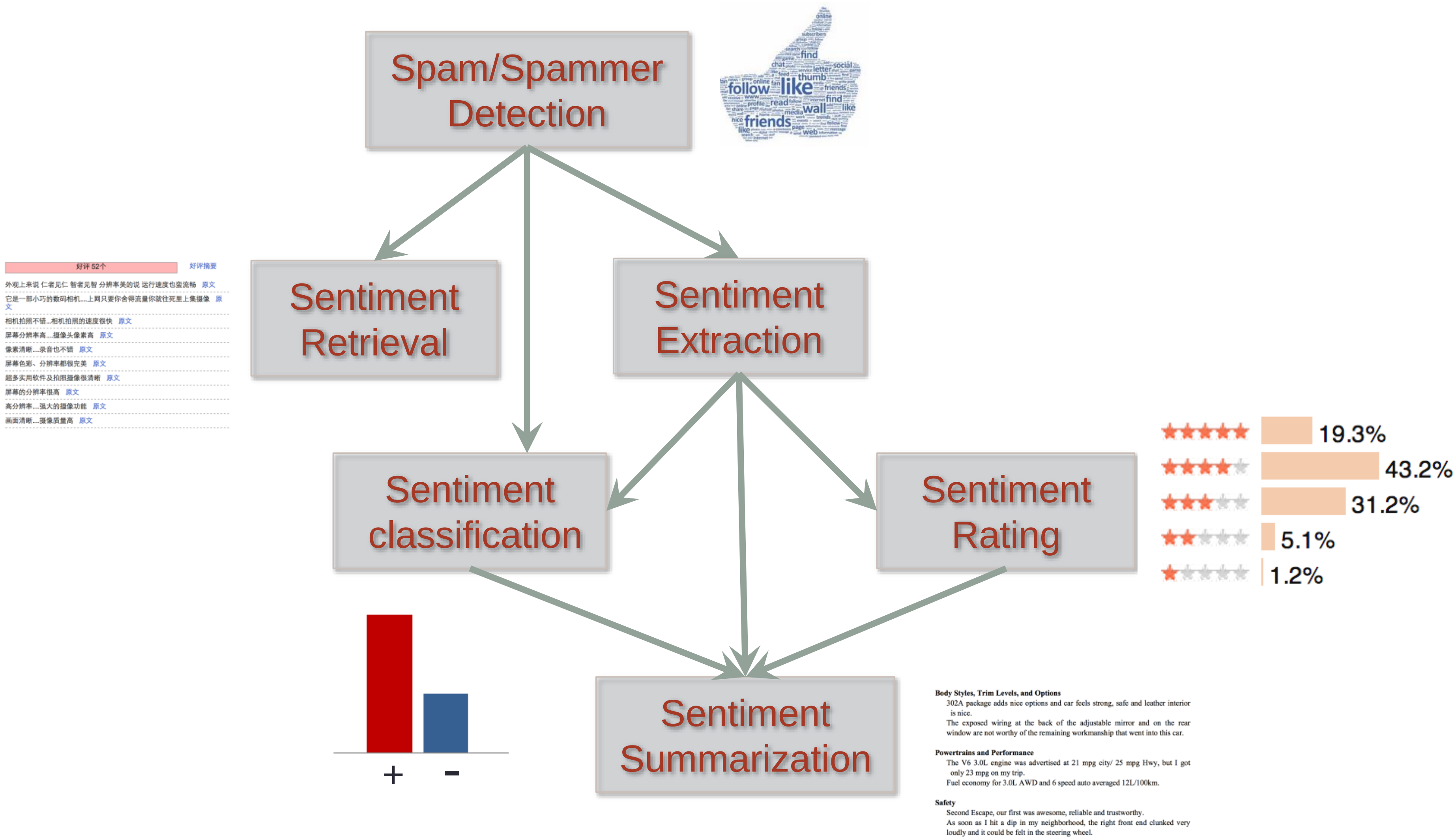
What is Sentiment Analysis?

- Sentiment analysis (SA) or opinion mining
  - computational study of opinion, sentiment, appraisal, evaluation, and emotion.
- Why is it important?
  - Opinions are key influencers of our behaviors.
  - Rise of AI and chatbots
    - Emotion and sentiment are key to human communication

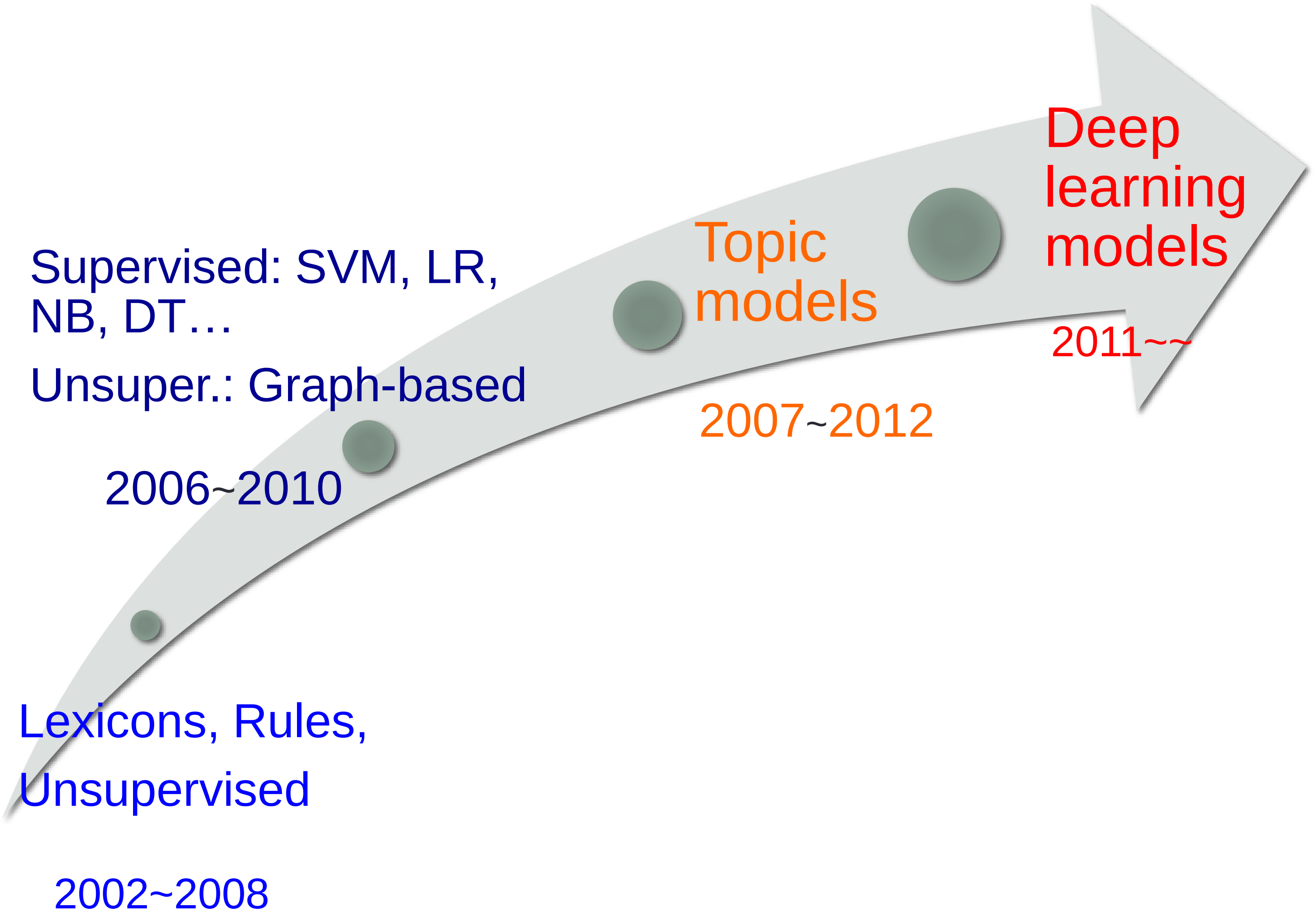
Slides from Prof. Bing Liu, UIC

Roadmap of Sentiment Analysis

'Your brand is not what ***you*** say but what ***they*** say'!



