Graph Adaptive Semantic Transfer for Cross-domain Sentiment Classification

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Outline

1. Introduction
2. Related Work
3. The GAST Model
4. Experiment
5. Conclusions

Introduction

Cross-domain Sentiment Classification (CDSC)

Refers to the use the similarity knowledge learned in the source domain to the target domain.

- **Source → Target**
- **Single → Invariant**

Source Domain $\sim P_S(X,Y)$ $\neq$ Target Domain $\sim P_T(Z,H)$

lots of **labeled** data — unlabeled or limited labels

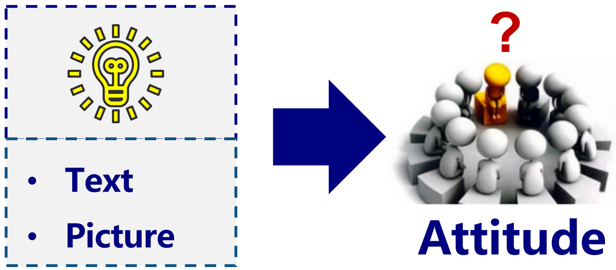
$D_S = \{(\mathbf{x}_i, y_i), \forall i \in \{1,\ldots,N\}\}$

$D_T = \{(\mathbf{z}_j, ?), \forall j \in \{1,\ldots,M\}\}$

Values

The use of similarities between tasks to apply knowledge learned from a old field to a new field.

- **Unlabeled data**
- **Cold start**
- **Model versatility**
- **Weak computing …**



Introduction

Challenges

1. **Making full use of domain shared features is pivotal for cross-domain sentiment classification. So , what information do we need to focus on in the whole sentence? How to pay attention?**
2. **How to mine and utilize this information that is critical for cross-domain classification tasks?**

Outline

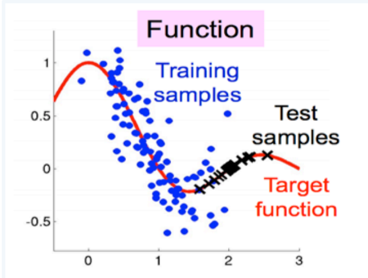
Related Work

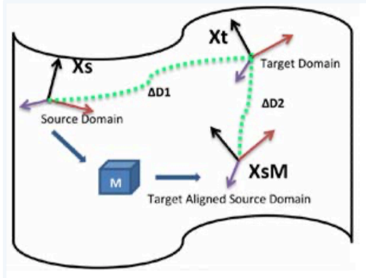
Source Domain $\sim P_S(X,Y)$ $\neq$ Target Domain $\sim P_T(Z,H)$

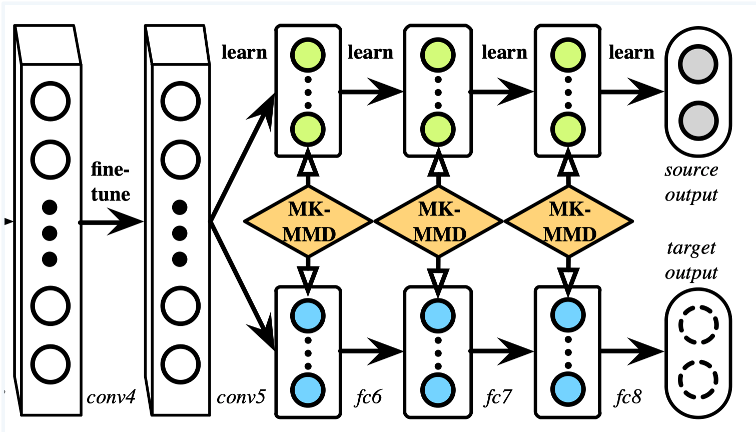
lots of **labeled** data | unlabeled or limited labels

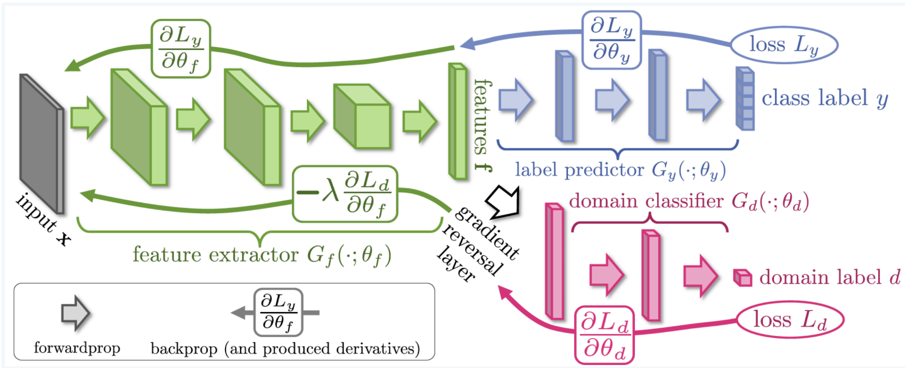
$$D_S = \{(\mathbf{x}_i, y_i), \forall i \in \{1,\ldots,N\}\} \qquad D_T = \{(\mathbf{z}_j, ?), \forall j \in \{1,\ldots,M\}\}$$

