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Fine-Grained Opinion Mining: Current Trend and Cutting-Edge Dimensions

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Information Systems

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Part III

Target-Oriented Sentiment Classification

Outline

- **Background**
- Methodology
- Summary

Background

- Sentence/Document-Level Sentiment Classification
  - Input
    - A sentence or document
  - Output
    - **Overall sentiment polarity**
      - Positive, Negative, Neutral
  - Example

The movie was fabulous, and the characters are quite engaging!

The restaurant was horrible, and their service was also poor!

Background

- Target-oriented Sentiment Classification (TSC)
  - Input
    - A sentence or document
    - An **opinion target**
      - 1. Aspect Term (Aspect-Level Sentiment Classification)
      - 2. Aspect Category (Aspect Category-Based Sentiment Classification)
      - 3. Target Entity (Entity-Level Sentiment Classification)
  - Output
    - **Sentiment polarity** towards the **opinion target**
      - Positive, Negative, Neutral

Background

- Examples (Product Review)
  - Aspect-Level Sentiment Classification

The [**fish**] was rather *over cooked*, but the [**staff**] was *quite nice*!

- ➢ sentiment over **fish**: negative
- ➢ sentiment over **staff**: positive

Background

- Examples (Product Review)
  - Aspect Category-Based Sentiment Classification

The [**fish**] was rather *over cooked*, but the [**staff**] was *quite nice*!

- sentiment over **food**: negative
- sentiment over **service**: positive
- sentiment over **ambience**: N.A
- sentiment over **price**: N.A
- sentiment over **miscellaneous**: N.A

Background

- Examples (Tweet)
  - Entity-Level Sentiment Classification

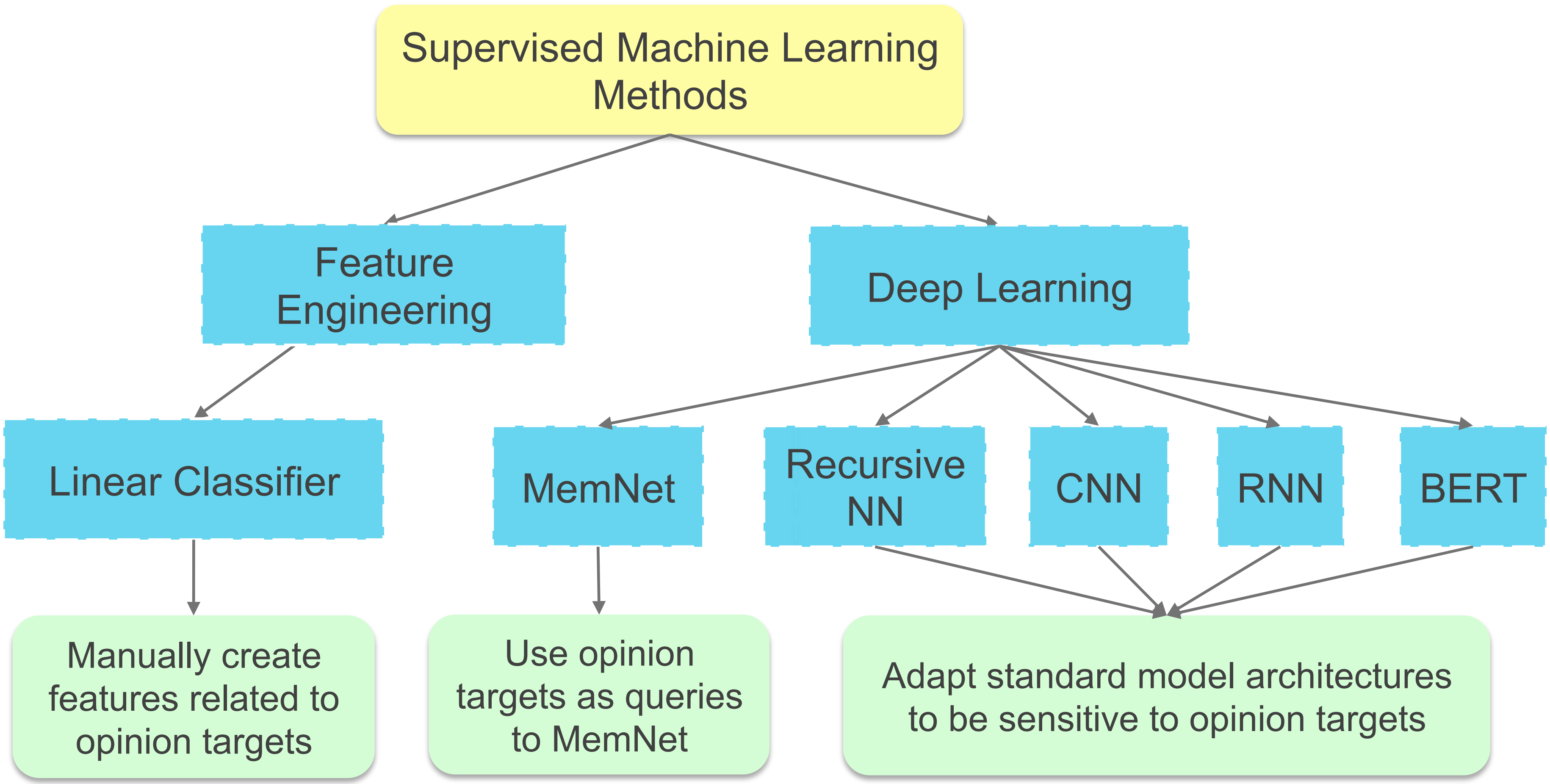
[**Georgina Hermitage**] is a #one2watch since she broke the [**400m T37]** WR!

- sentiment over **Georgina Hermitage**: positive
- sentiment over **400m T37**: neutral

Outline

- Background
- **Methodology**
- Summary

Methodology – Big Picture

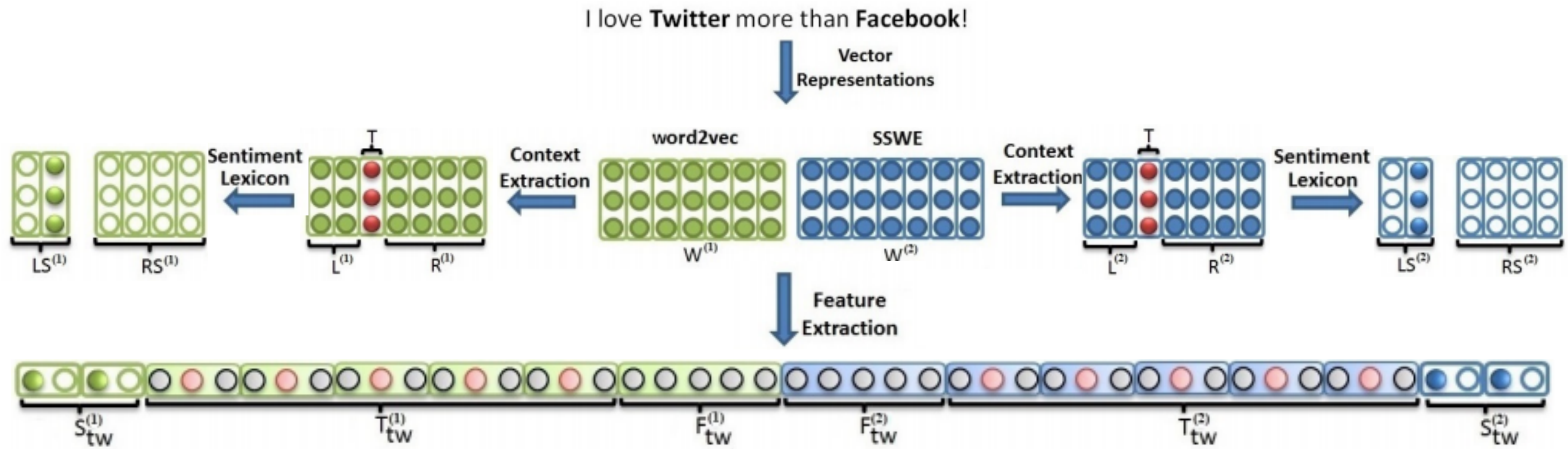


Outline

- Background
- **Methodology**
  - **Linear Classifier**
  - Recursive Neural Network
  - Memory Network
  - CNN-based Methods
  - RNN-based Methods
  - BERT-based Methods
- Summary

Linear Classifier

- Extract various features



School of Information Systems

Duy-Tin Vo, and Yue Zhang. 2015. Target-dependent twitter sentiment classification with rich automatic features. In Proceedings of IJCAI .

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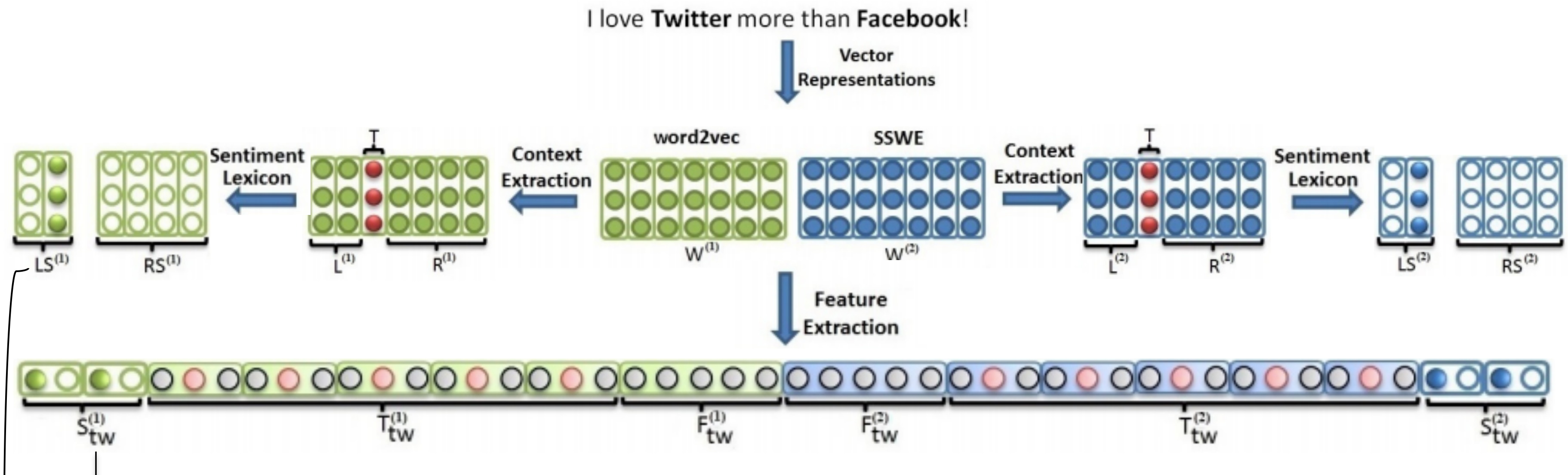
Linear Classifier

Methodology

- Extract various features



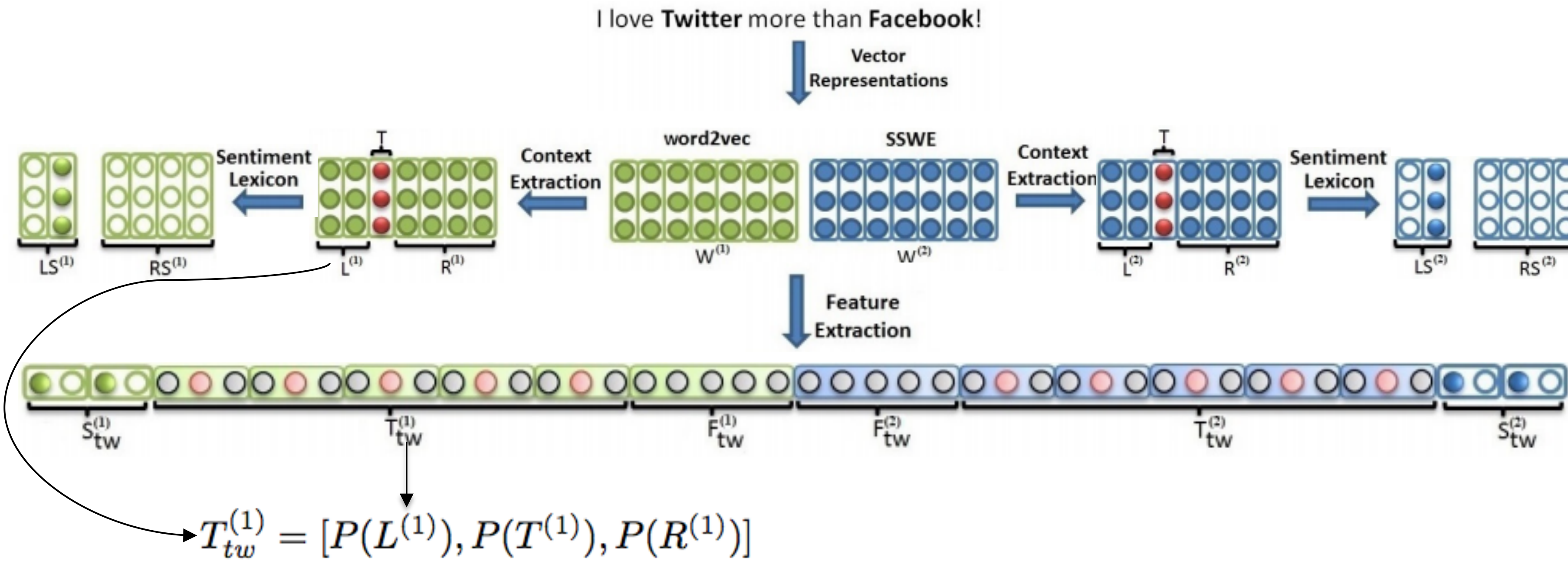
$$S_{tw}^{(1)} = [P(LS^{(1)}), P(RS^{(1)})]$$

– Target-dependent features from words filtered by sentiment lexicon

Duy-Tin Vo, and Yue Zhang. 2015. Target-dependent twitter sentiment classification with rich automatic features. In Proceedings of IJCAI .

Linear Classifier

- Extract various features

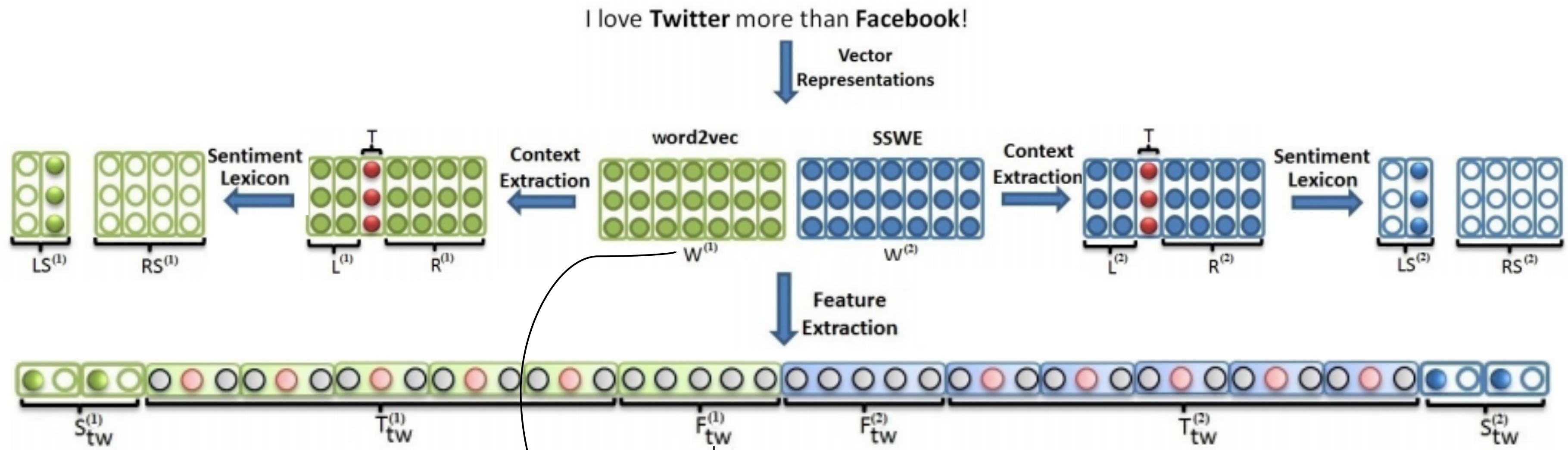


  - Target-dependent features from the left context, right context, and target, respectively

Duy-Tin Vo, and Yue Zhang. 2015. Target-dependent twitter sentiment classification with rich automatic features. In Proceedings of IJCAI .

Linear Classifier

- Extract various features



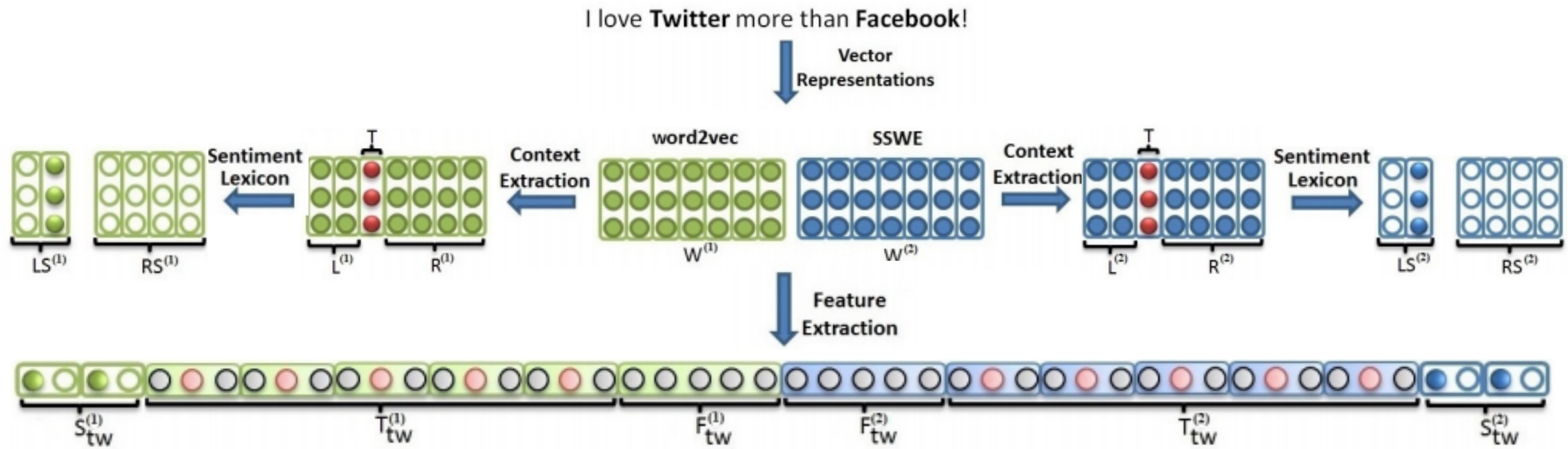
$$F_{tw}^{(1)} = P(W^{(1)})$$

  – Full tweet features

Duy-Tin Vo, and Yue Zhang. 2015. Target-dependent twitter sentiment classification with rich automatic features. In Proceedings of IJCAI .