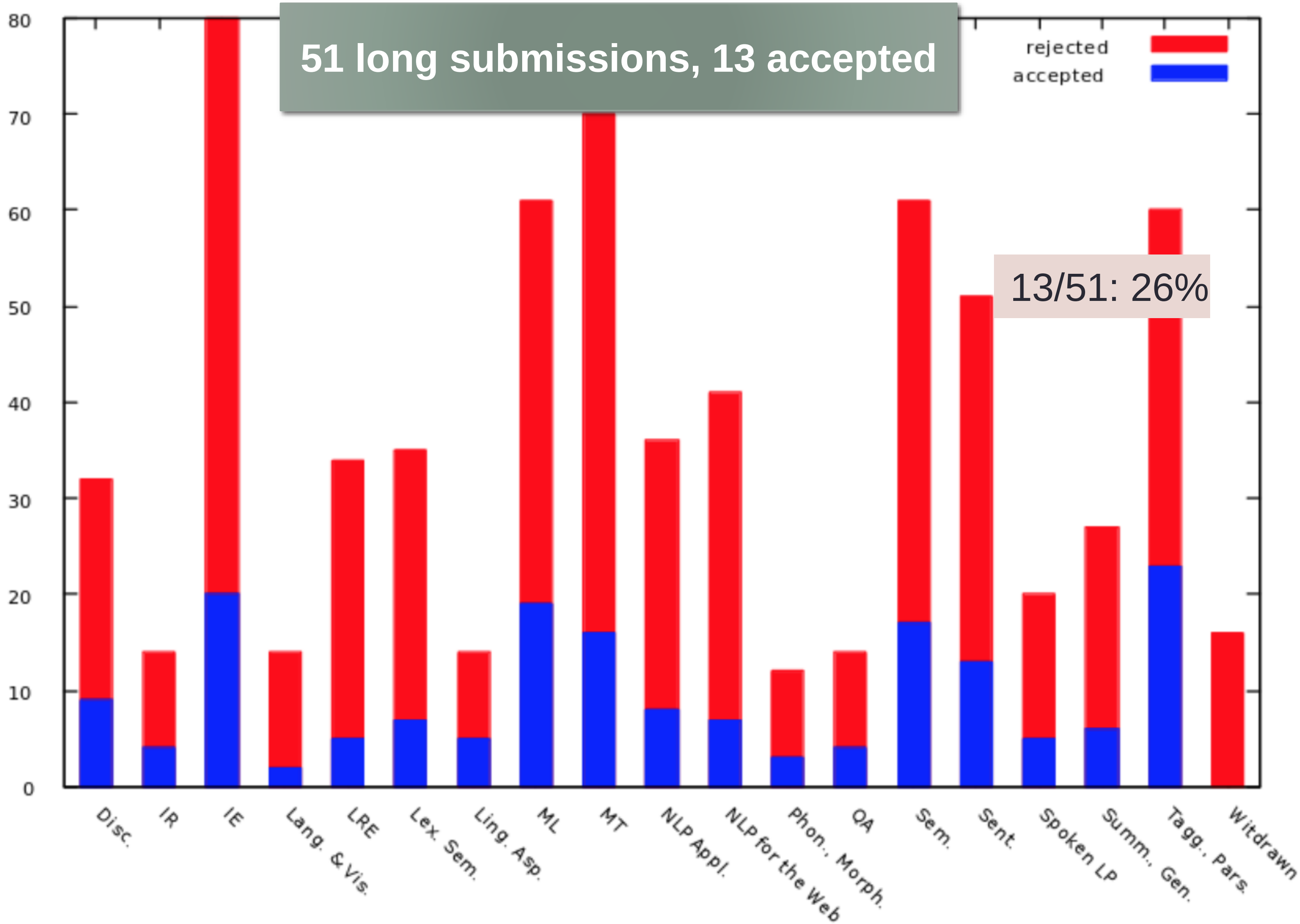
Phases for Sentiment Analysis



- Trends Revealed by Major NLP Conferences

Statistics from ACL 2015

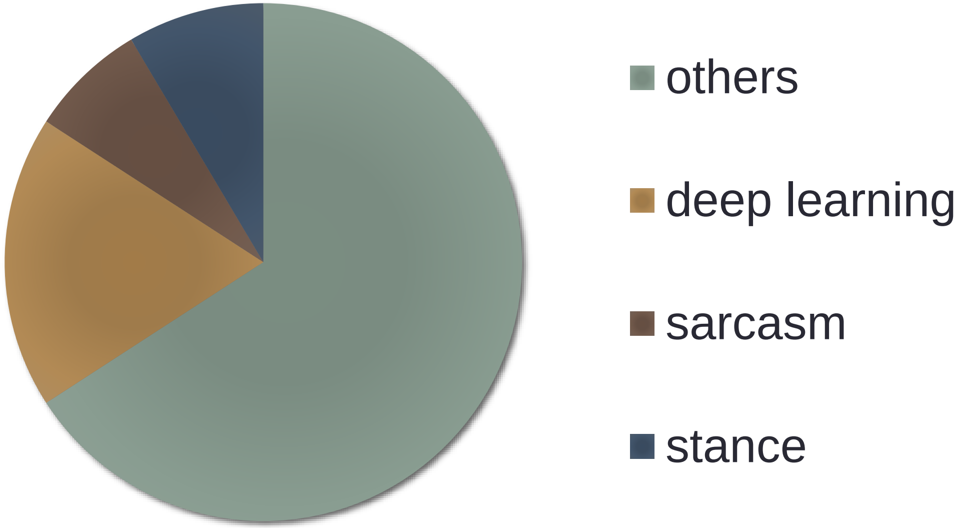
51 long submissions, 13 accepted



13/51: 26%

Statistics from ACL 2016

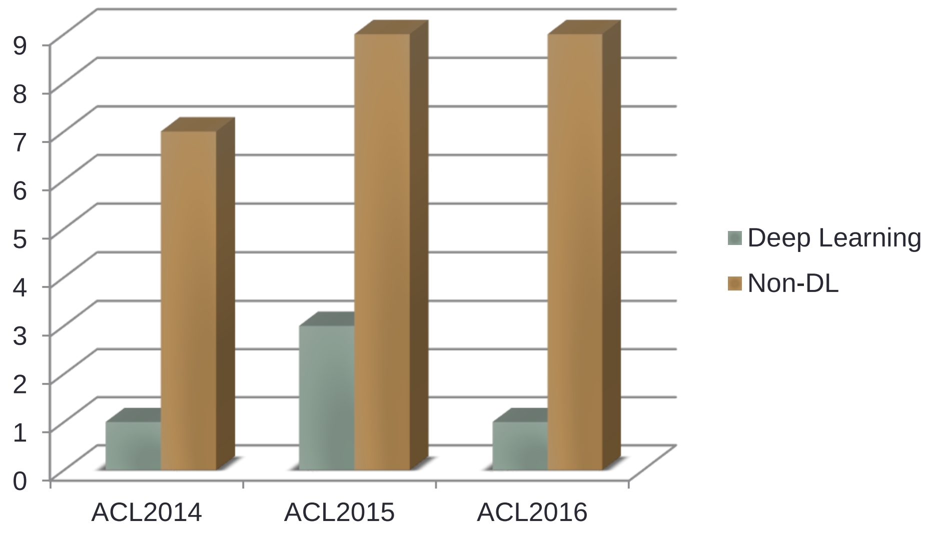
- 82 long submissions, accepted 8, <10%
- Among the 82 submissions:
  - Deep Learning: 15
  - Stance: 7
  - Sarcasm: 6

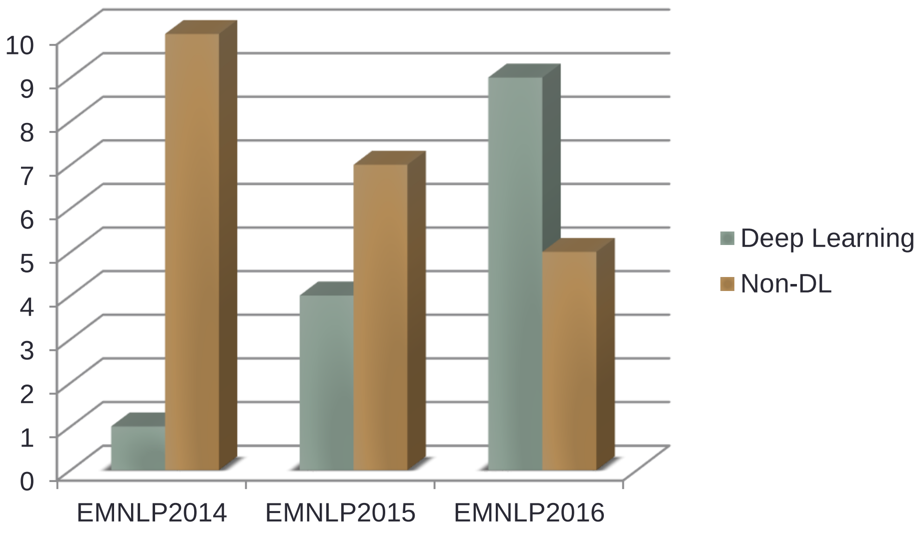


[More statistics can be seen: https://www.aclweb.org/aclwiki/index.php?title=Areas,_chairs,_and_area_submissions](https://www.aclweb.org/aclwiki/index.php?title=Areas,_chairs,_and_area_submissions)

What Were Accepted?

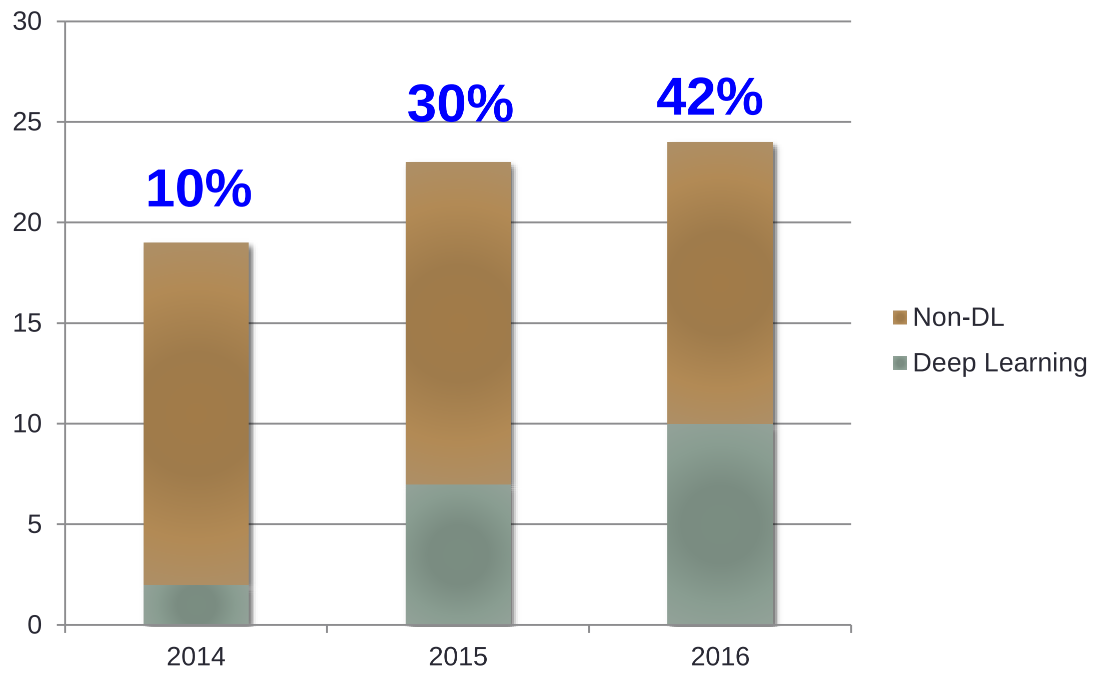
- ACL long papers: 2014/2015/2016: 8/12/10
- EMNLP long papers: 2014/2015/2016: 11/11/14





What Were Accepted?

- The percent of DL papers among what were accepted by ACL/EMNLP rises from **10%→30%→42%**



Ohh, Deep Learning in Sentiment Analysis…

Sentiment Classification on SST

Model	Fine-grained		Positive/Negative	