- **Unlabeled problem**
  - Sample re-weighting
  - Subspace matching
  - Deep methods







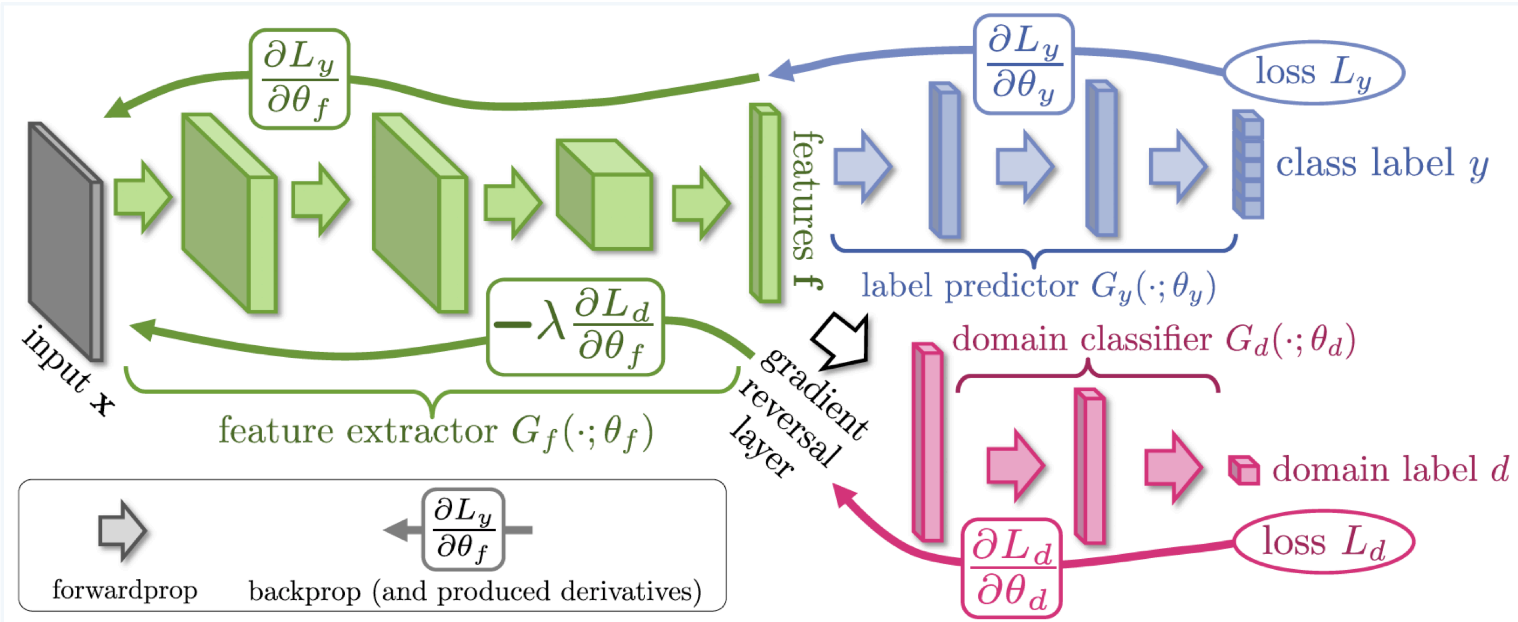


Maximum Mean Discrepancy M. Long, et al. ICML 2015 | Reverse Gradient Y. Ganin and V. Lempitsky ICML 2015

Related Work

Domain-Adversarial Neural Networks（ICML 2015）

- **Input：** $x \in X$, **input space of the image data**
- **Output：** $y \in Y$, $Y = \{1, 2, 3, \dots, n\}$, **label space of image data**
- **Goal：predict the classification labels of input images in the target domain**