Linear Classifier

- Extract various features



  – Feed the concatenated features to a discriminative classifier
    - SVM

Duy-Tin Vo, and Yue Zhang. 2015. Target-dependent twitter sentiment classification with rich automatic features. In Proceedings of IJCAI.

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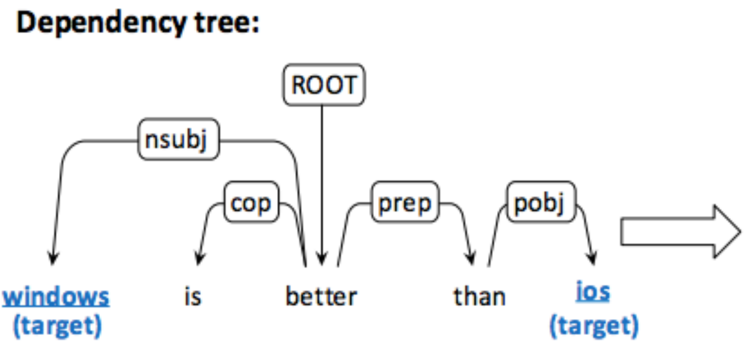
Recursive Neural Network

- Dependency Tree-based Approach
  - AdaRNN
    - propagate sentiment information to the target node in a bottom-up manner



Li Dong, Furu Wei, Chuanqi Tan, Duyu Tang, Ming Zhou, and Ke Xu. 2014. Adaptive Recursive Neural Network for Target-dependent Twitter Sentiment Classification. In Proceedings of ACL, 49-54.

Recursive Neural Network

- Dependency Tree-based Approach
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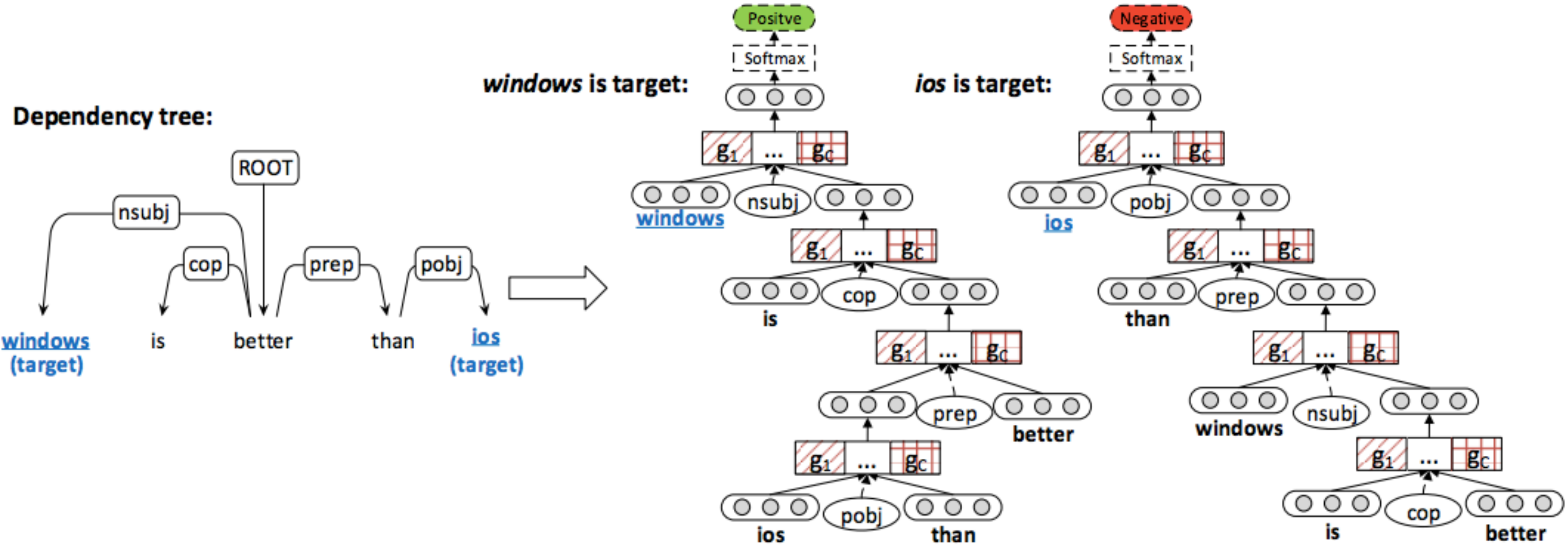
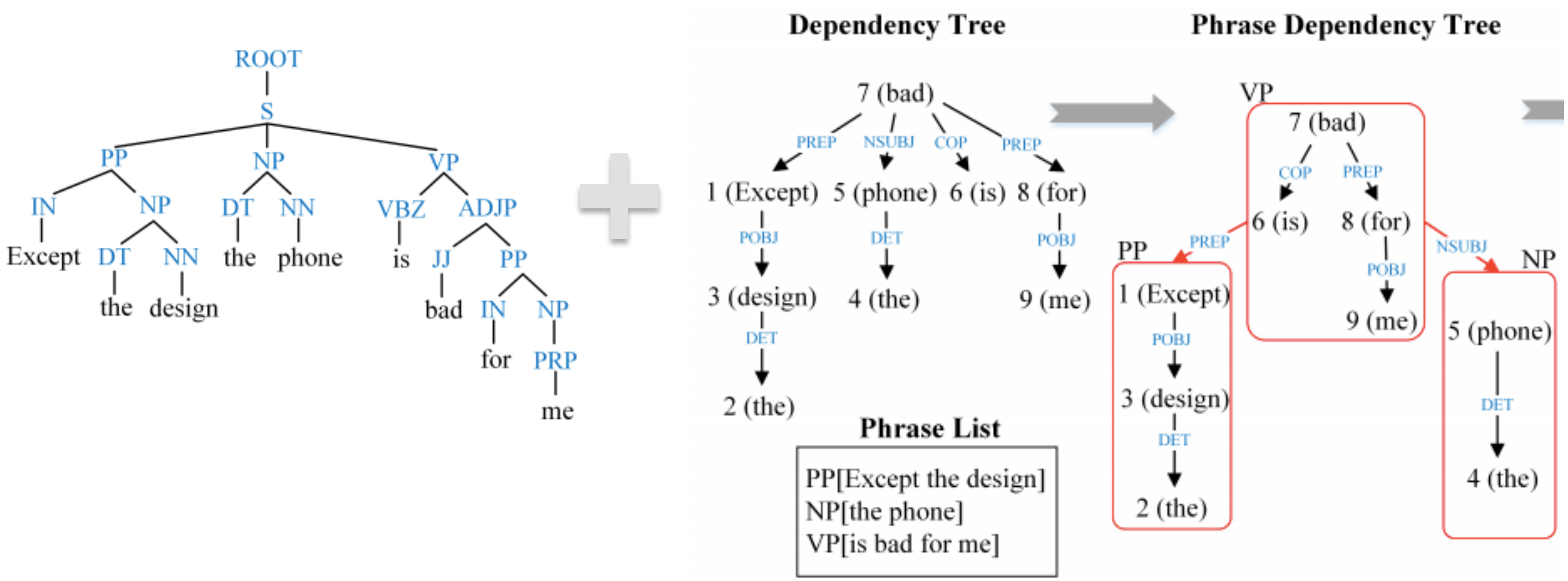
    - propagate sentiment information to the target node in a bottom-up manner



Li Dong, Furu Wei, Chuanqi Tan, Duyu Tang, Ming Zhou, and Ke Xu. 2014. Adaptive Recursive Neural Network for Target-dependent Twitter Sentiment Classification. In Proceedings of ACL, 49-54.

Recursive Neural Network

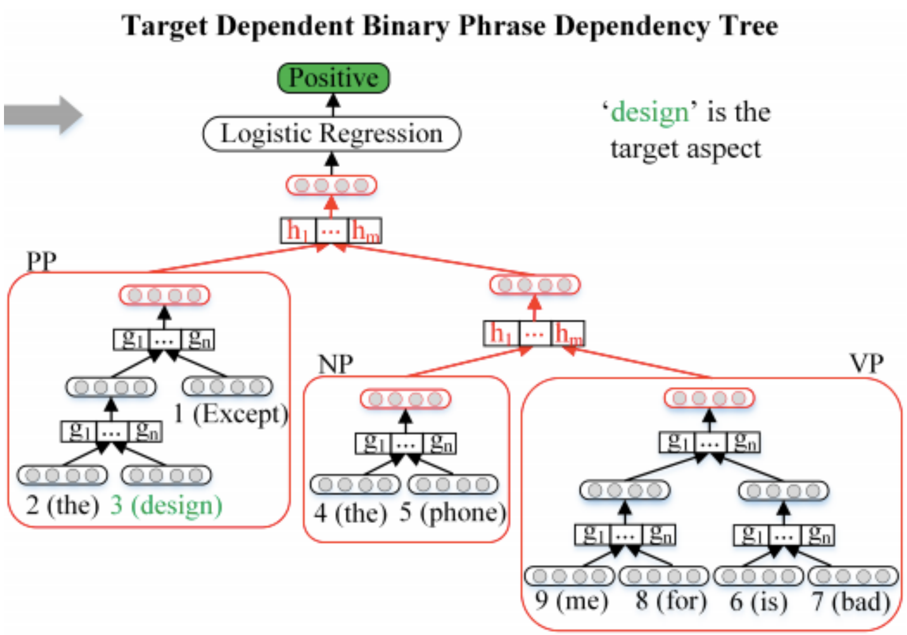
- Dependency + Constituent tree-based Approach
  - PhraseRNN

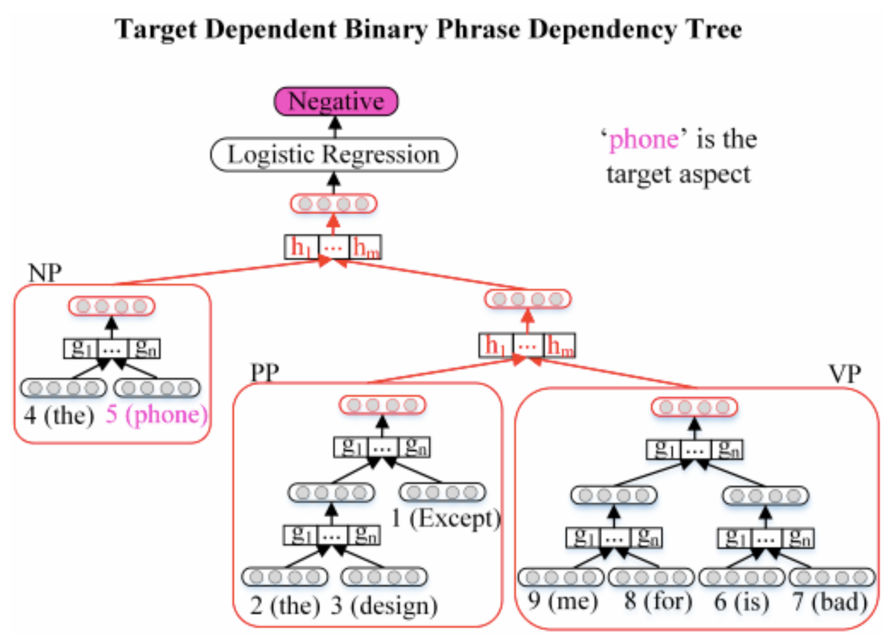


Thien Hai Nguyen, and Kiyoaki Shirai. 2015. PhraseRNN: Phrase Recursive Neural Network for Aspect-based Sentiment Analysis. In Proceedings of EMNLP, 2509-2514.

Recursive Neural Network

- Dependency + Constituent tree-based Approach
  - PhraseRNN





Thien Hai Nguyen, and Kiyoaki Shirai. 2015. PhraseRNN: Phrase Recursive Neural Network for Aspect-based Sentiment Analysis. In Proceedings of EMNLP, 2509-2514.

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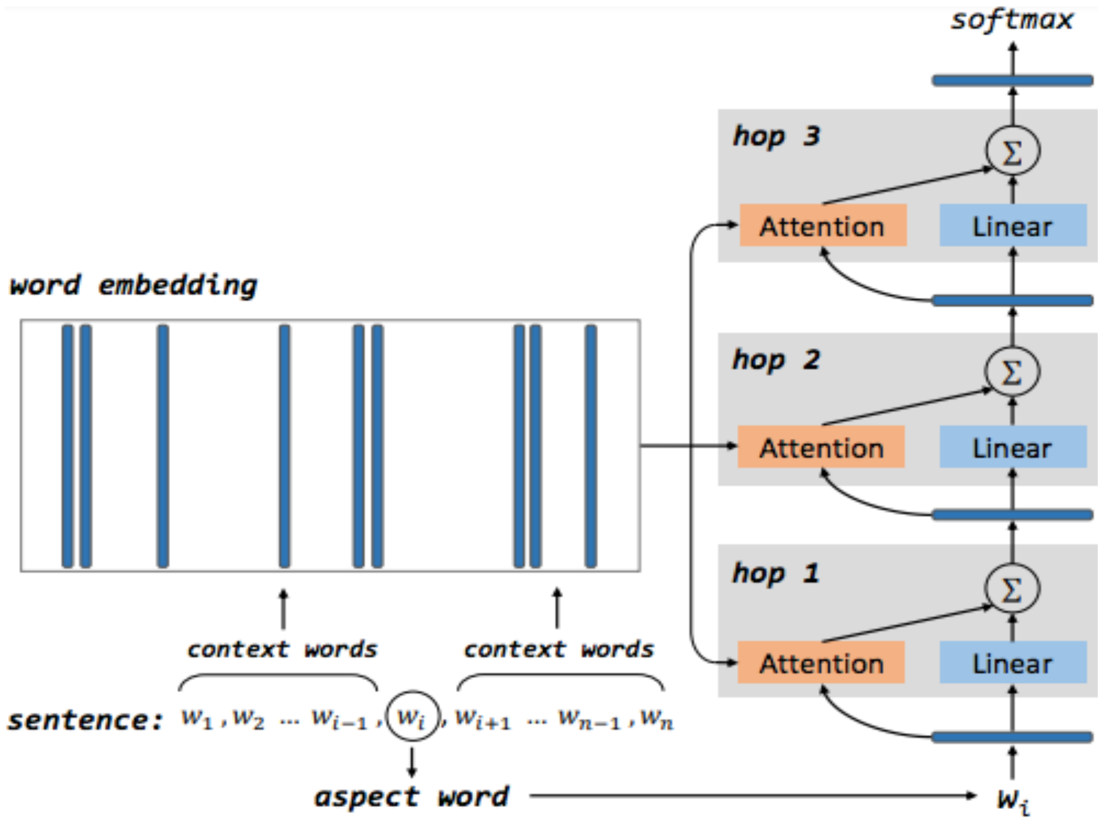
Memory Network

- MemNet
  - Word embedding of target words as queries to MemNet



The Model Architecture of MemNet

Duyu Tang, Bing Qin, Ting Liu, et al. Aspect level sentiment classification with deep memory network. In EMNLP , 2016.

Outline

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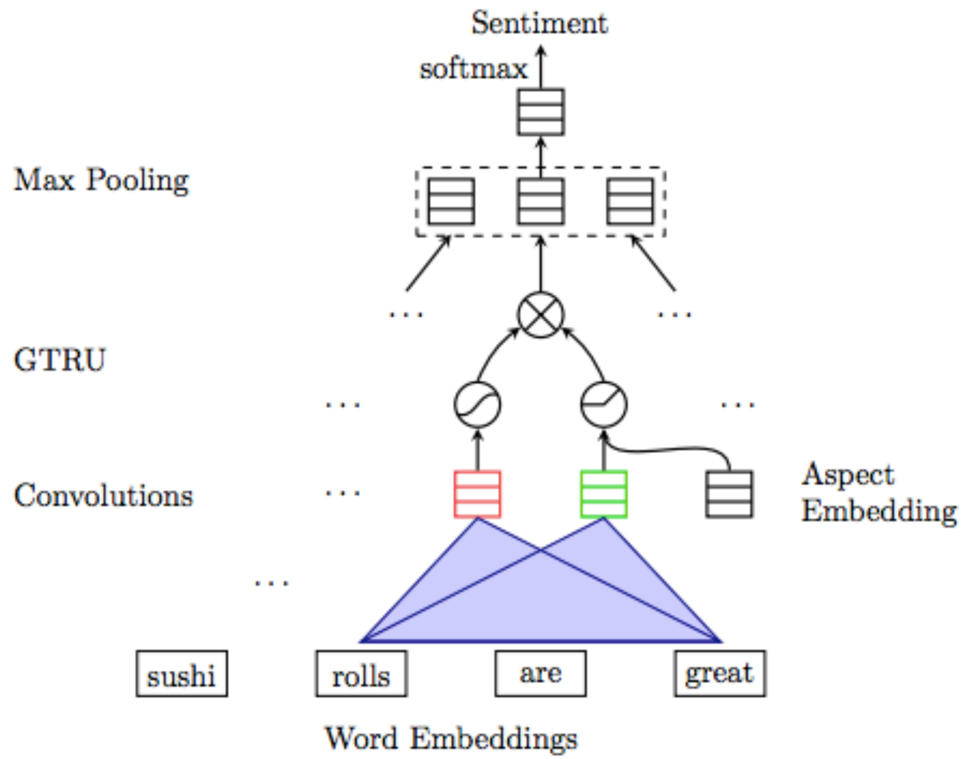
CNN-based Methods

Methodology

- GCN (Gated Convolutional Networks)
  - Incorporate gate mechanism to be sensitive to be opinion targets

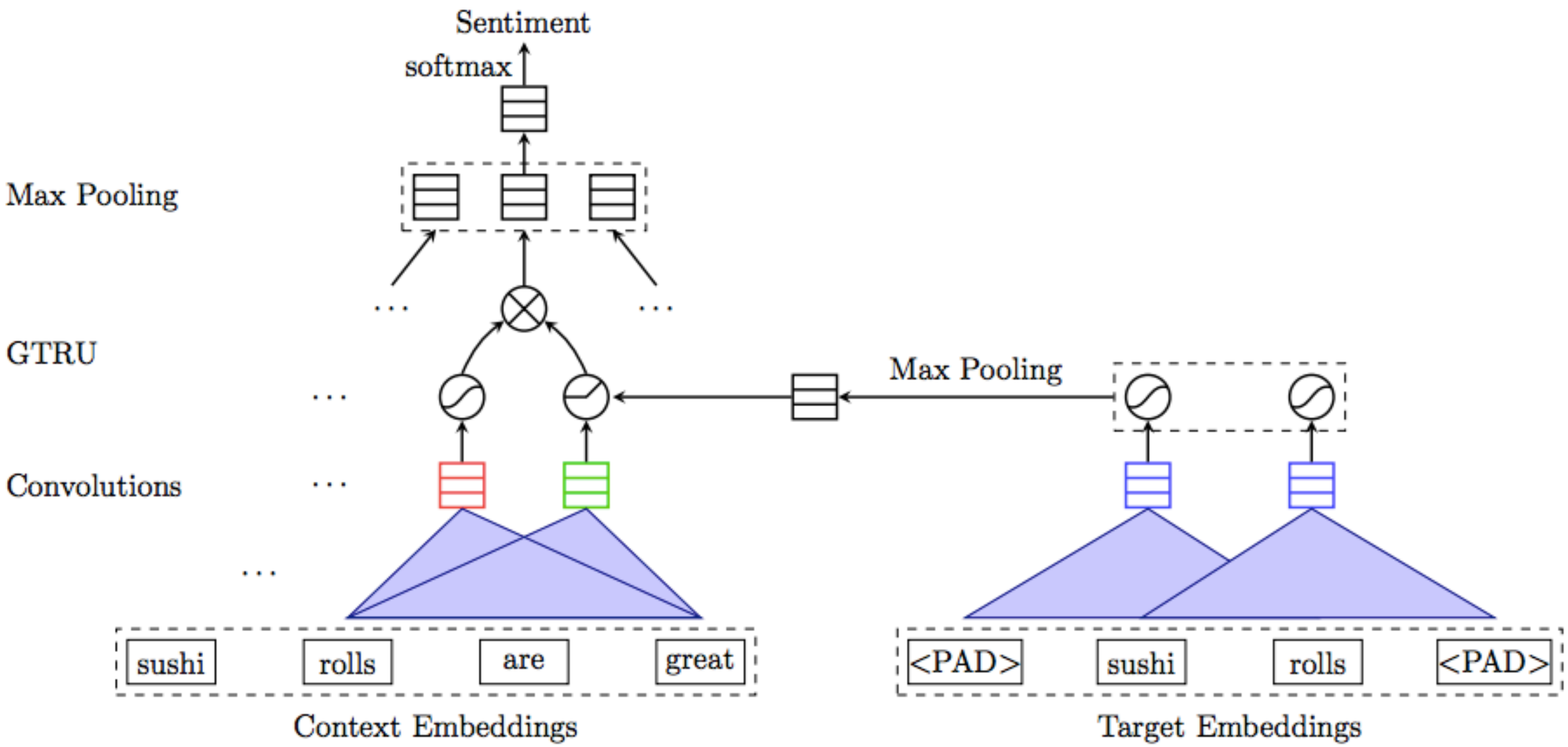


Model I. GCN for Aspect Category-based Sentiment Classification

Xue, Wei, and Tao Li. "Aspect Based Sentiment Analysis with Gated Convolutional Networks." In Proceedings of ACL 2018.