	All	Root	All	Root
NB	67.2	41.0	82.6	81.8
SVM	64.3	40.7	84.6	79.4
BiNB	71.0	41.9	82.7	83.1
VecAvg	73.3	32.7	85.1	80.1
RNN	79.0	43.2	86.1	82.4
MV-RNN	78.7	44.4	86.8	82.9
RNTN	**80.7**	**45.7**	**87.6**	**85.4**

From Socher et al. 2013

Method	Fine-grained
SVM [Pang and Lee 2008]	40.7
MNB [Wang and Manning 2012]	41.0
bi-MNB [Wang and Manning 2012]	41.9
RNN [Socher et al. 2011]	43.2
RNTN [Socher et al. 2013]	45.7
MV-RNN [Socher et al. 2012]	44.4
AdaMC-RNN [Dong et al. 2014]	45.8
AdaMC-RNTN [Dong et al. 2014]	46.7
DRNN [Irsoy and Cardie 2014]	49.8
TG-RNN (ours)	46.1(0.3)
TE-RNN (ours)	47.8(0.3)
TE-RNTN (ours)	48.8(0.4)
CNN [Kim 2014]	48.0
DCNN [Kalchbrenner et al. 2014]	48.5
LSTM [Tai et al. 2015]	46.4(1.1)
Bi-directional LSTM [Tai et al. 2015]	49.1(1.0)
Tree-LSTM [Tai et al. 2015]	51.0(0.5)
TW-LSTM (ours)	49.9(0.4)
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TW-LSTM+c (ours)	52.0(0.4)
TW-LSTM+c,p (ours)	52.1(0.4)
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TE-LSTM+c,p (ours)	52.6(0.6)

Why, DL to TEXT is not that useful as to IMAGE?