CNN-based Methods

- GCN (Gated Convolutional Networks)
  - Incorporate gating mechanism to be sensitive to be opinion targets



Model II. GCN for Aspect-Level Sentiment Classification

Xue, Wei, and Tao Li. "Aspect Based Sentiment Analysis with Gated Convolutional Networks." In Proceedings of ACL 2018.

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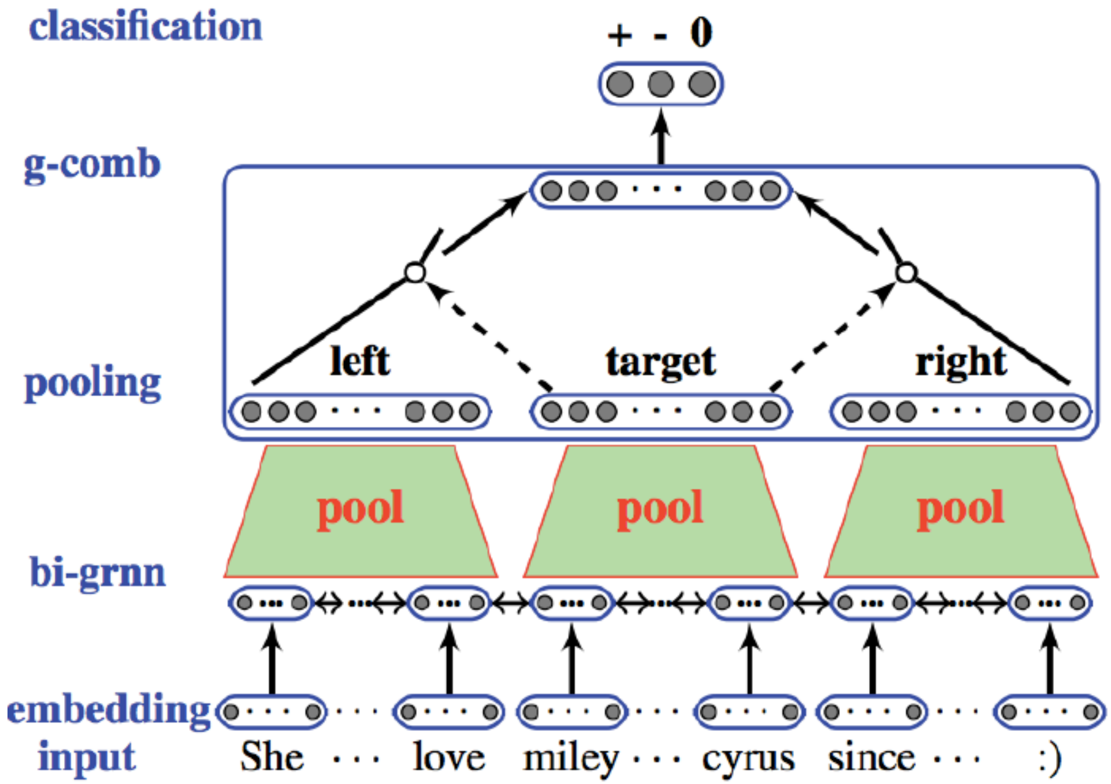
RNN-based Methods

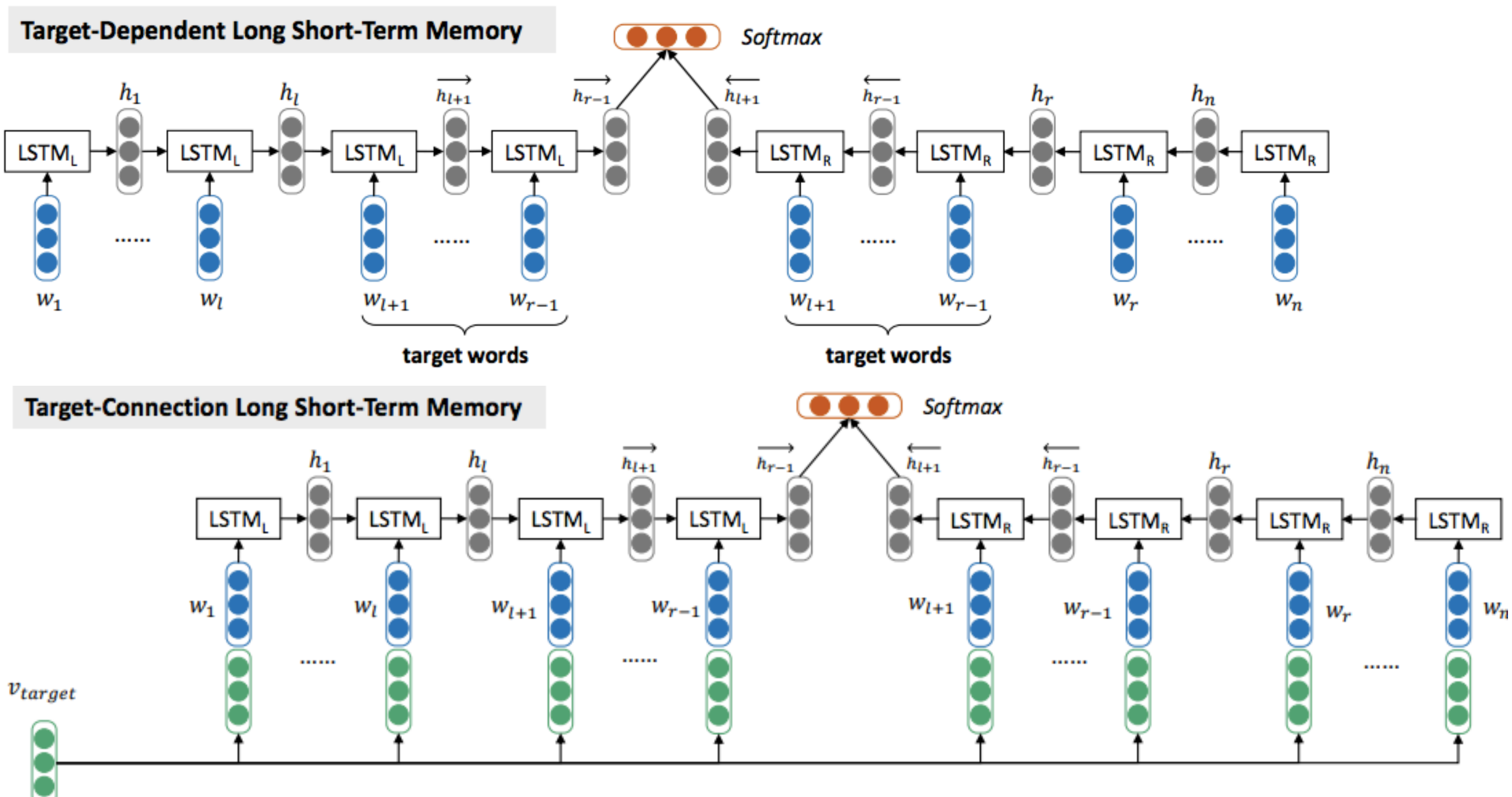
- GRU
  - Gating Mechanism



Meishan Zhang, Yue Zhang, and Duy-Tin Vo. Gated Neural Networks for Targeted Sentiment Analysis. In Proceedings of AAAI 2016.

RNN-based Methods

- LSTM
  - Sentence Encoding

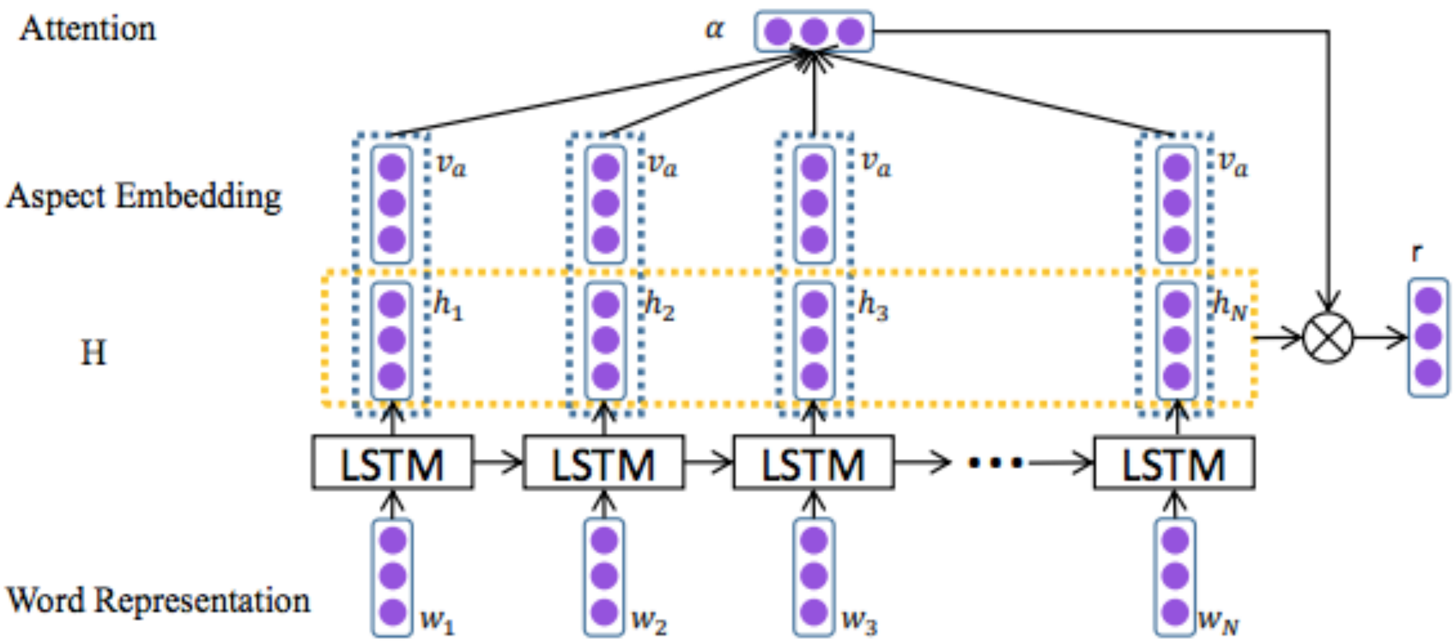


The Model Architecture of TD-LSTM and TC-LSTM

Duyu Tang, Bing Qin, Xiaocheng Feng, and Ting Liu. Effective LSTMs for target-dependent sentiment classification. In COLING, 2016.

RNN-based Methods

- LSTM
  - Attention Mechanism

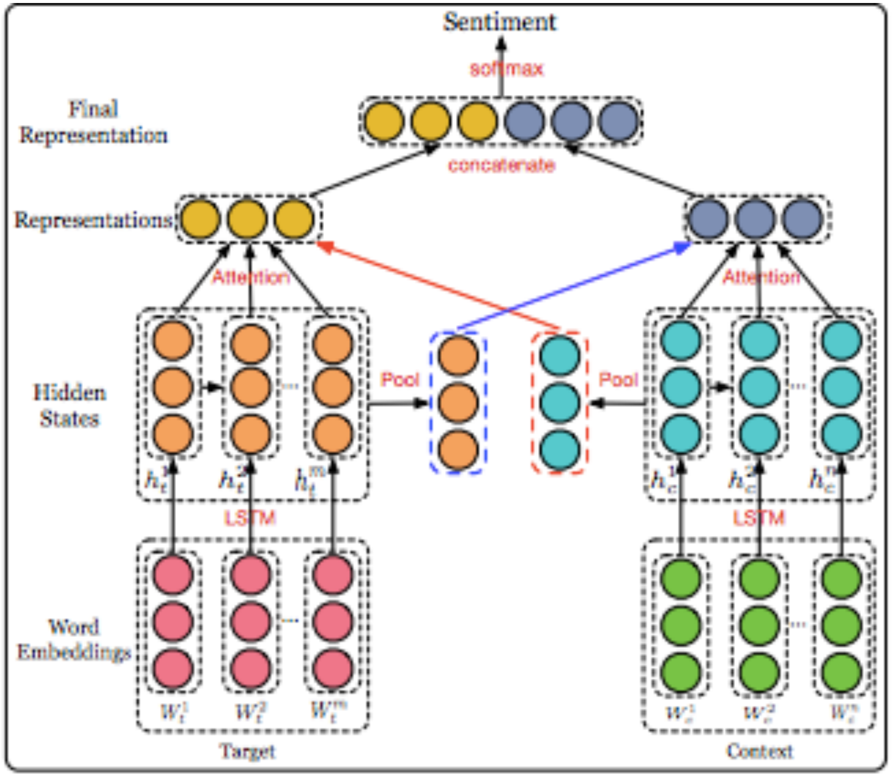


The Model Architecture of AE-LSTM

Yequan Wang, Minlie Huang, Li Zhao, et al. Attention-based LSTM for aspect-level sentiment classification. In EMNLP, 2016.

RNN-based Methods

- LSTM
  - IAN
    - Interactive Attention Mechanism

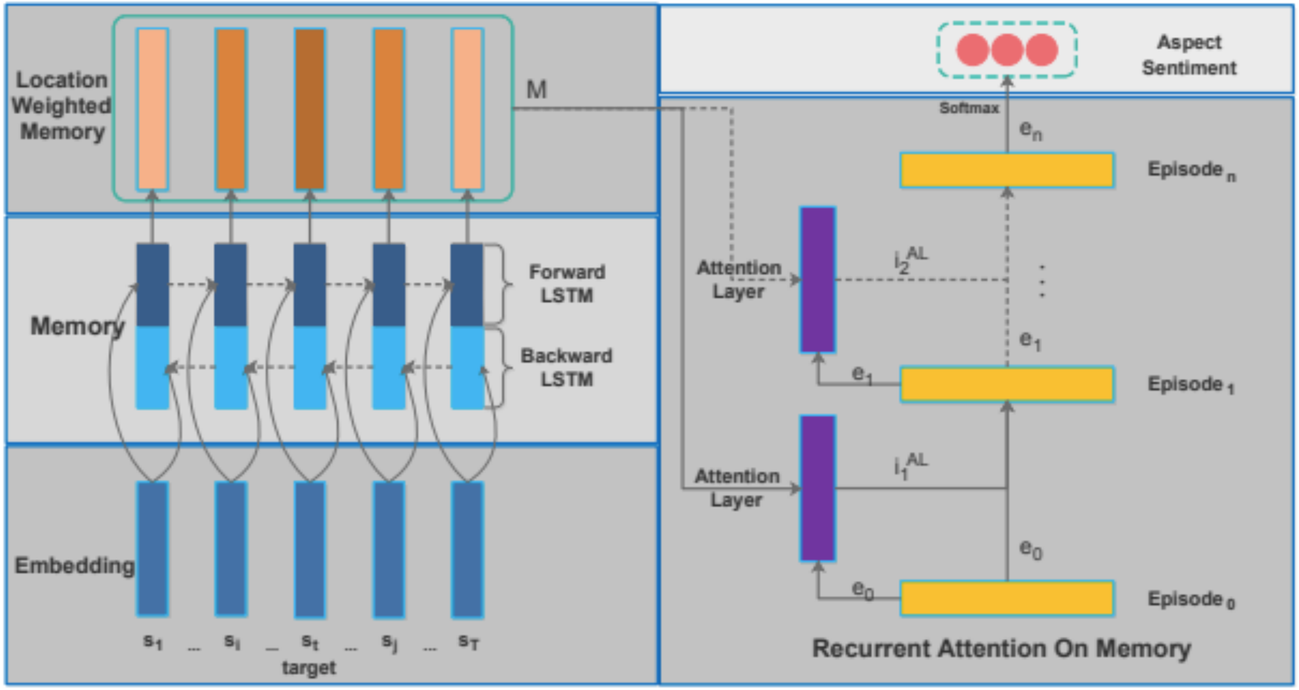


The Model Architecture of IAN

Dehong Ma, Sujian Li, Xiaodong Zhang, and Houfeng Wang. Interactive attention networks for aspect-level sentiment classification. In IJCAI, 2017.