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1000-way image classification on ImageNet

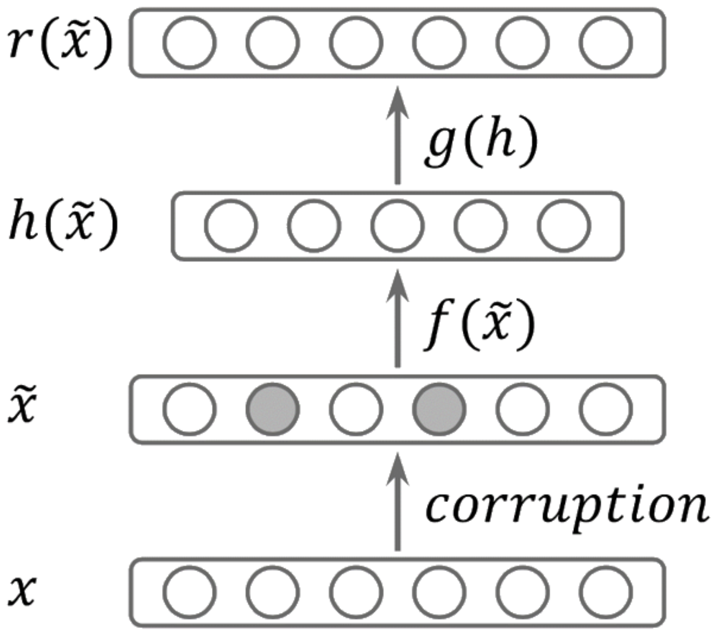
Team	Time	Place	Top-5 error
SuperVision	2012	1	16.42%
ISI	2012	2	26.17%
VGG	2012	3	26.98%
Clarifai	2013	1	11.74%
NUS	2013	2	12.95%
ZF	2013	3	13.51%
GoogLeNet	2014	1	6.66%
VGG	2014	2	7.32%
MSRA	2014	3	8.06%
Andrew Howard	2014	4	8.11%
DeeperVision	2014	5	9.51%
Human	2014	-	5.1%
MSRA PReLU-nets	2015.2	-	4.94%
BN-Inception	2015.2	-	4.82%
Deep Image	2015.5	-	4.58%

Deep Learning Models for Sentiment Analysis

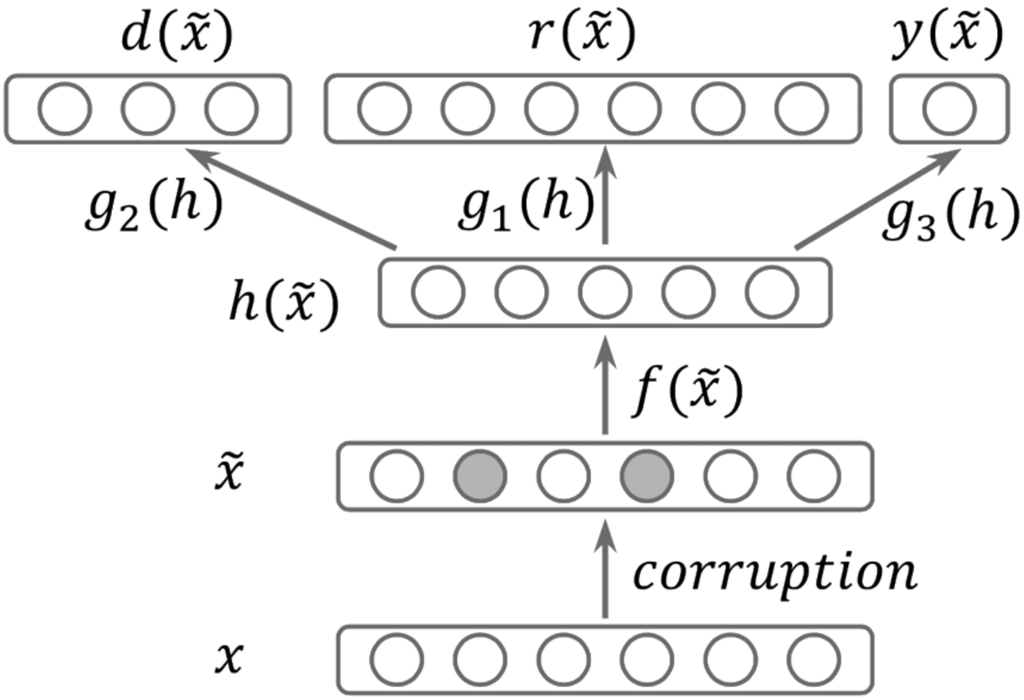
- Bag-of-words representation
  - Denoising autoencoders
  - Restricted boltzmann machine
- Sequence-based representation
  - CNN
  - Recurrent NN
  - LSTM
- Tree-based representation
  - Recursive NN
  - Tree-LSTM

Bag-of-words Represent. Models

- Document-/sentence-level classification



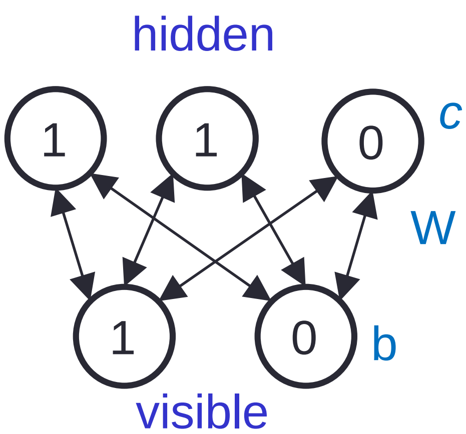
Glorot et al. ICML 2011
Chen et al. 2012