RNN-based Methods

- LSTM
  - RAM
    - Position-based Weighting Strategy
    - Multi-Hop Attention Mechanism

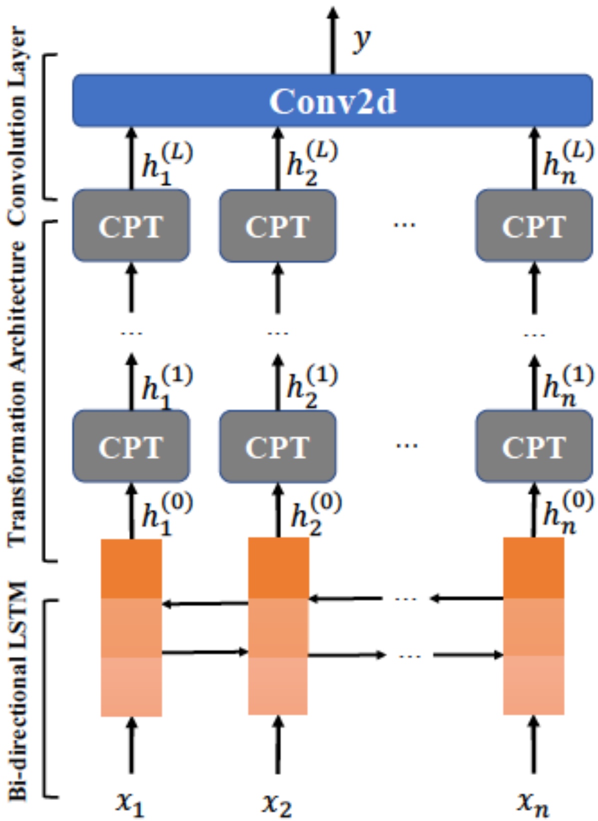


The Model Architecture of RAM

Peng Chen, Zhongqian Sun, Lidong Bing, and Wei Yang. Recurrent attention network on memory for aspect sentiment analysis. In EMNLP, 2017.

RNN-based Methods

- LSTM
  - TNet



Introduce position information to detect the most salient features more accurately

Refine word-level representations with the input target and the contextual information

Generating contextualized word representations

The Model Architecture of TNet

Xin Li, Lidong Bing, Wai Lam, and Bei Shi. Transformation networks for target-oriented sentiment classification. In ACL, 2018.

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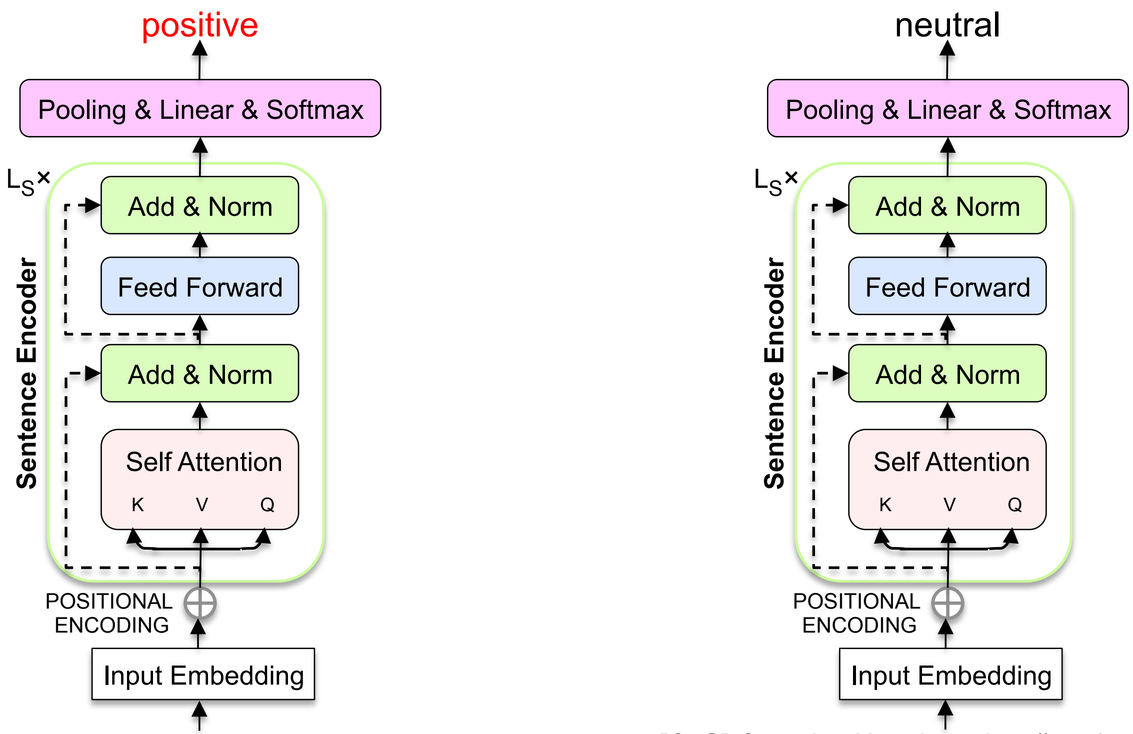
BERT-based Methods

- Feed the transformed sentence to BERT

[**Georgina Hermitage**] is a #one2watch since she broke the [**400m T37]** WR!



[CLS] \$T\$ is a #one2watch since she broke the 400m T37 WR. **[SEP]** Georgina Hermitage **[SEP]**

[CLS] Georgina Hermitage is a #one2watch since she broke the \$T\$ WR. **[SEP]** 400m T37 **[SEP]**

Jianfei Yu and Jing Jiang. Adapting BERT for Target-Oriented Multimodal Sentiment Classification. In IJCAI, 2019.

Outline

- Background
- Methodology
- **Summary**

Summary

- Three Benchmark Datasets

Data Set	#Training Samples			#Test Samples		
	POS	NEG	NEU	POS	NEG	NEU
Laptop	980	858	454	340	128	171
Restaurant	2159	800	623	730	195	196
Twitter-2014	1567	1563	3127	147	147	346

  - Laptop, Restaurant are from SemEval-2014
  - Twitter-2014 from (Dong et al. ACL 2014)
  - Another two Restaurant datasets from SemEval-2015, SemEval-2016

Jianfei Yu and Jing Jiang. Adapting BERT for Target-Oriented Multimodal Sentiment Classification. In IJCAI, 2019.

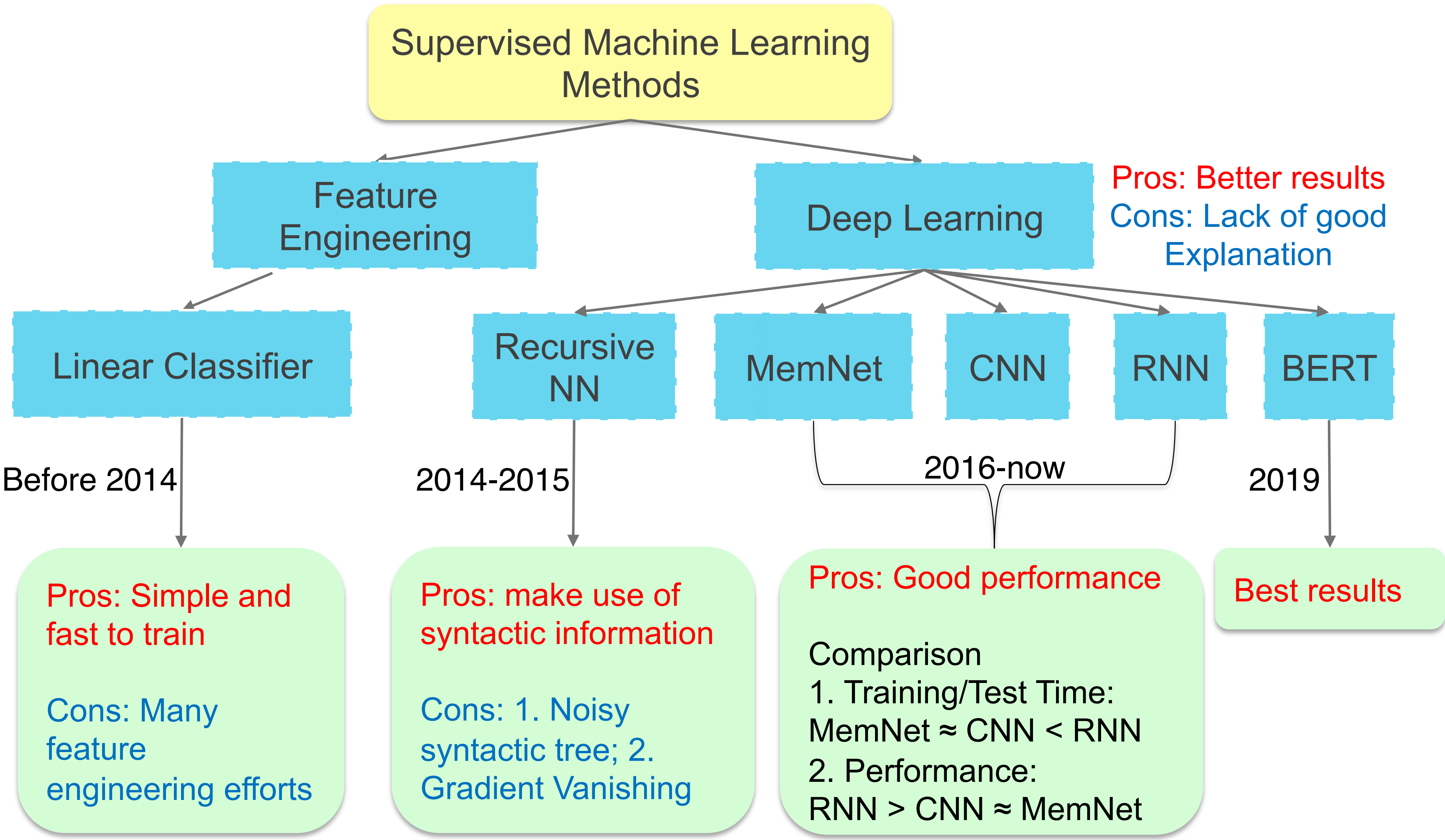
Summary

- Experimental Results on Three Benchmark Datasets

Method	Laptop		Restaurant		Twitter-2014	
	Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1
SVM	70.49	-	80.16	-	63.40	63.30
AE-LSTM	68.90	-	76.60	-	-	-
IAN	72.10	-	78.60	-	-	-
TD-LSTM	71.83	68.43	78.00	66.73	66.62	64.01
MemNet	70.33	64.09	78.16	65.83	68.50	66.91
RAM	75.01	70.51	79.79	68.86	71.88	70.33
TNet-LF	76.01	71.47	80.79	70.84	74.68	73.36
TNet-AS	76.54	71.75	80.69	71.27	74.97	73.60
MGAN	75.39	72.47	81.25	71.94	72.54	70.81
BERT	**76.96**	**73.67**	**84.29**	**77.22**	**75.14**	**74.15**

Jianfei Yu and Jing Jiang. Adapting BERT for Target-Oriented Multimodal Sentiment Classification. In IJCAI, 2019.

Summary



Supervised Machine Learning Methods
Feature Engineering
Deep Learning
Pros: Better results
Cons: Lack of good Explanation
Linear Classifier
Recursive NN
MemNet
CNN
RNN
BERT
Before 2014
2014-2015
2016-now
2019
Pros: Simple and fast to train
Cons: Many feature engineering efforts
Pros: make use of syntactic information
Cons: 1. Noisy syntactic tree; 2. Gradient Vanishing
Pros: Good performance
Comparison
1. Training/Test Time:
MemNet ≈ CNN < RNN
2. Performance:
RNN > CNN ≈ MemNet
Best results

Part V

Cutting-Edge Dimensions of Fine-Grained Opinion Mining

Outline

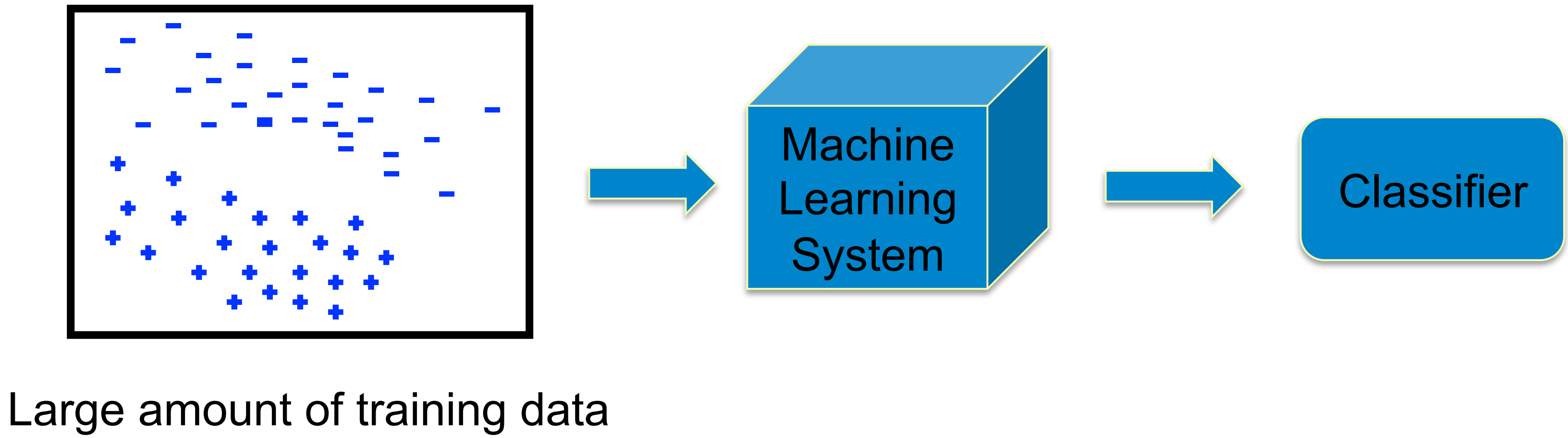
- Transfer Learning
- Multi-Task Learning
- Multimodal Learning
- Summary

Outline

- **Transfer Learning**
  - Cross-Domain
  - Cross-Lingual
  - Short Summary
- Multi-Task Learning
- Multimodal Learning
- Summary

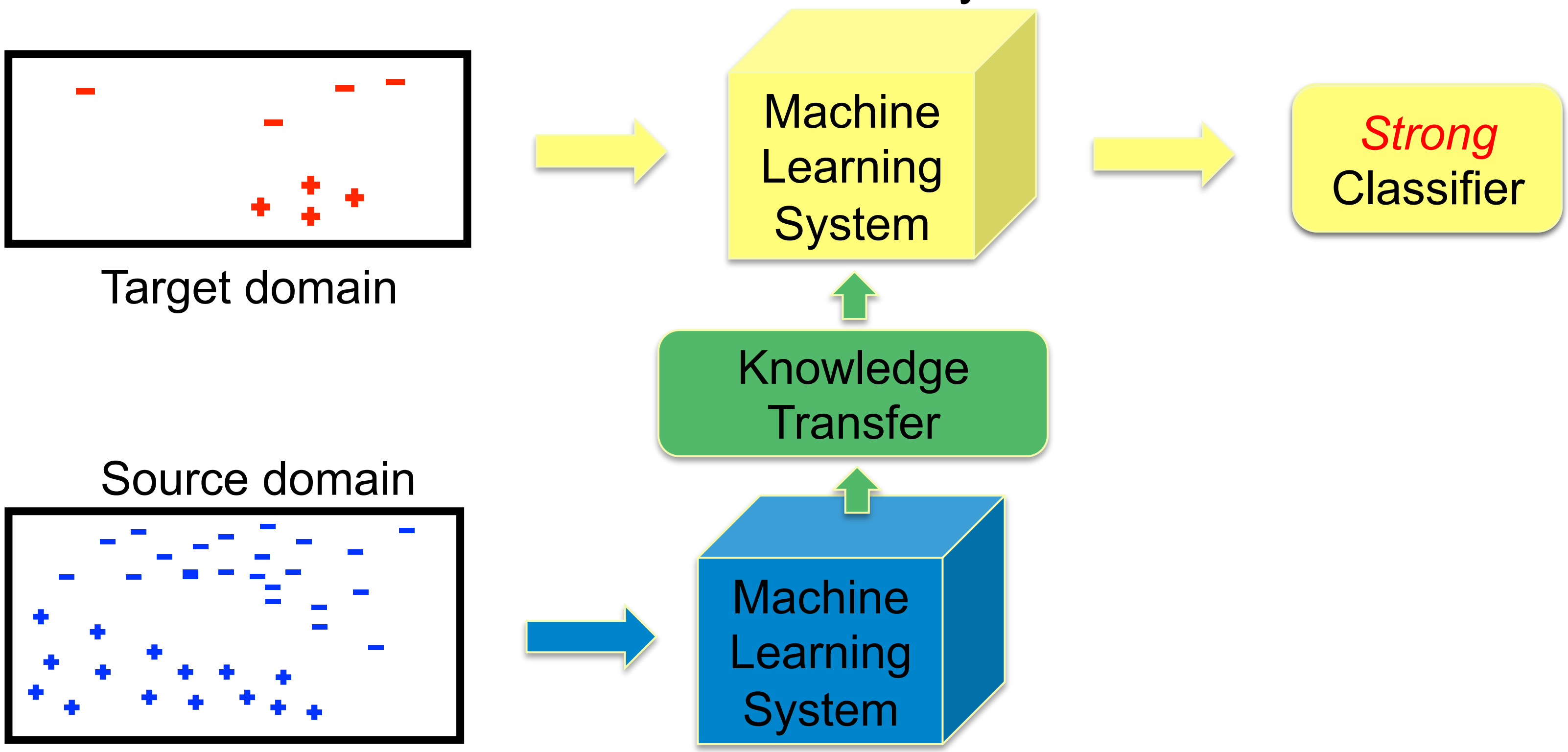
Cross-Domain

- Background
  - Popular Methods for Fine-Grained Opinion Mining
    - Supervised Machine Learning (NN)



Cross-Domain

- Background
  - Real Scenario
    - *Limited or no* Labeled Data for many domains



➢ **Domain Adaptation:** recognize and apply knowledge and skills learned in previous domain to novel domains

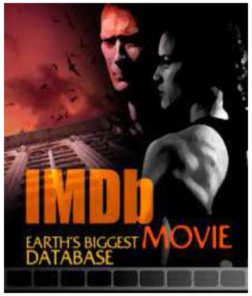
Transfer Learning

Cross-Domain

- Background
  - Challenge of Domain Adaptation

Training Data

Movie



Opinion Target Extraction Model

Test Data

Movie

78%

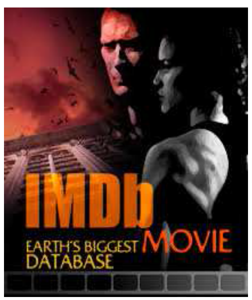
Cross-Domain

Transfer Learning

- Background
  - Challenge of Domain Adaptation

Training Data

Movie

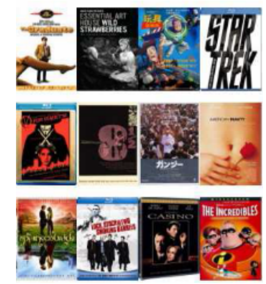


(*Source* Domain)

Opinion Target Extraction Model

Test Data

Movie



78%

Digital Device

45%

(*Target* Domain)

Transfer Learning

Cross-Domain

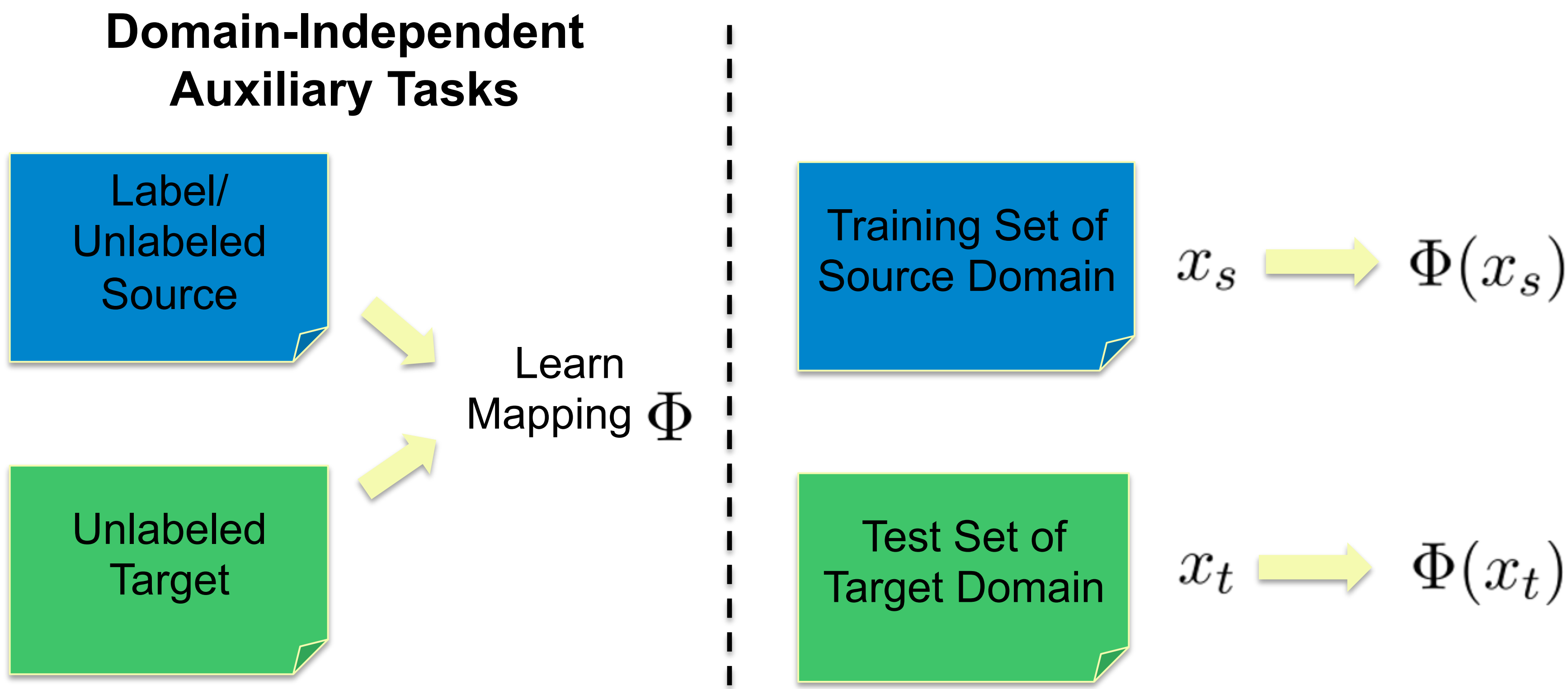
- Background
  - Reasons behind performance drop

Movie (source domain)	Digital Device (target domain)
The [movie] is great.	The [camera] is excellent.
I really like his [characters].	I highly recommend this [laptop].
The [plot] is quite dull.	The [Mac OS] is quite fast.

- Opinion targets in the source domain
  movie, characters, plot
- Opinion targets in the target domain
  camera, laptop, Mac OS

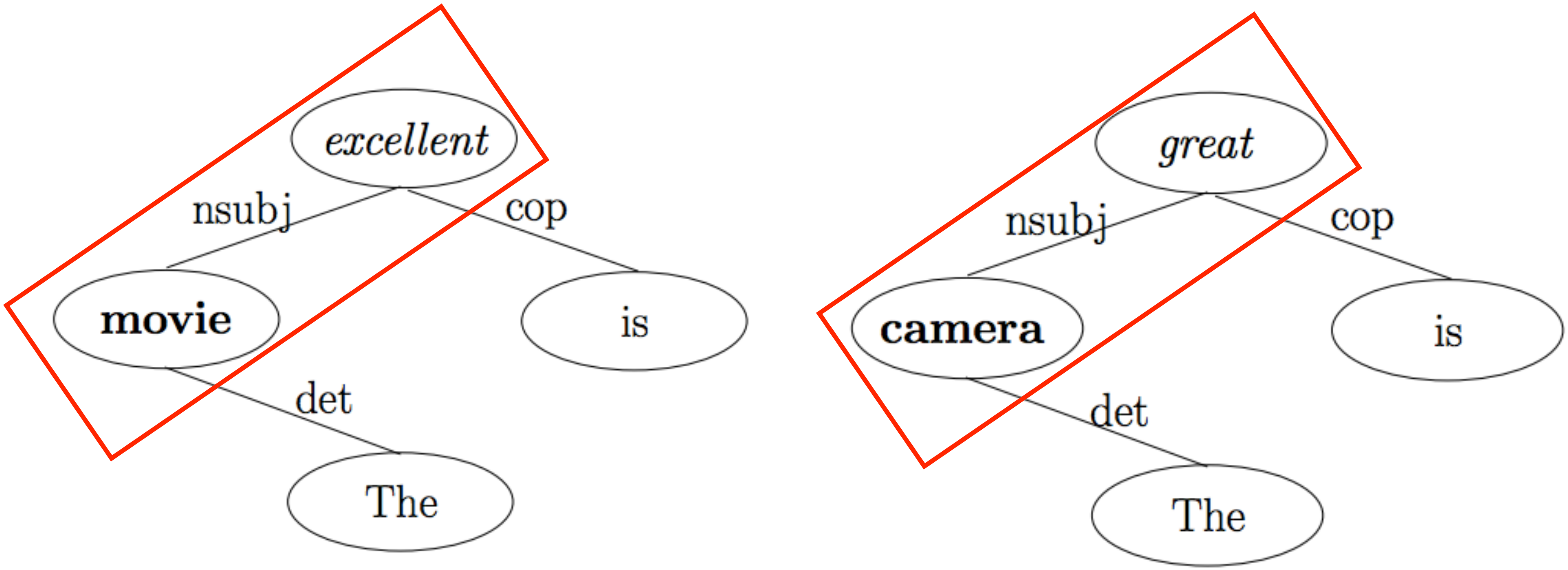
Cross-Domain

- Background
  - General Solution
    - Learn a shared representation across domains



Cross-Domain

- Cross-Domain Opinion Target Extraction
  - Domain-Independent Auxiliary Task
    - Syntactic structures are shared across domains.



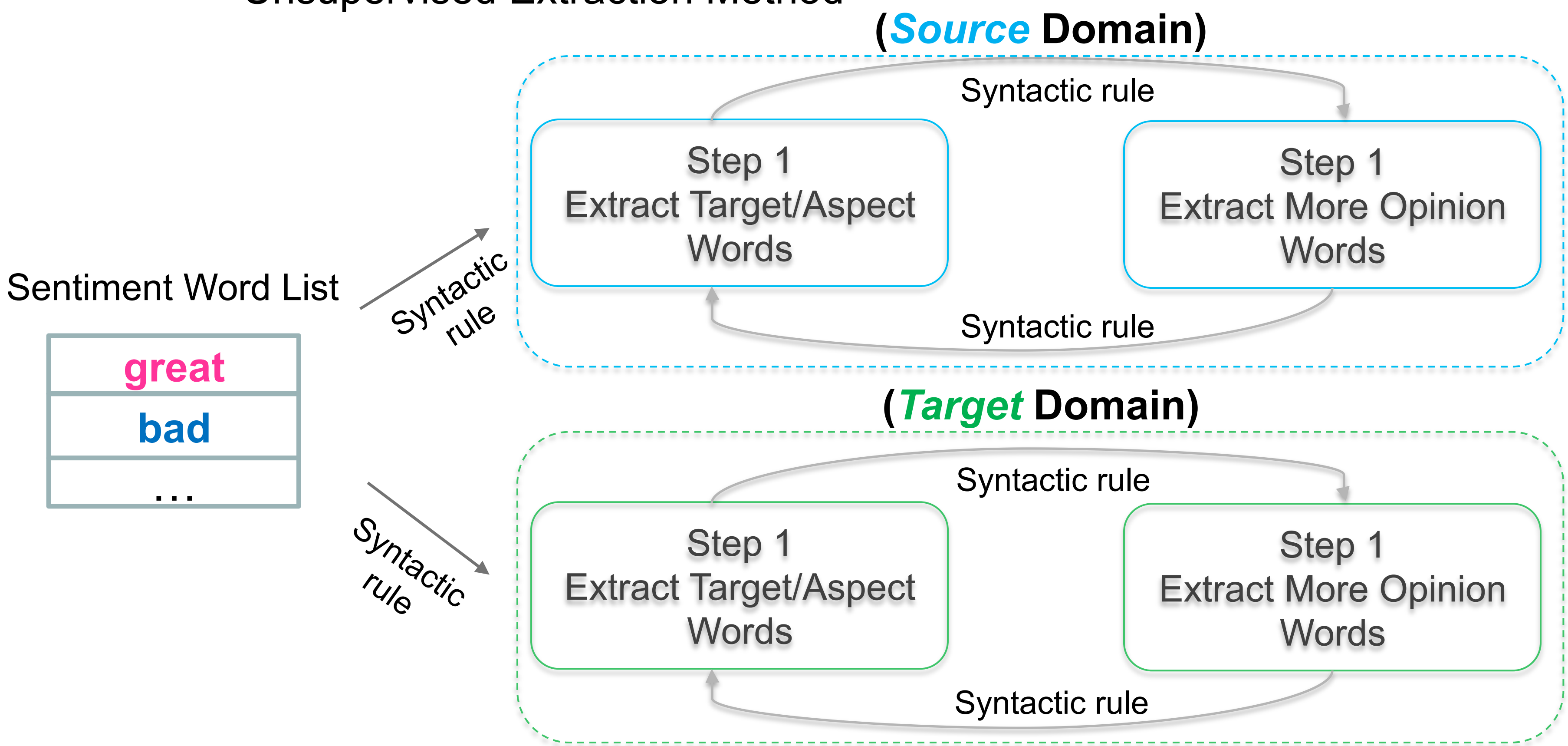
(*Source* Domain) (*Target* Domain)

Ying Ding, Jianfei Yu, and Jing Jiang. Recurrent neural networks with auxiliary labels for crossdomain opinion target extraction. In AAAI 2017.

Transfer Learning

Cross-Domain

- Cross-Domain Opinion Target Extraction
  - The same task as our Auxiliary Tasks
    - Unsupervised Extraction Method

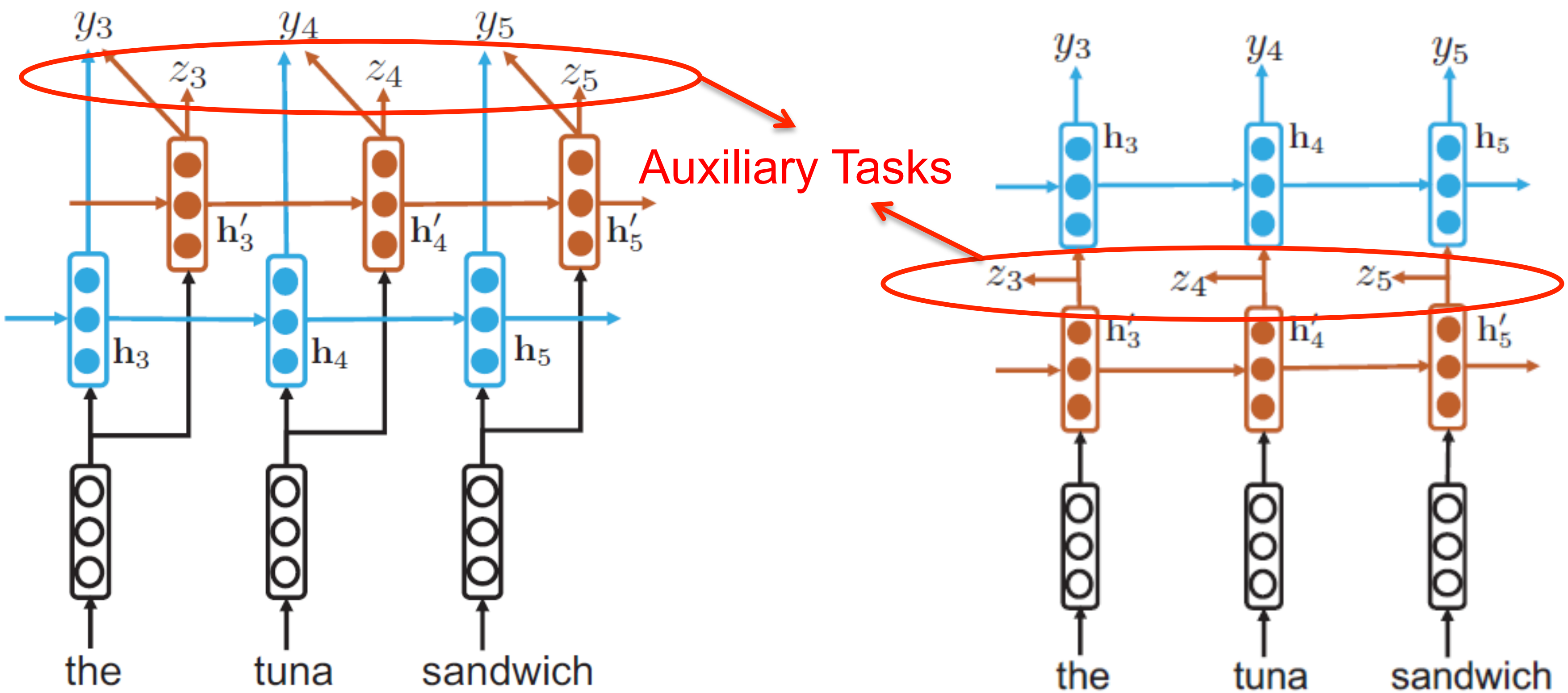


Ying Ding, Jianfei Yu, and Jing Jiang. Recurrent neural networks with auxiliary labels for crossdomain opinion target extraction. In AAAI 2017.

Cross-Domain

Transfer Learning

- Cross-Domain Opinion Target Extraction
  - RNN with Auxiliary Tasks (AuxRNN)

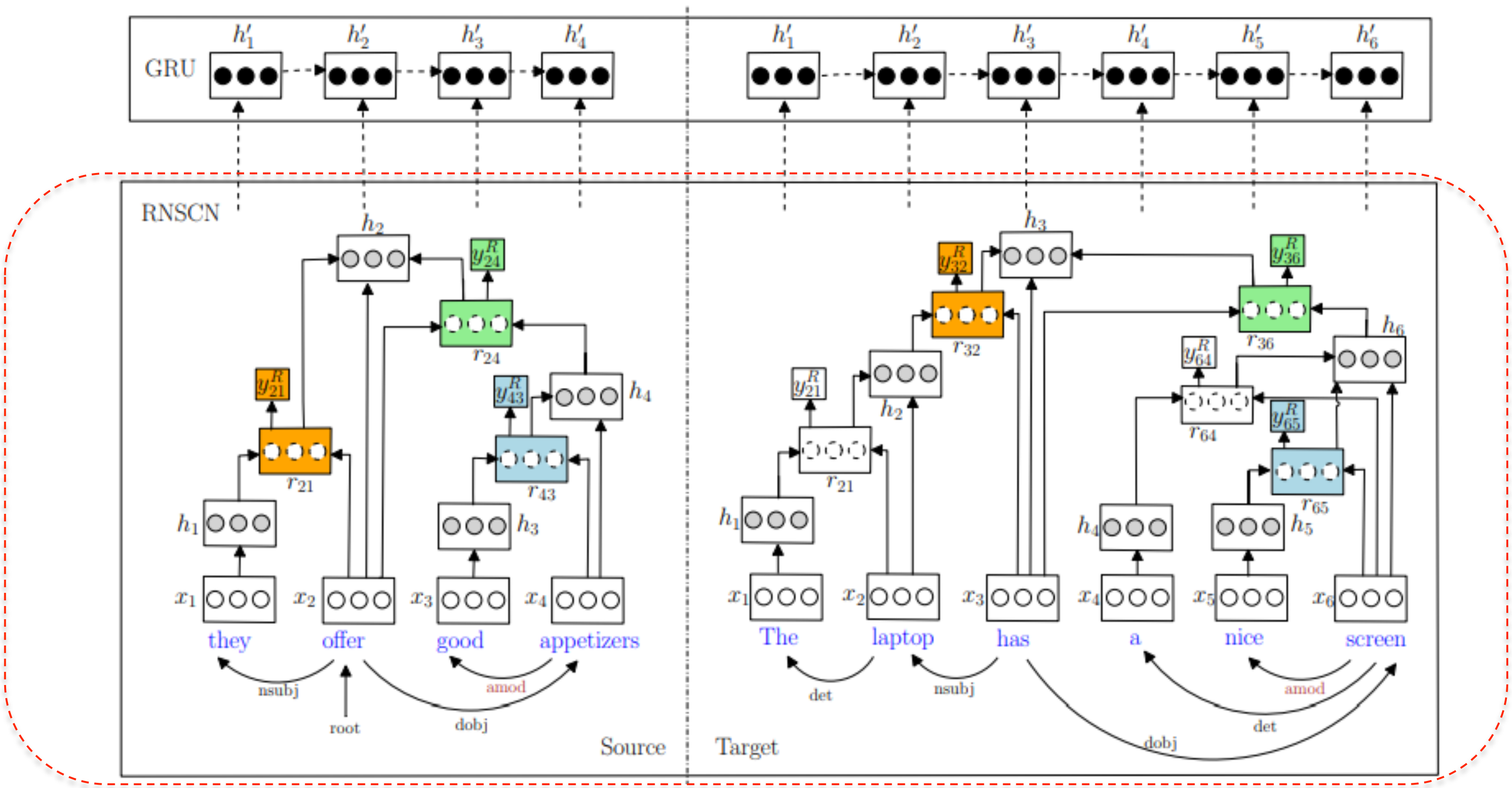


Ying Ding, Jianfei Yu, and Jing Jiang. Recurrent neural networks with auxiliary labels for crossdomain opinion target extraction. In AAAI 2017.