Liu et al. IJCAI 2015

Bag-of-words Represent. Models

- Sentiment Extraction



Restricted Boltzmann Machine

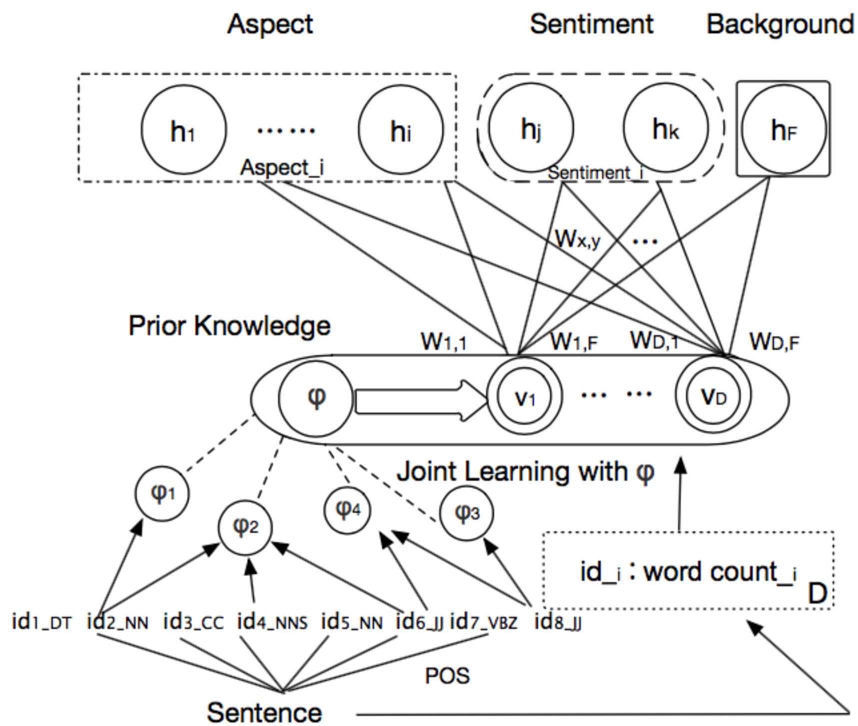
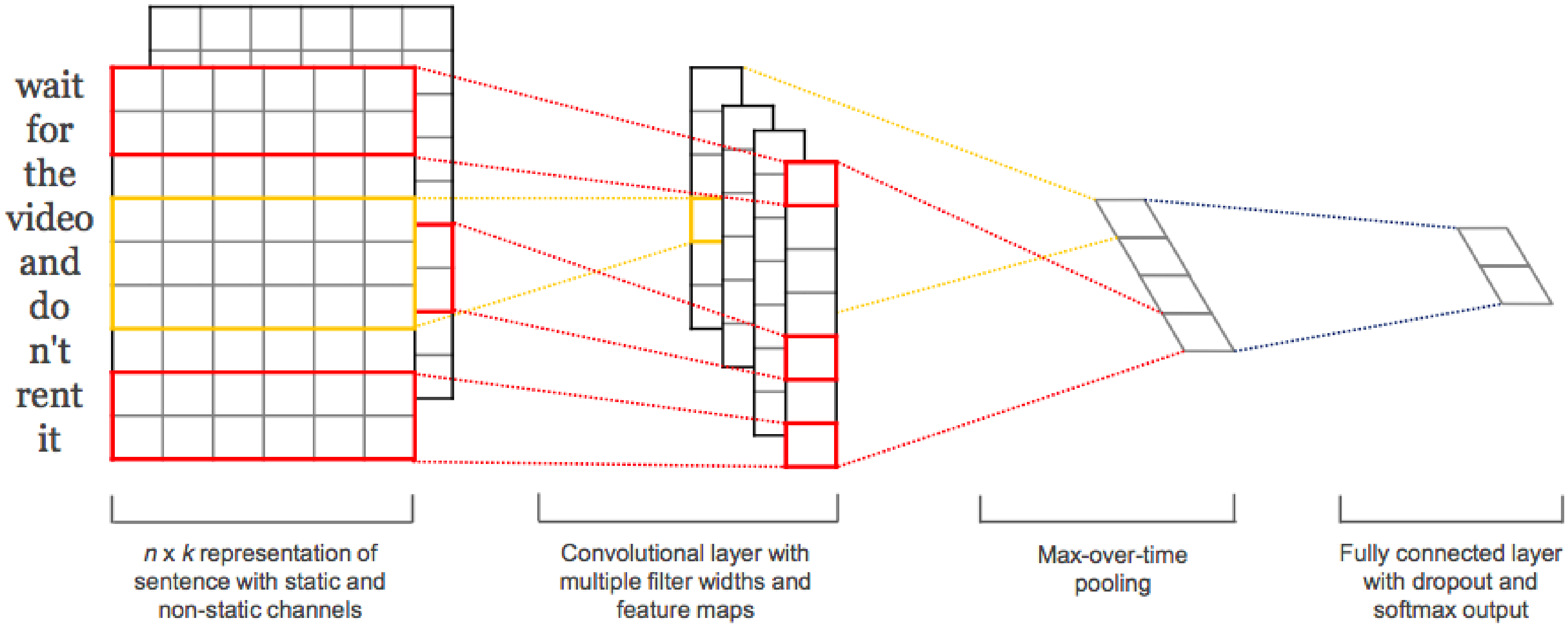


Figure 2: Sentiment-Aspect Extraction Model

Wang et al. ACL2015

Sequence Represent. Models

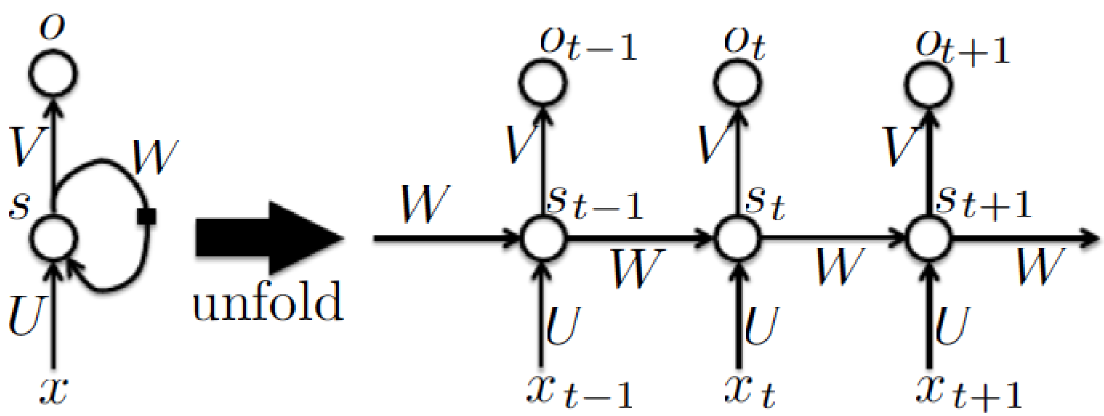
- Convolutional Neural Network



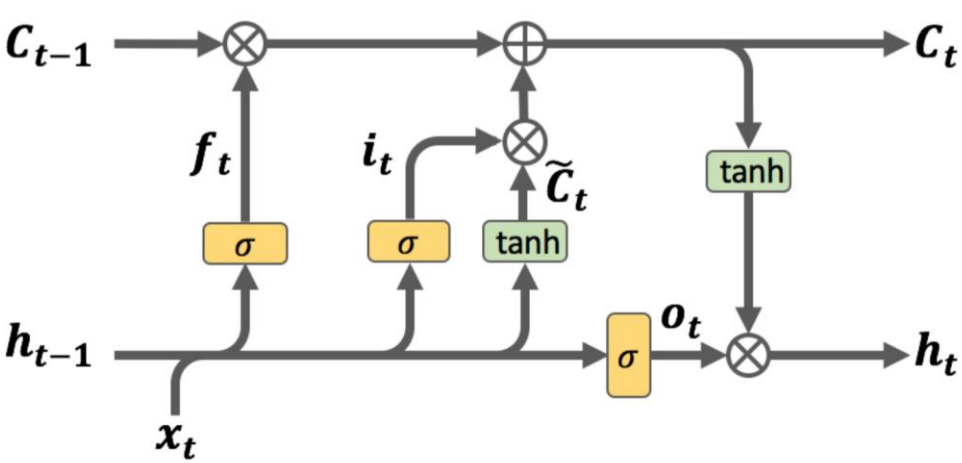
Kim 2014; Kalchbrenner et al. 2014; Wang et al., 2014; Johnson and Zhang, 2014/2015; Tang et al, 2014