Cross-Domain

Transfer Learning

- Cross-Domain Aspect and Opinion Terms Co-Extraction
  - Recursive Neural Structural Correspondence Network (RNSCN)



Wenya Wang and Sinno Jialin Pan. Recursive Neural Structural Correspondence Network for Cross-domain Aspect and Opinion Co-Extraction. In Proc. ACL, 2018.

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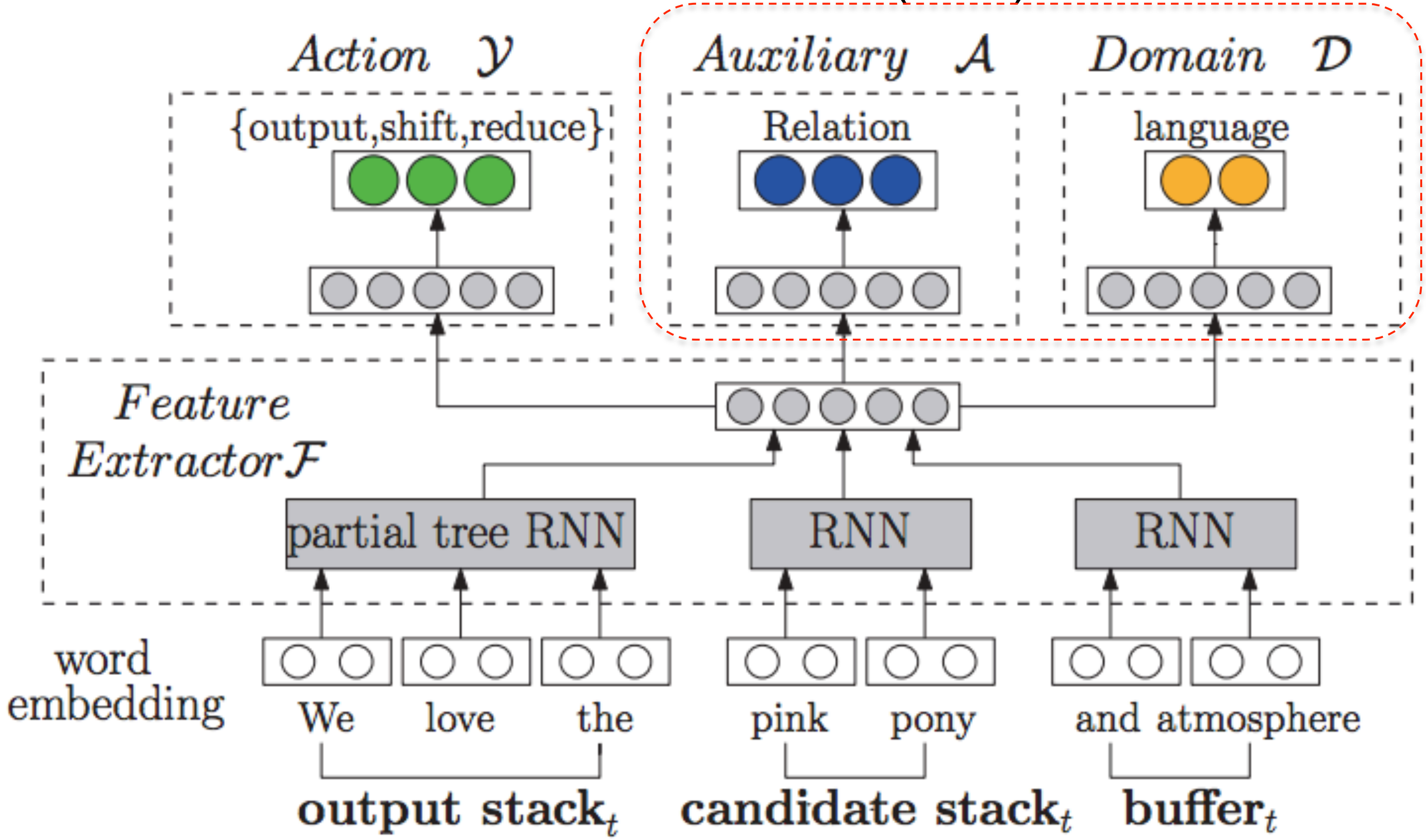
Cross-Lingual

Transfer Learning

- Cross-Lingual Aspect Term Extraction
  - Transition-based Adversarial Network (TAN)



Wenya Wang and Sinno Jialin Pan. Transition-based Adversarial Network for Cross-lingual Aspect Extraction. In Proc. IJCAI, 2018.

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Short Summary

- Key to Cross-Domain/Lingual
  - Step 1: Identify shared knowledge across domains or languages
    - General Sentiment Words like ***good***, ***bad***, etc
    - Syntactic Structure
    - Domain/Language Discriminator
    - Auto-encoder (reconstruction of the input)
  - Step 2: Design auxiliary tasks based on these shared knowledge

Short Summary

Transfer Learning

- Benchmark Datasets for Cross-Domain Aspect and Opinion Terms Co-Extraction

Data Set	#Sentences	Train	Test
Laptop	3,845	2,884	961
Restaurant	5,841	4,381	1,460
Digital Device	3,836	2,877	959

  – Laptop from SemEval-2014
  – Restaurant from SemEval-2014, 2015
  – Digital Device from (Hu and Liu, KDD2004)

Transfer Learning

Short Summary

- Results on Benchmark Datasets
  - Hier-Joint: (Ding, Yu and Jiang, AAAI 2017)
  - RNSCN: (Wang and Sinno, ACL 2018)

Models	R→L		R→D		L→R		L→D		D→R		D→L	
	AS	OP	AS	OP	AS	OP	AS	OP	AS	OP	AS	OP
CrossCRF	19.72 (1.82)	59.20 (1.34)	21.07 (0.44)	52.05 (1.67)	28.19 (0.58)	65.52 (0.89)	29.96 (1.69)	56.17 (1.49)	6.59 (0.49)	39.38 (3.06)	24.22 (2.54)	46.67 (2.43)
RAP	25.92 (2.75)	62.72 (0.49)	22.63 (0.52)	54.44 (2.20)	46.90 (1.64)	67.98 (1.05)	34.54 (0.64)	54.25 (1.65)	45.44 (1.61)	60.67 (2.15)	28.22 (2.42)	59.79 (4.18)
Hier-Joint	33.66 (1.47)	- -	33.20 (0.52)	- -	48.10 (1.45)	- -	31.25 (0.49)	- -	47.97 (0.46)	- -	34.74 (2.27)	-
RNCRF	24.26 (3.97)	60.86 (3.35)	24.31 (2.57)	51.28 (1.78)	40.88 (2.09)	66.50 (1.48)	31.52 (1.40)	55.85 (1.09)	34.59 (1.34)	63.89 (1.59)	40.59 (0.80)	60.17 (1.20)
RNGRU	24.23 (2.41)	60.65 (1.04)	20.49 (2.68)	52.28 (2.69)	39.78 (0.61)	62.99 (0.95)	32.51 (1.12)	52.24 (2.37)	38.15 (2.82)	64.21 (1.11)	39.44 (2.79)	60.85 (1.25)
RNSCN-CRF	35.26 (1.31)	61.67 (1.35)	32.00 (1.48)	52.81 (1.29)	**53.38** (1.49)	67.60 (0.99)	34.63 (1.38)	56.22 (1.10)	48.13 (0.71)	65.06 (0.66)	46.71 (1.16)	61.88 (1.52)
RNSCN-GRU	37.77 (0.45)	62.35 (1.85)	33.02 (0.58)	57.54 (1.27)	53.18 (0.75)	71.44 (0.97)	35.65 (0.77)	60.02 (0.80)	**49.62** (0.34)	69.42 (2.27)	45.92 (1.14)	63.85 (1.97)
RNSCN$^+$-GRU	**40.43** (0.96)	**65.85** (1.50)	**35.10** (0.62)	**60.17** (0.75)	52.91 (1.82)	**72.51** (1.03)	**40.42** (0.70)	**61.15** (0.60)	48.36 (1.14)	**73.75** (1.76)	**51.14** (1.68)	**71.18** (1.58)

➢ Incorporating domain-independent auxiliary tasks can indeed significantly outperform the baseline approach.

Short Summary

Transfer Learning

- Benchmark Datasets for Cross-Lingual Aspect Term Extraction

Data Set	#Sentences	Train	Test
English	2,676	2,000	676
French	2,429	1,733	696
Spanish	2,951	2,070	881

  - All from SemEval-2016 Task 5

Transfer Learning

Short Summary

- Results on Benchmark Datasets
  - CL-DSCL: (Ding, Yu and Jiang, AAAI 2017)
  - TAN: (Wang and Sinno, IJCAI 2018)

Models	En→Fr		En→Es		Fr→En		Fr→Es		Es→En		Es→Fr	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
Translate-TAN	45.09	40.74	45.85	41.08	39.28	38.74	32.27	34.54	45.94	41.28	41.52	36.38
Translate-CRF	25.23	23.15	28.26	30.10	25.89	26.79	31.55	30.63	32.24	26.66	24.05	20.90
NoAdp	27.71	26.13	27.56	31.31	41.21	38.29	45.43	48.21	37.52	30.39	37.95	37.89
A-RNN	22.92	20.54	31.11	34.04	29.62	27.11	40.58	40.77	35.49	30.26	34.52	31.02
A-R^2NN	27.92	23.41	28.63	28.65	36.43	33.25	38.55	39.45	40.83	34.16	42.83	37.19
CrossCRF	20.41	16.83	16.17	18.22	21.63	19.02	6.90	6.81	10.13	8.28	12.01	10.24
CL-DSCL	33.67	31.48	44.56	45.01	51.75	47.27	53.23	55.89	50.22	**45.90**	38.66	34.17
TAN	**53.27**	**50.02**	**49.38**	**50.52**	**55.38**	**50.30**	**55.32**	**57.65**	**51.99**	44.14	**51.16**	**48.78**

➢ Incorporating language-independent auxiliary tasks can indeed significantly outperform the baseline approach.

Outline

- Transfer Learning
- **Multi-Task Learning**
  - Aspect and Opinion Terms Co-Extraction
  - End to End ABSA
    - Aspect Term Extraction + Aspect-Level Sentiment Classification
- Multimodal Learning
- Summary

Background

Multi-Task Learning

- Aspect and Opinion Terms Co-extraction
  - Input
    - A sentence or document
  - Output
    - **Aspect Term**
    - **Opinion Term**
  - Example

The **fish** was rather *over cooked*, but the **staff** was *quite nice*!

> - **Aspect Term: fish, staff**
> - **Opinion Term:** over cooked**,** nice

  - Sequence Labeling Problems

Outline

- Transfer Learning
- **Multi-Task Learning**
  - Aspect and Opinion Terms Co-Extraction
  - End to End ABSA
    - Aspect Term Extraction + Aspect-Level Sentiment Classification
- Multimodal Learning
- Summary

Background

Multi-Task Learning

- End to End Aspect-Based Sentiment Analysis
  - Input
    - A sentence or document
  - Output
    - **Aspect Term**
    - **Sentiment polarity** towards the **aspect term**
      - Positive, Negative, Neutral
  - Example

The **fish** was rather *over cooked*, but the **staff** was *quite nice*!

➢ **(fish,** negative), **(staff,** positive)

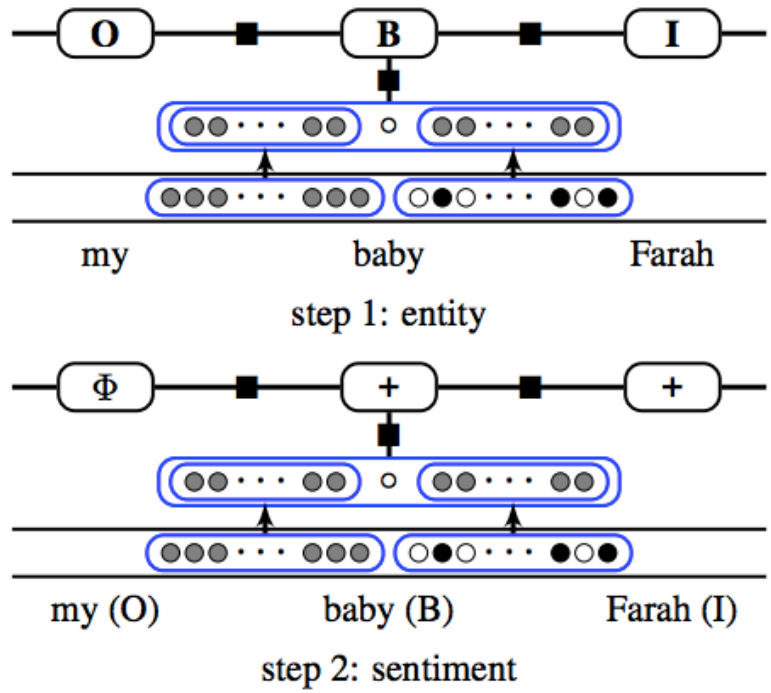
Background

Multi-Task Learning

- End to End Aspect-Based Sentiment Analysis
  - Neural CRF
    - Method 1: pipeline

sentence:	So	excited	to	meet	my	baby	Farah	!!!
entity:	O	O	O	O	O	B	I	O
sentiment:	Φ	Φ	Φ	Φ	Φ	+	+	Φ

Two Sequence Labeling Tasks



Pipeline Model

Meishan Zhang, Yue Zhang, and Duy-Tin Vo. 2015. Neural networks for open domain targeted sentiment. In Proceedings of EMNLP 2015.

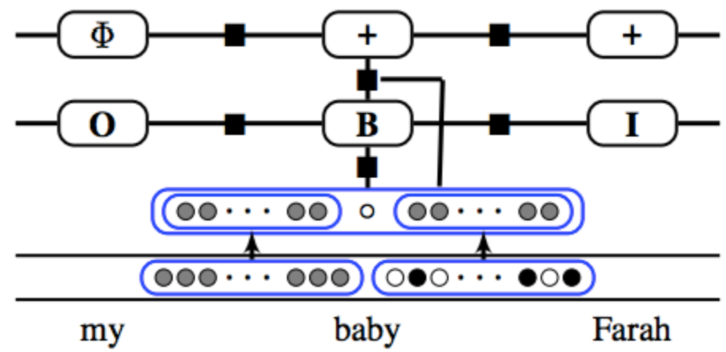
Background

Multi-Task Learning

- End to End Aspect-Based Sentiment Analysis
  - Neural CRF
    - Method 2: joint

sentence:	So	excited	to	meet	my	baby	Farah	!!!
entity:	O	O	O	O	O	B	I	O
sentiment:	Φ	Φ	Φ	Φ	Φ	+	+	Φ

Two Sequence Labeling Tasks



Joint Model

Meishan Zhang, Yue Zhang, and Duy-Tin Vo. 2015. Neural networks for open domain targeted sentiment. In Proceedings of EMNLP 2015.

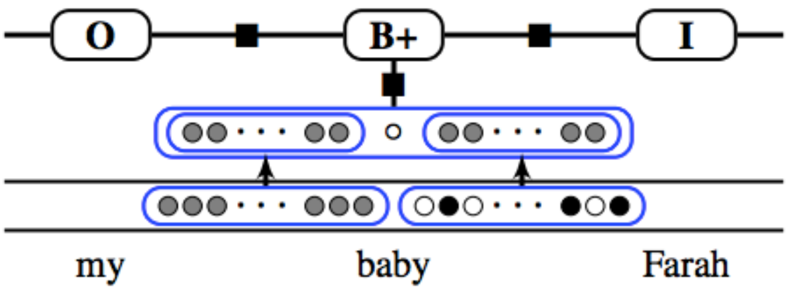
Background

Multi-Task Learning

- End to End Aspect-Based Sentiment Analysis
  - Neural CRF
    - Method 3: collapsed

sentence:	So	excited	to	meet	my	baby	Farah	!!!
collapsed:	O	O	O	O	O	B+	I+	O

One Sequence Labeling Task



Collapsed Model

Meishan Zhang, Yue Zhang, and Duy-Tin Vo. 2015. Neural networks for open domain targeted sentiment. In Proceedings of EMNLP 2015.

Background

Multi-Task Learning

- End to End Aspect-Based Sentiment Analysis
  - Neural CRF
    - Comparison

Model	English						Spanish					
	Entity			SA			Entity			SA		
	P	R	F	P	R	F	P	R	F	P	R	F
Pipeline												
discrete	59.37	34.83	43.84	42.97	25.21	31.73	**70.77**	47.75	57.00	**46.55**	31.38	37.47
neural	53.64	44.87	48.67	37.53	31.38	34.04	65.59	47.82	55.27	41.50	30.27	34.98
integrated	**60.69**	**51.63**	**55.67**	**43.71**	**37.12**	**40.06**	70.23	**62.00**	**65.76**	45.99	**40.57**	**43.04**
Joint												
discrete	59.55	34.06	43.30	43.09	24.67	31.35	71.08	47.56	56.96	46.36	31.02	37.15
neural	54.45	42.12	47.17	37.55	28.95	32.45	65.05	47.79	55.07	40.28	29.58	34.09
integrated	**61.47**	**49.28**	**54.59**	**44.62**	**35.84**	**39.67**	**71.32**	**61.11**	**65.74**	**46.67**	**39.99**	**43.02**
Collapsed												
discrete	**64.16**	26.03	36.95	**48.35**	19.64	27.86	73.18	35.11	47.42	**49.85**	23.91	32.30
neural	58.53	37.25	45.30	43.12	27.44	33.36	67.43	43.2	52.64	42.61	27.27	33.25
integrated	63.55	**44.98**	**52.58**	46.32	**32.84**	**38.36**	**73.51**	**53.3**	**61.71**	47.69	**34.53**	**40.00**

Meishan Zhang, Yue Zhang, and Duy-Tin Vo. 2015. Neural networks for open domain targeted sentiment. In Proceedings of EMNLP 2015.

Background

Multi-Task Learning

- End to End Aspect-Based Sentiment Analysis
  - Unified Solution

Input	The	AMD	Turin	Processor	seems	to	always	perform	much	better	than	Intel	.
Joint	O	B	I	E	O	O	O	O	O	O	O	S	O
	O	POS	POS	POS	O	O	O	O	O	O	O	NEG	O
Unified (✔)	O	B-POS	I-POS	E-POS	O	O	O	O	O	O	O	S-NEG	O

Two Sequence Labeling Tasks

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Xin Li, Lidong Bing, Piji Li and Wai Lam. A Unified Model for Opinion Target Extraction and Target Sentiment Prediction. In AAAI 2019.