Sequence Represent. Models

- Recurrent Neural Network and Long Short-term Memory



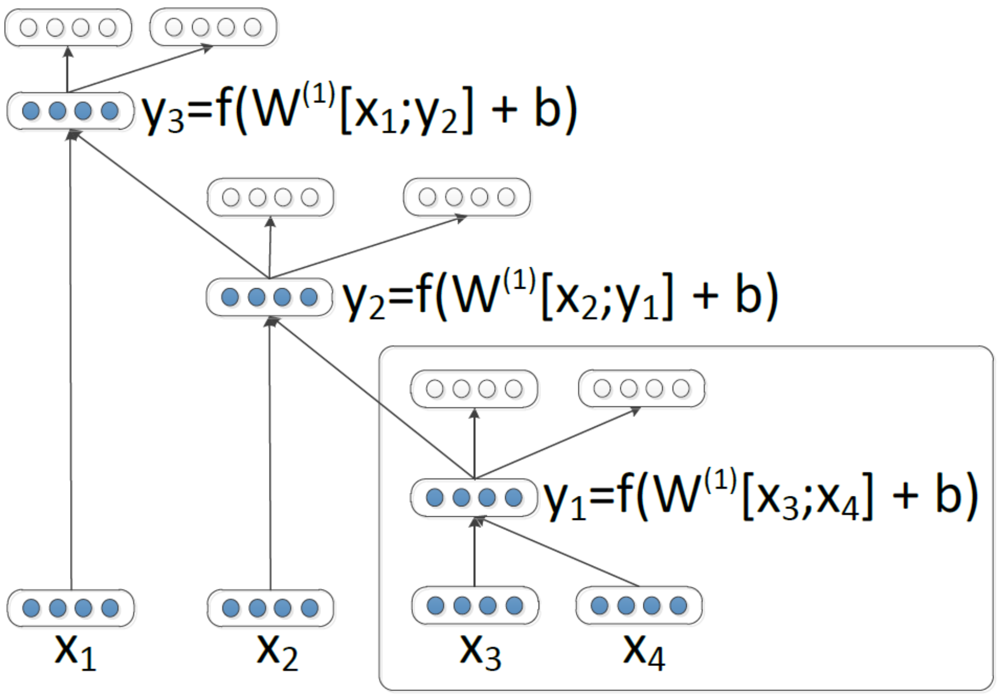
Tang et al. 2015



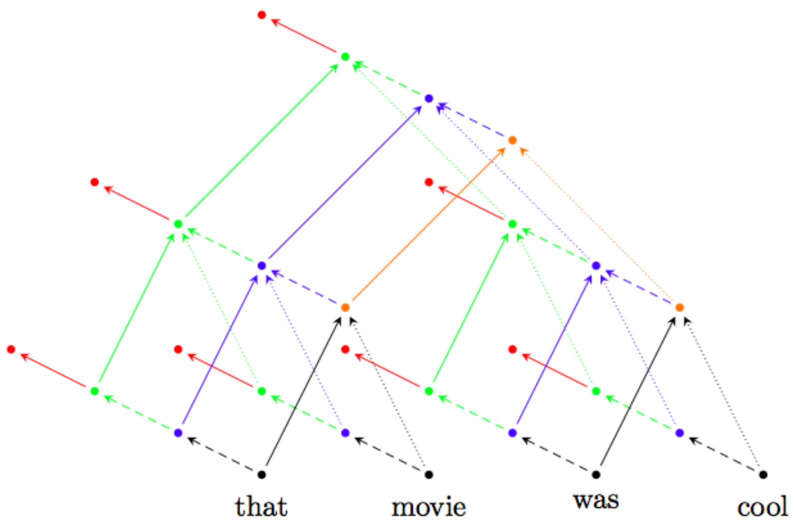
Tang et al. 2016
Wang et al. 2016
Liu et al., 2016
Chen et al., 2015

Tree Represent. Models

Recursive autoencoders



Deep recursive autoencoders

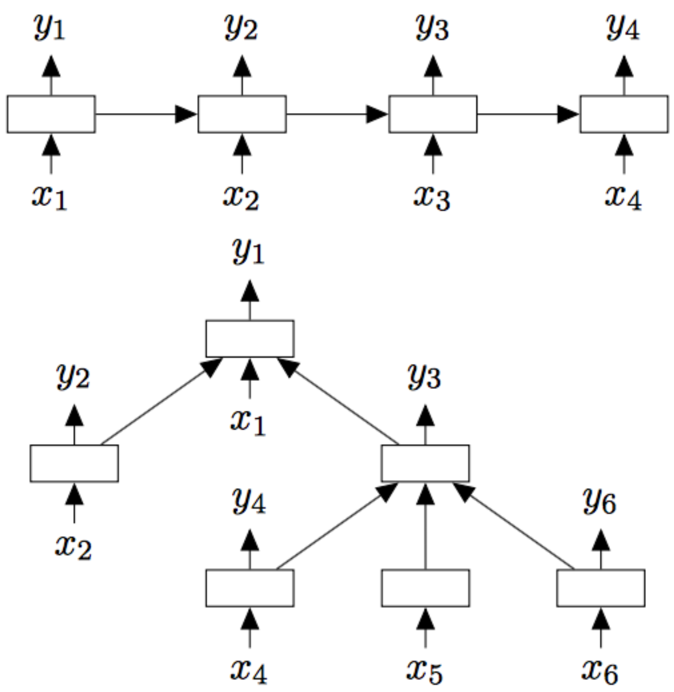


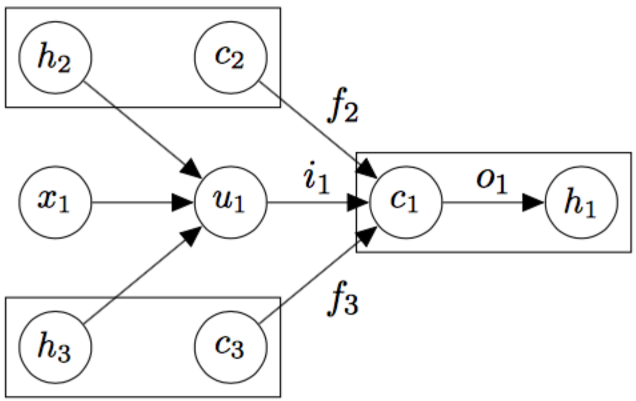
Socher et al. 2011/2012/2013
Dong et al. AAAI2014
Qian et al. ACL2015