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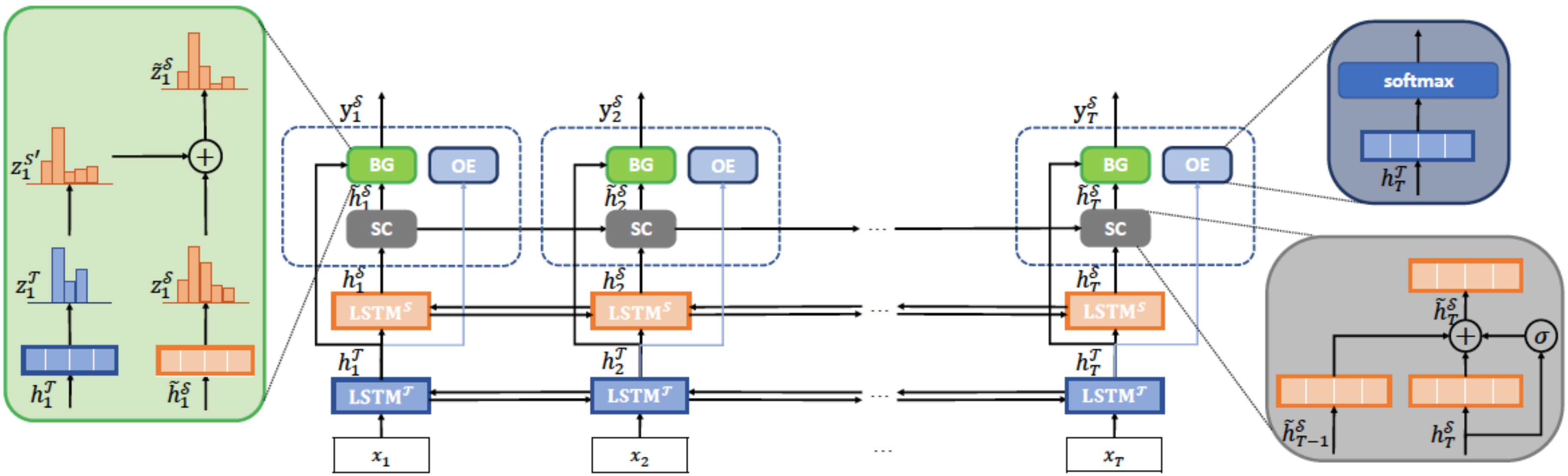
Background

Multi-Task Learning

- End to End Aspect-Based Sentiment Analysis
  - Unified Solution



- Two LSTMs for the target boundary detection task (auxiliary) and the complete TBSA task (primary).
- BG component: exploiting boundary information
- SC component: maintaining sentiment consistency
- OE component: improving the quality of the boundary information

Xin Li, Lidong Bing, Piji Li and Wai Lam. A Unified Model for Opinion Target Extraction and Target Sentiment Prediction. In AAAI 2019.

Background

Multi-Task Learning

- End to End Aspect-Based Sentiment Analysis
  - Span Extraction-based approach

Sentence:	I love Windows 7 ... over Vista .
Pipeline/ Joint:	O O B I O B O 0 0 + + 0 - 0
Collapsed:	O O B+ I+ O B- O

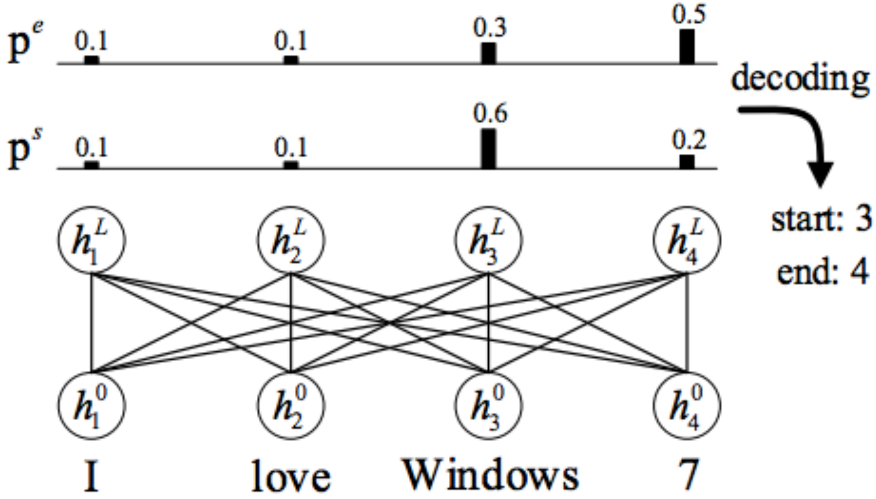
Sentence:	I love Windows 7 ... over Vista .
Pipeline/ Joint:	Target start: 3, 11 Target end: 4, 11 Polarity: +, -
Collapsed:	Target start: 3+, 11- Target end: 4+, 11-

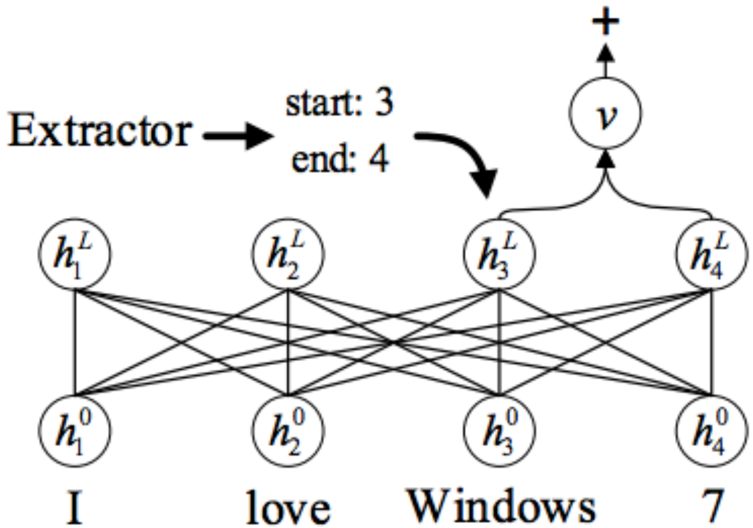
Open-Domain Targeted Sentiment Analysis via Span-Based Extraction and Classification. Minghao Hu, Yuxing Peng, Zhen Huang, Dongsheng Li, Yiwei Lv. In Proceedings of ACL. 2019.

Background

Multi-Task Learning

- End to End Aspect-Based Sentiment Analysis
  - Span Extraction-based approach
    - BERT as encoder





- The last block's hidden states are used to propose one or multiple candidate targets based on the probabilities of the start and end positions
- Predict the sentiment polarity using the span representation of the given target

Open-Domain Targeted Sentiment Analysis via Span-Based Extraction and Classification. Minghao Hu, Yuxing Peng, Zhen Huang, Dongsheng Li, Yiwei Lv. In Proceedings of ACL. 2019.

Background

Multi-Task Learning

- End to End Aspect-Based Sentiment Analysis
  - Comparison of previous three approaches
    - Benchmark Datasets

Data Set	#Training Samples			#Test Samples		
	POS	NEG	NEU	POS	NEG	NEU
Laptop	980	858	454	340	128	171
Restaurant	2159	800	623	730	195	196
Twitter-2014	1567	1563	3127	147	147	346

- Laptop, Restaurant are from SemEval-2014
- Twitter-2014 from (Dong et al. ACL 2014)
- Another two Restaurant datasets from SemEval-2015, SemEval-2016

Jianfei Yu and Jing Jiang. Adapting BERT for Target-Oriented Multimodal Sentiment Classification. In IJCAI, 2019.

Background

Multi-Task Learning

- End to End Aspect-Based Sentiment Analysis
  - Comparison of previous three approaches
    - Unified Approach vs LSTM-based Methods

	Model	$\mathbb{D}_L$			$\mathbb{D}_R$			$\mathbb{D}_T$		
		P	R	F1	P	R	F1	P	R	F1
Existing Baselines	CRF-joint	57.38	35.76	44.06	60.00	48.57	53.68	43.09	24.67	31.35
	CRF-unified	59.27	41.86	49.06	63.39	57.74	60.43	48.35	19.64	27.86
	NN-CRF-joint	55.64	34.48	45.49	61.56	50.00	55.18	44.62	35.84	39.67
	NN-CRF-unified	58.72	45.96	51.56	62.61	60.53	61.56	46.32	32.84	38.36
Pipeline Baselines	CRF-pipeline	59.69	47.54	52.93	52.28	51.01	51.64	42.97	25.21	31.73
	NN-CRF-pipeline	57.72	49.32	53.19	60.09	61.93	61.00	43.71	37.12	40.06
	HAST-TNet	56.42	54.20	55.29	62.18	73.49	67.36	46.30	49.13	47.66
Unified Baselines	LSTM-unified	57.91	46.21	51.40	62.80	63.49	63.14	51.45	37.62	43.41
	LSTM-CRF-1	58.61	50.47	54.24	66.10	66.30	66.20	51.67	44.08	47.52
	LSTM-CRF-2	58.66	51.26	54.71	61.56	67.26	64.29	53.74	42.21	47.26
	LM-LSTM-CRF	53.31	59.4	56.19	68.46	64.43	66.38	43.52	52.01	47.35
OURS	Base model	60.00	46.85	52.61	61.48	66.16	63.73	53.02	41.47	46.50
	Base model + **BG**	58.58	50.63	54.31	67.51	66.42	66.96	52.26	43.84	47.66
	Base model + **BG** + **SC**	58.95	53.00	55.81	63.95	69.65	66.68	53.12	43.60	47.79
	Base model + **BG** + **OE**	63.43	49.53	55.62	62.85	66.77	65.22	53.10	43.50	47.78
	Full model	61.27	54.89	**57.90**$^{\natural,\sharp}$	68.64	71.01	**69.80**$^{\natural,\sharp}$	53.08	43.56	**48.01**$^{\sharp}$

Open-Domain Targeted Sentiment Analysis via Span-Based Extraction and Classification. Minghao Hu, Yuxing Peng, Zhen Huang, Dongsheng Li, Yiwei Lv. In Proceedings of ACL. 2019.

Background

Multi-Task Learning

- End to End Aspect-Based Sentiment Analysis
  - Comparison of previous three approaches
    - BERT-based Methods vs Unified Approach

Model	LAPTOP			REST			TWITTER		
	Prec.	Rec.	F1	Prec.	Rec.	F1	Prec.	Rec.	F1
UNIFIED	61.27	54.89	57.90	68.64	71.01	69.80	53.08	43.56	48.01
TAG-pipeline	65.84	67.19	66.51	71.66	76.45	73.98	54.24	54.37	54.26
TAG-joint	65.43	66.56	65.99	71.47	75.62	73.49	54.18	54.29	54.20
TAG-collapsed	63.71	66.83	65.23	71.05	75.84	73.35	54.05	54.25	54.12
SPAN-pipeline	69.46	66.72	**68.06**	76.14	73.74	**74.92**	60.72	55.02	**57.69**
SPAN-joint	67.41	61.99	64.59	72.32	72.61	72.47	57.03	52.69	54.55
SPAN-collapsed	50.08	47.32	48.66	63.63	53.04	57.85	51.89	45.05	48.11

Open-Domain Targeted Sentiment Analysis via Span-Based Extraction and Classification. Minghao Hu, Yuxing Peng, Zhen Huang, Dongsheng Li, Yiwei Lv. In Proceedings of ACL. 2019.

Outline

- Transfer Learning
- Multi-Task Learning
- **Multimodal Learning**
  - Target-Oriented Multimodal Sentiment Classification
- Summary

Recall

Multimodal Learning

- **Target-oriented Sentiment Classification (TSC)**
  - Input
    - A sentence or document
    - An **opinion target**
  - Output
    - **Sentiment polarity** towards the **opinion target**

- Examples

The ***fish*** was rather *over cooked*, but the ***chicken*** was *fine*!

- sentiment over ***fish***: negative
- sentiment over ***chicken***: positive

Motivation

Multimodal Learning

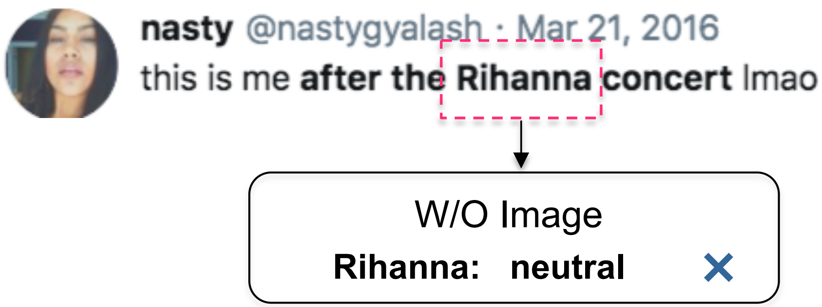
- **Limitation of TSC**
  - **Ineffective for multimodal social media posts**
    - **Incomplete Textual Contents**

Jianfei Yu and Jing Jiang. Adapting BERT for Target-Oriented Multimodal Sentiment Classification. In IJCAI 2019.

Motivation

Multimodal Learning

- **Limitation of TSC**
  - **Ineffective for multimodal social media posts**
    - **Incomplete Textual Contents**



Jianfei Yu and Jing Jiang. Adapting BERT for Target-Oriented Multimodal Sentiment Classification. In IJCAI 2019.

Motivation

Multimodal Learning

- **Limitation of TSC**
  - **Ineffective for multimodal social media posts**
    - **Incomplete Textual Contents**

nasty @nastygyalash · Mar 21, 2016
this is me **after the Rihanna concert** lmao

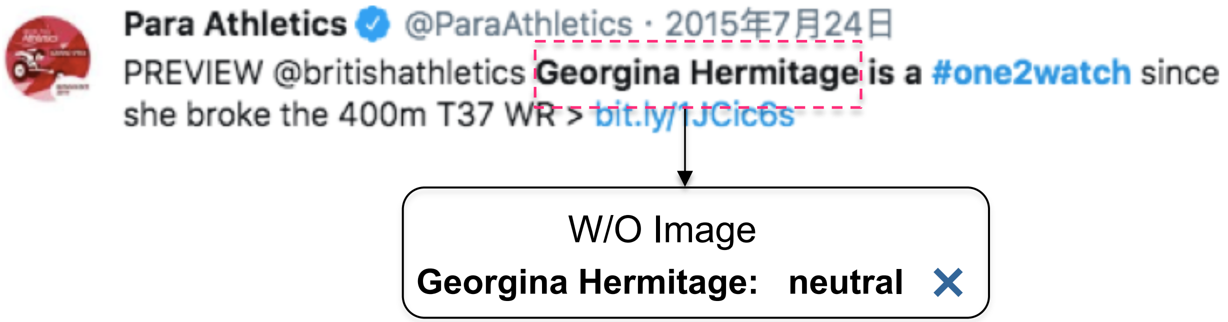
With Image
Rihanna: ***positive*** √

Jianfei Yu and Jing Jiang. Adapting BERT for Target-Oriented Multimodal Sentiment Classification. In IJCAI 2019.

Motivation

Multimodal Learning

- **Limitation of TSC**
  - **Ineffective for multimodal social media posts**
    - Incomplete Textual Contents
    - **Irregular Expressions**



Motivation

Multimodal Learning

- **Limitation of TSC**
  - **Ineffective for multimodal social media posts**
    - Incomplete Textual Contents
    - **Irregular Expressions**

Para Athletics @ParaAthletics · 2015年7月24日
PREVIEW @britishathletics **Georgina Hermitage** is a #one2watch since she broke the 400m T37 WR > bit.ly/1JCic6s

With Image
Georgina Hermitage : *positive* √

Jianfei Yu and Jing Jiang. Adapting BERT for Target-Oriented Multimodal Sentiment Classification. In IJCAI 2019.

Motivation

Multimodal Learning

- Target-oriented Multimodal Sentiment Classification (TMSC)
  - Input
    - A sentence or document
    - An opinion target
    - An ***associated image***
  - Output
    - Sentiment polarity towards the opinion target

Jianfei Yu and Jing Jiang. Adapting BERT for Target-Oriented Multimodal Sentiment Classification. In IJCAI 2019.

Methodology -- BERT

Multimodal Learning

- Base model with BERT
  - Input Transformation
    - **Context** as the **first** sentence
    - **Opinion Target** as the **second** sentence
  - Example

[**Georgina Hermitage**]$_{positive}$ is a #one2watch since she broke the [**400m T37**]$_{\textbf{neutral}}$ WR!

Opinion Target	**BERT Input**	**Label**
Georgina Hermitage	**[CLS]** T is a #one2watch since she broke the 400m T37 WR. **[SEP]** Georgina Hermitage **[SEP]**	Positive
400m T37	**[CLS]** Georgina Hermitage is a #one2watch since she broke the T WR. **[SEP]** 400m T37 **[SEP]**	Neutral

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Jianfei Yu and Jing Jiang. Adapting BERT for Target-Oriented Multimodal Sentiment Classification. In IJCAI 2019.