Irsoy and Cardie ACL2014

Tree Represent. Models

- Tree-structured LSTM

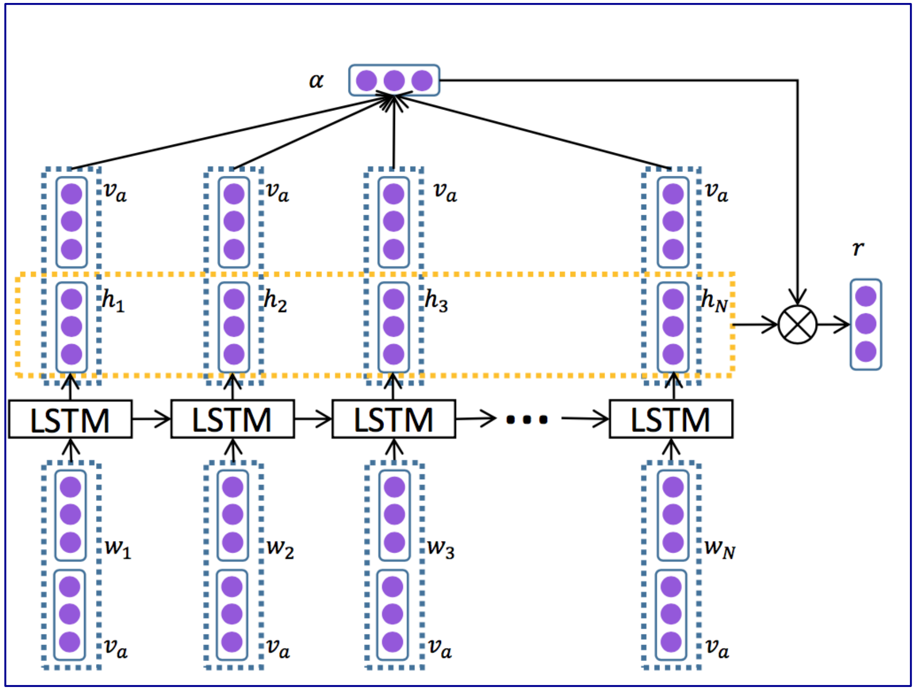




Tai et al. arXiv 2015
Zhu et al. ICML2015

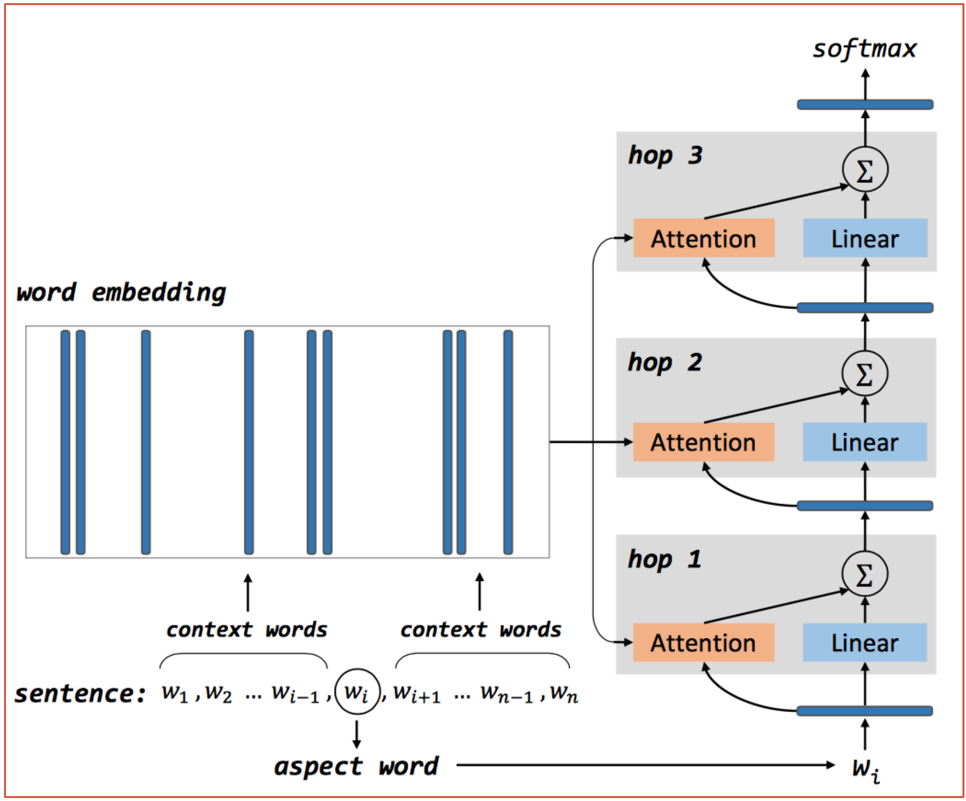
Other Models– Attention and Memory

Attention-based Aspect level SC



Wang et al. EMNLP 2016

Memory-based Aspect level SC



Tang et al. EMNLP 2016

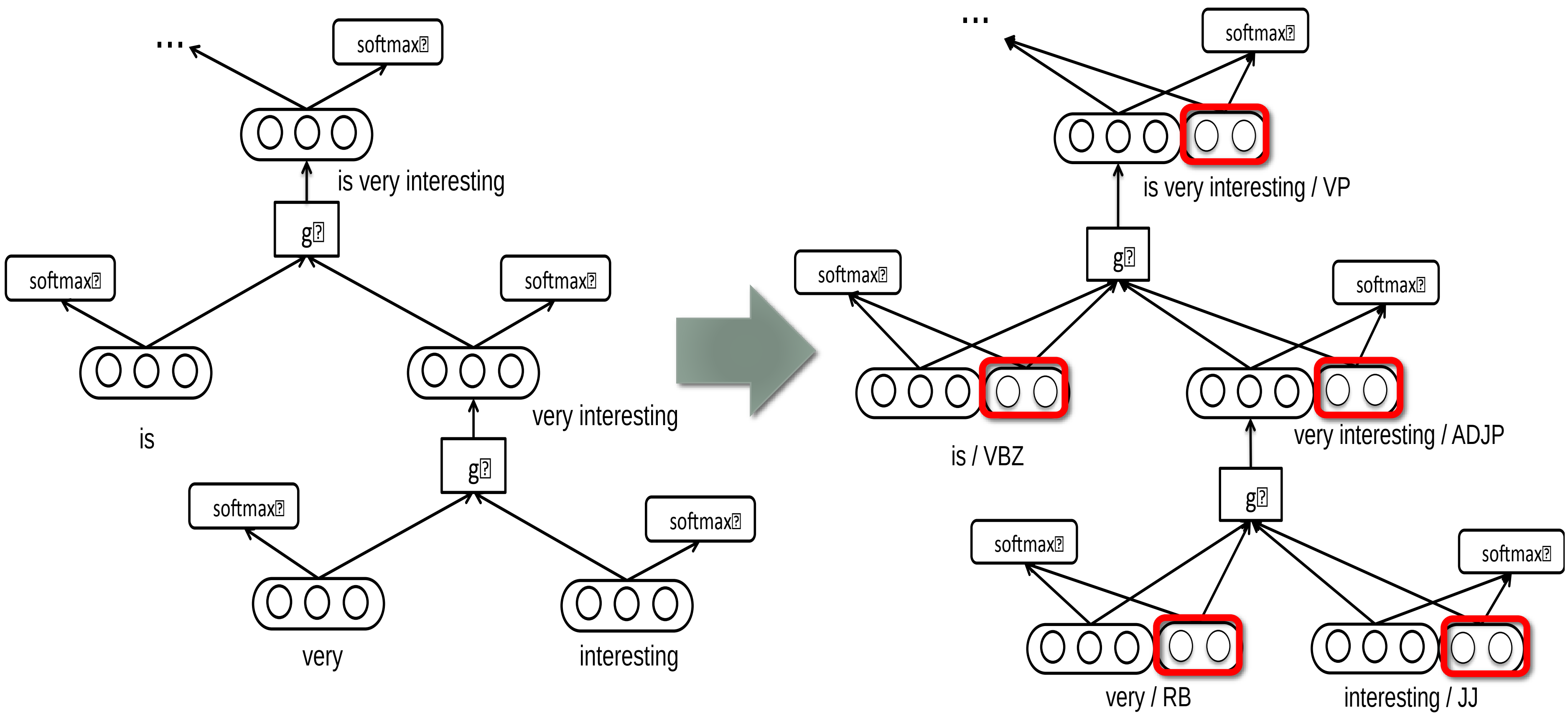
Are We Overly End-to-End?