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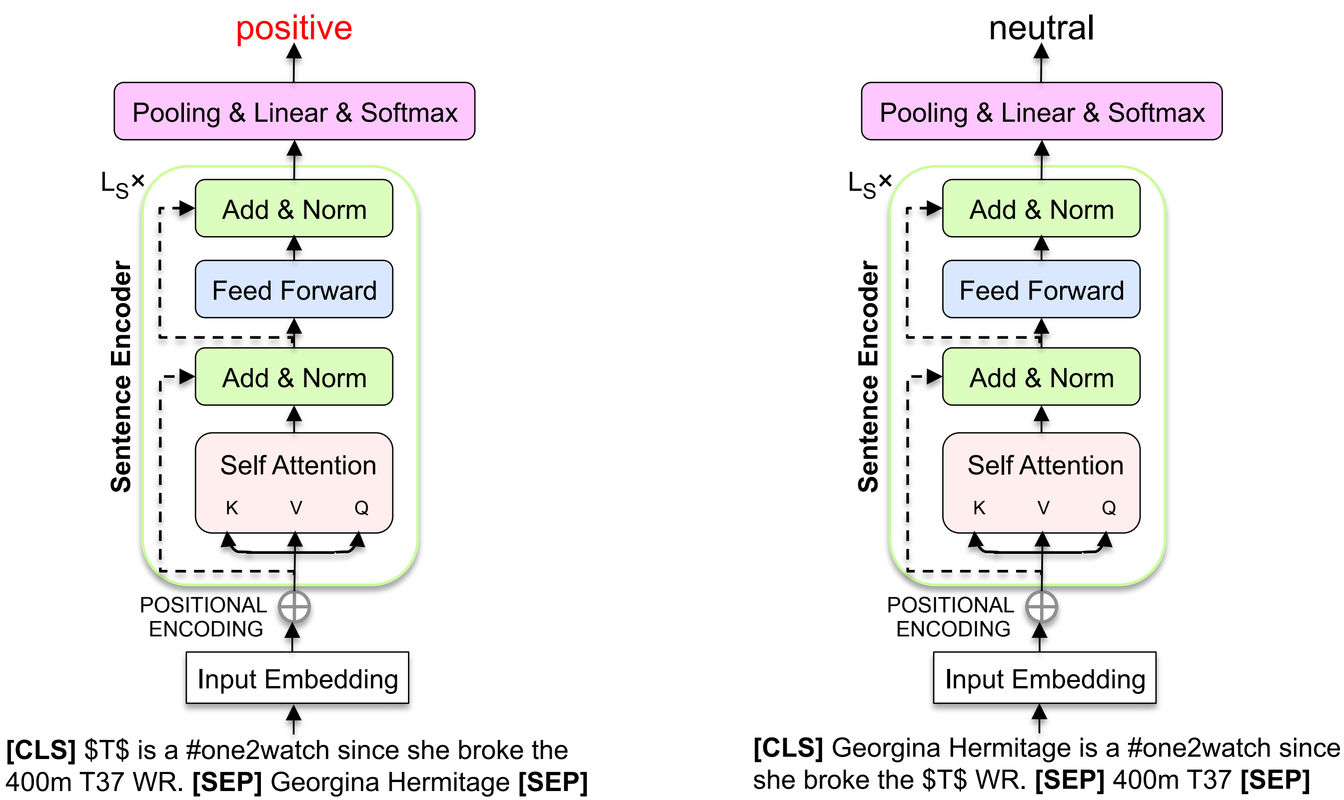
Methodology -- BERT

Multimodal Learning

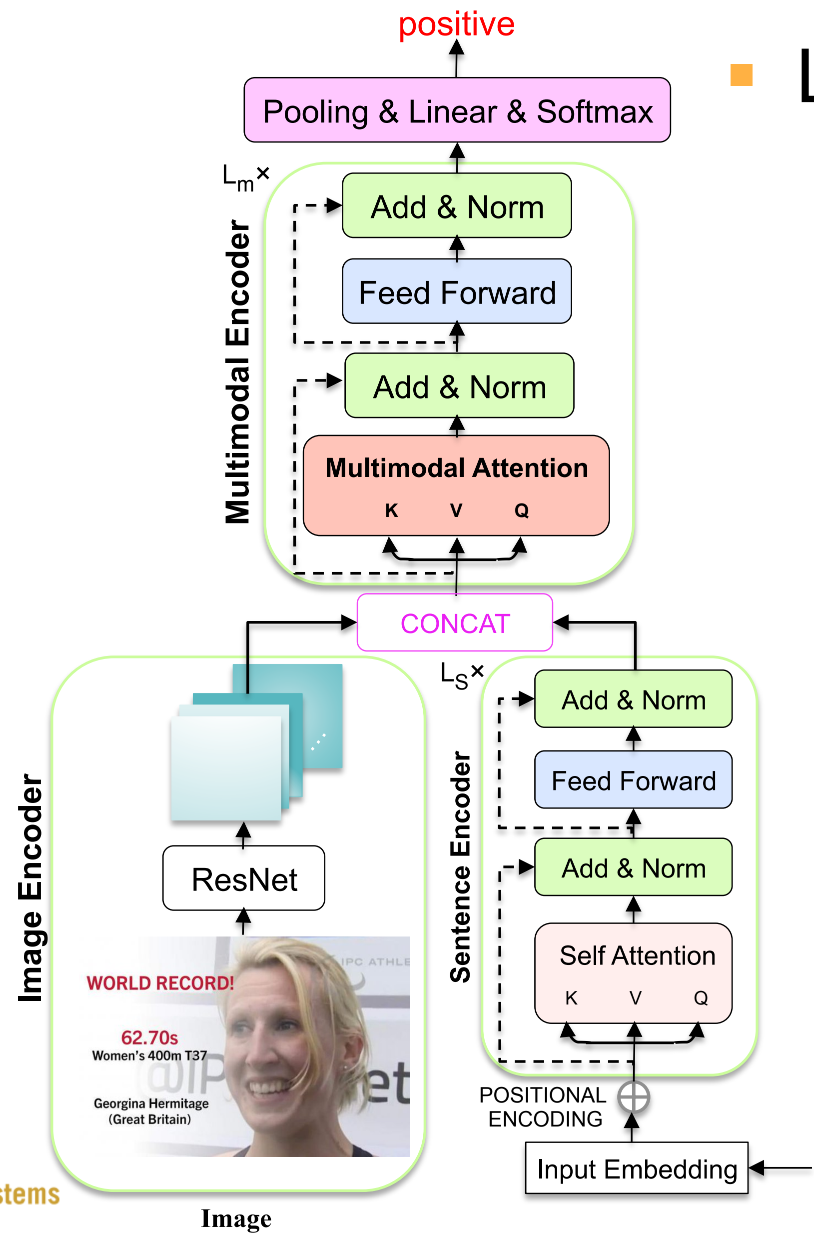
- Apply BERT to TSC
  - Feed the transformed sentence to BERT



(a). Georgina Hermitage **(b).** 400m T37

Jianfei Yu and Jing Jiang. Adapting BERT for Target-Oriented Multimodal Sentiment Classification. In IJCAI 2019.

Methodology -- multimodal BERT (mBERT)

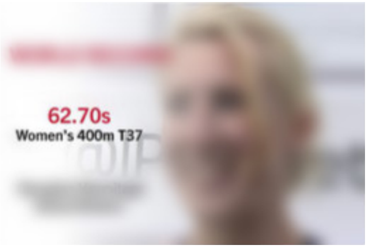


[CLS] \$T\$ is a #one2watch since she broke the 400m T37 WR. **[SEP]** Georgina Hermitage **[SEP]**

Multimodal Learning

- Limitation
  - Image features are not sensitive to opinion targets
    - Georgina Hermitage

    - 400m T37



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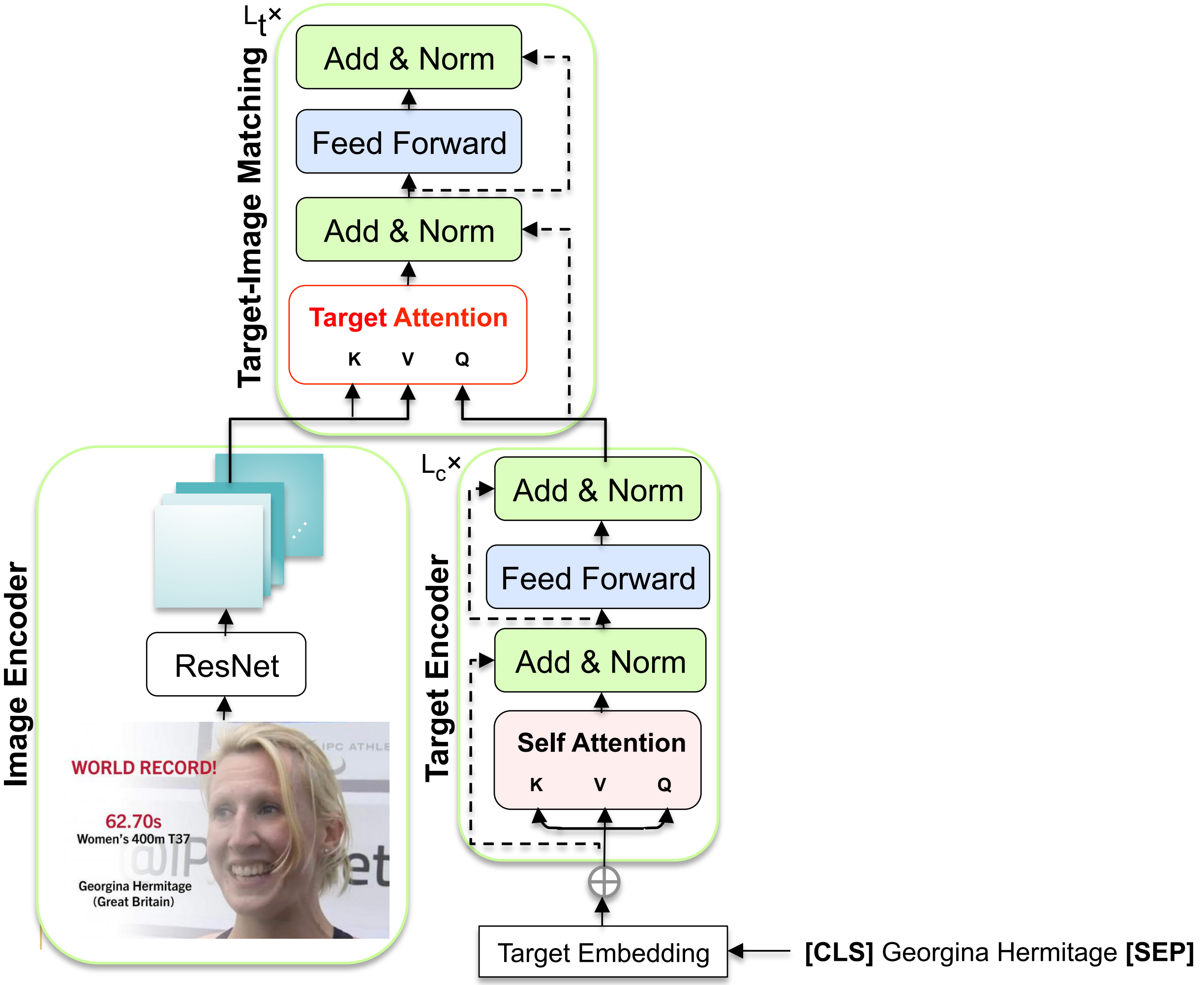
Methodology -- Target-oriented mBERT (TomBERT)

Multimodal Learning

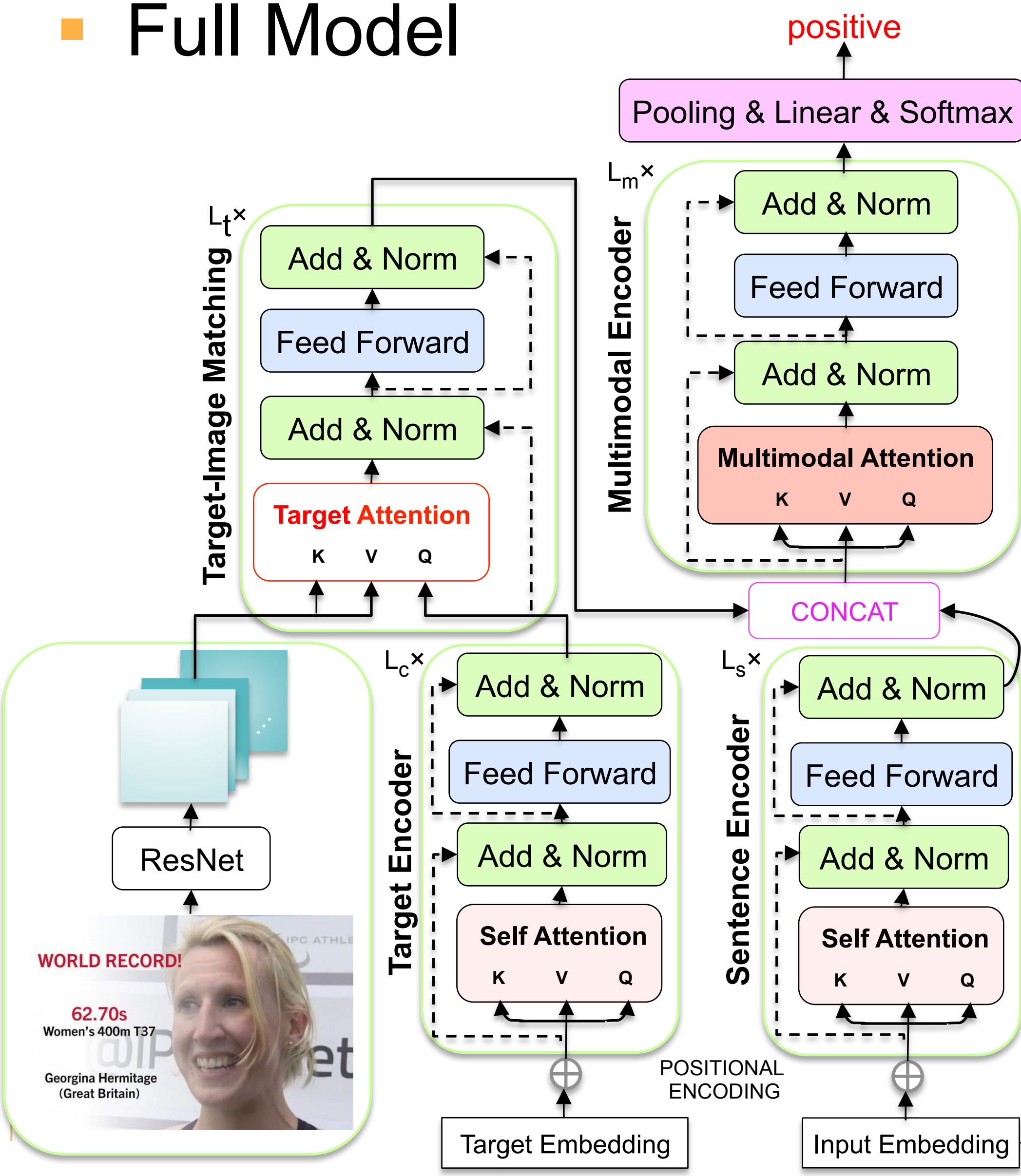
- Target Attention
  - Target as queries, images as keys and values



Methodology -- Target-oriented mBERT (TomBERT)

- Full Model

Multimodal Learning



[CLS] T is a #one2watch since she broke the 400m T37 WR. **[SEP]** Georgina Hermitage **[SEP]**

Experiments

- Two Multimodal Datasets

Modality	Data Set	#Training Samples			#Dev Samples			#Test Samples		
		POS	NEG	NEU	POS	NEG	NEU	POS	NEG	NEU
Text+Image	Twitter-2015	928	368	1883	303	149	670	317	113	607
	Twitter-2017	1508	416	1638	515	144	517	493	168	573

  - The two multimodal Twitter datasets are based on two public multimodal Named Entity Recognition (NER) datasets

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Experimental Results

- Results on the Two Multimodal Datasets

Modality	Method	Twitter-2015		Twitter-2017	
		Accuracy	Macro-F1	Accuracy	Macro-F1
Visual	Res-Target	59.88	46.48	58.59	53.98
Text	AE-LSTM	70.30	63.43	61.67	57.97
	MemNet	70.11	61.76	64.18	60.90
	RAM	70.68	63.05	64.42	61.01
	MGAN	71.17	64.21	64.75	61.46
	BERT	74.15	68.86	68.15	65.23
	BERT+BL	**74.25**	**70.04**	**68.88**	**66.12**

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Text + Visual	Res-MGAN	71.65	63.88	66.37	63.04
	Res-MGAN-TFN	70.30	64.14	64.10	59.13
	Res-BERT+BL	75.02	69.21	69.20	66.48
	Res-BERT+BL-TFN	73.58	68.74	67.18	64.29
	mBERT	***75.31***	***70.18***	***69.61***	***67.12***
	TomBERT	**77.15**	**71.75**	**70.34**	**68.03**

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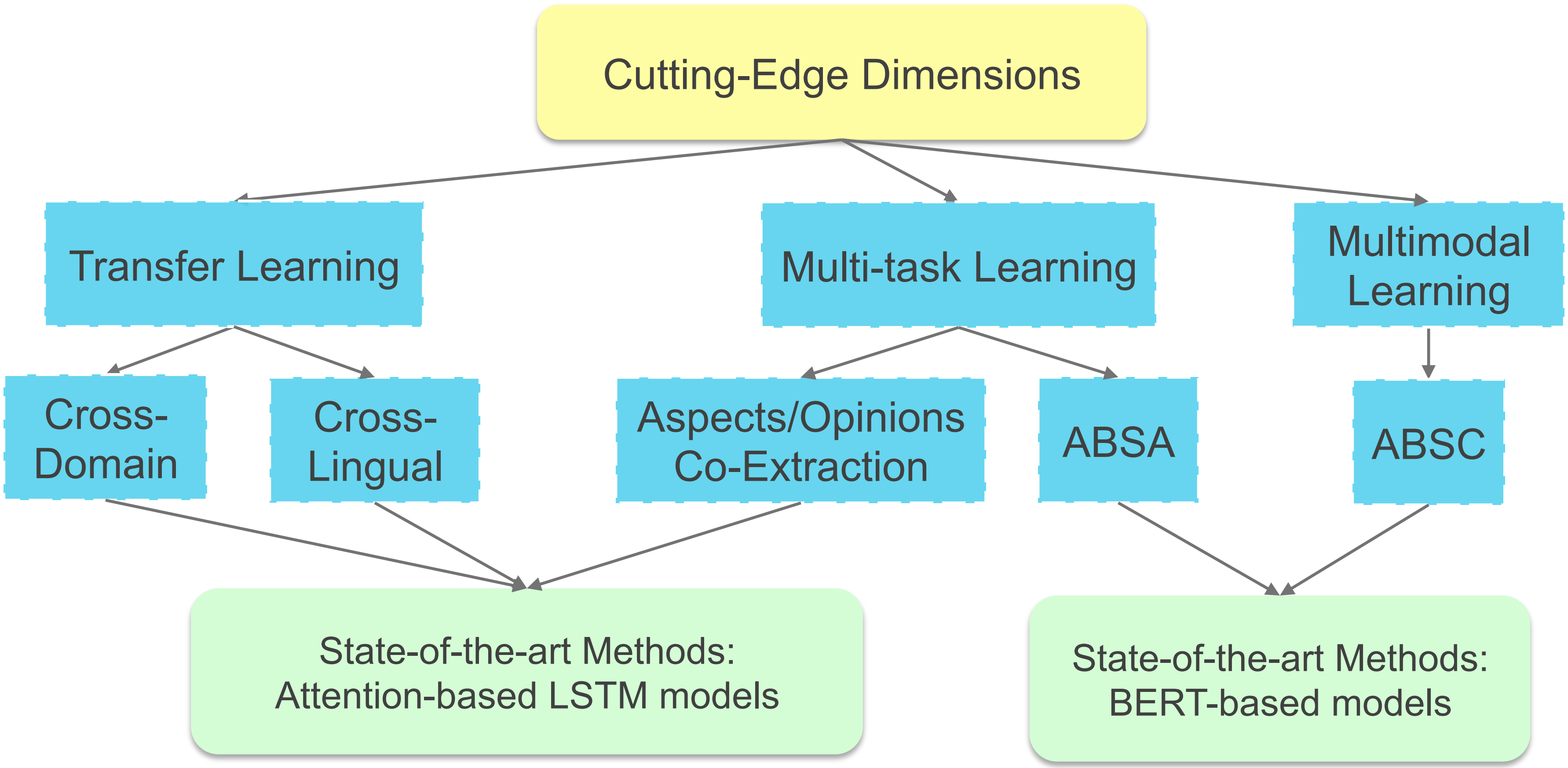
Outline

- Transfer Learning
- Multi-Task Learning
- Multimodal Learning
- **Summary**

Summary


Cutting-Edge Dimensions
Transfer Learning
Multi-task Learning
Multimodal Learning
Cross-Domain
Cross-Lingual
Aspects/Opinions Co-Extraction
ABSA
ABSC
State-of-the-art Methods: Attention-based LSTM models
State-of-the-art Methods: BERT-based models

Thank you !