- End-to-End: simple, elegant

- How about linguistics?
  - Part-of-speech tags
  - Negation words (not, never, scarcely)
  - Intensity words (very, extremely)
  - Sentiment lexicons

Encoding More Linguistic Knowledge in Neural Networks

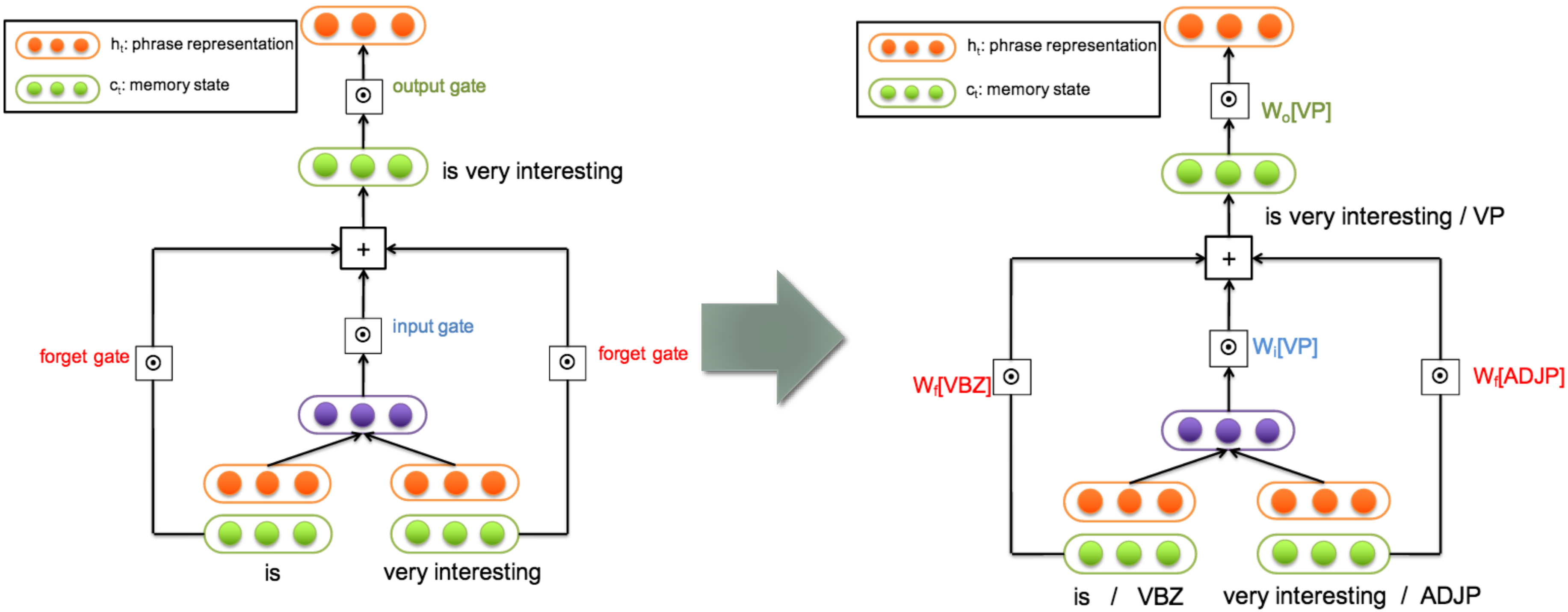
Encode POS in Recursive autoencoders



Qian et al. ACL 2015

Encoding More Linguistic Knowledge in Neural Networks

Encode POS in Tree-Structured LSTM



Huang et al. ACM TOIS subm.

Encoding More Linguistic Knowledge in Neural Networks

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5-way Classification Results on SST

Method	# of parameters
RNN [Socher et al. 2011]	$\approx 1.8K$
RNTN [Socher et al. 2013]	$\approx 108K$
AdaMC-RNN [Dong et al. 2014]	$\approx 18.7K$
AdaMC-RNTN [Dong et al. 2014]	$\approx 202K$
DRNN [Irsoy and Cardie 2014]	$\approx 451K$
TG-RNN (ours)	$\approx 8.8K$
TE-RNN (ours)	$\approx 1.7K$
TE-RNTN (ours)	$\approx 54K$

Model complexity

Method	# of parameters
CNN [Kim 2014]	$\approx 360K$
DCNN [Kalchbrenner et al. 2014]	$\approx 360K$
LSTM [Tai et al. 2015]	$\approx 720K$
Bi-directional LSTM [Tai et al. 2015]	$\approx 720K$
Tree-LSTM [Tai et al. 2015]	$\approx 900K$
TW-LSTM (ours)	$\approx 225K$
TW-LSTM+c (ours)	$\approx 945K$
TE-LSTM (ours)	$\approx 199K$
TE-LSTM+c (ours)	$\approx 919K$

Dilemma in Sentiment Analysis

- Everyone can do SA easily ☺
  - Easy to succeed in a limited domain
- Obvious bottleneck: ☹the easiest part has been solved
  - You cannot cross the line easily!
- Hard to make money (☹because everybody can do)
- To deal with the most essential generic NLP problems!

What is the Next?

- Domain adaptation
  - Work in one domain but does not in another
- Context-aware sentiment analysis
  - Context could be aspect, topic, sentence, etc.
  - Could be word-level, aspect-level, sentence-level, etc.
- Open-domain, social event topics, not just easy domains
  - Movie, digital products, hotel, automobile, etc.
  - General social topics
- New branches: experiences, explanations, causes, emotion, complains, stance, sarcasm, etc.
- **End-to-end is good, but don’t forget Linguistics**

Thanks for your attention

Why, DL to TEXT is not that useful as to IMAGE?

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