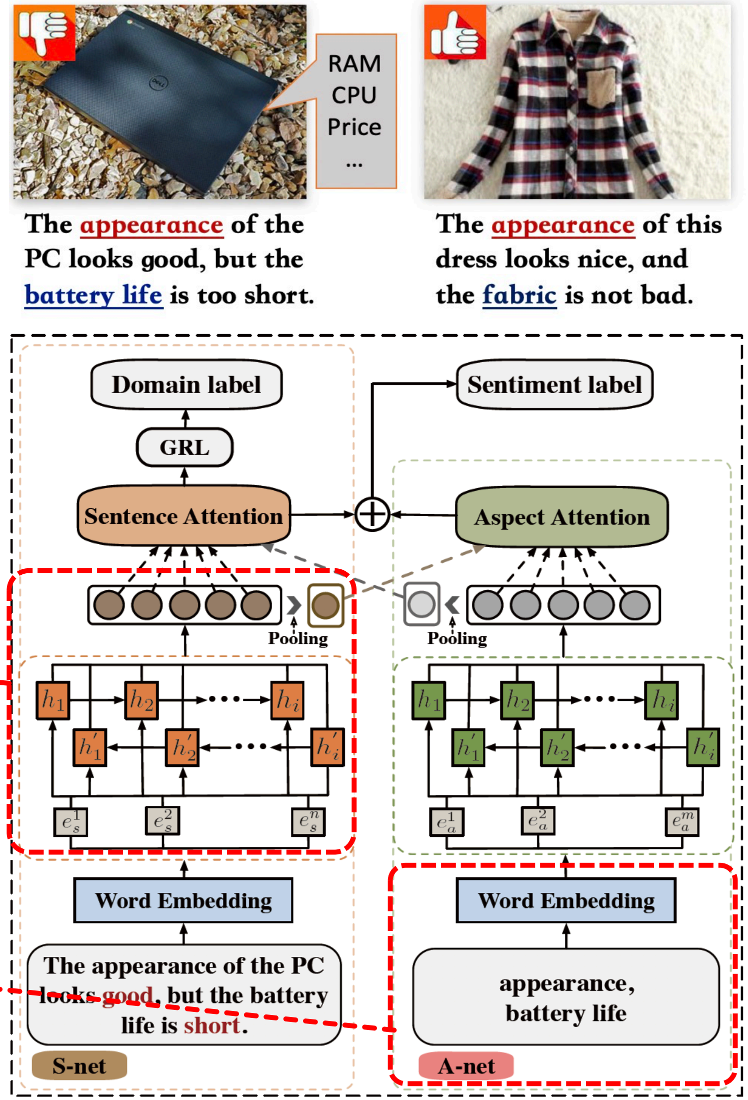
Related Work

IATN model

- Construct a better sentiment transfer network
- Make better use of Aspect information

Contains two parts :

1. S-Net
   - Learn shared information between domains
2. A-Net
   - Modeling Aspect Information



Outline

The GAST Model

Limitation of previous methods

1. DNN-based/ PLMs-based methods have become mainstream Encoders, and the model architecture is based on the evolution of the DANN framework
2. Design different deep, dedicated to mining better cross-domain semantic features

<u>There are some problems</u>

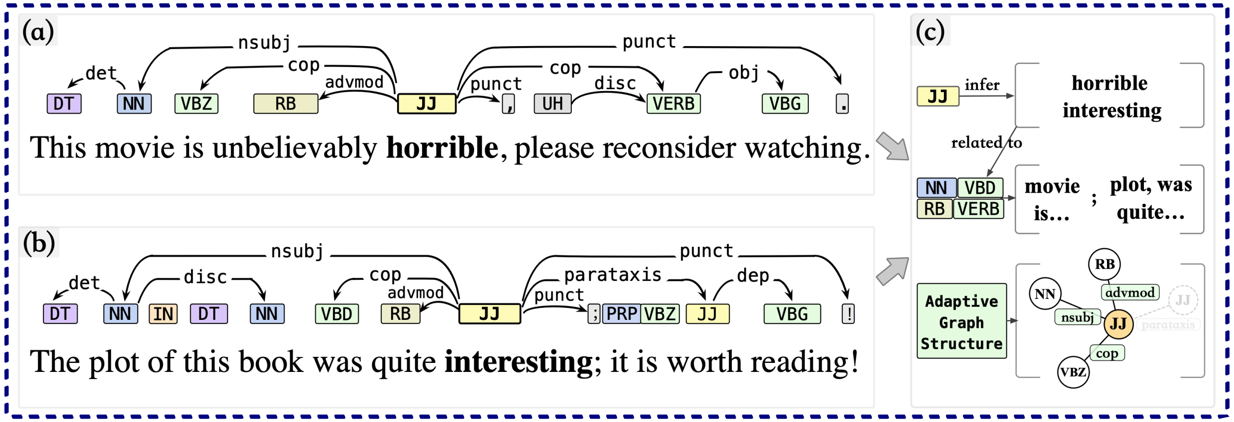
1. **Semantic representation:** Failure to fully utilize the internal information of the text (parsing & relation)
2. **Feature transfer:** ignoring important syntactic information in the process of cross-domain semantic transfer

GAST: Graph Adaptive Semantic Transfer for Cross-domain Sentiment Classification

The GAST Model

Motivation of our GAST model

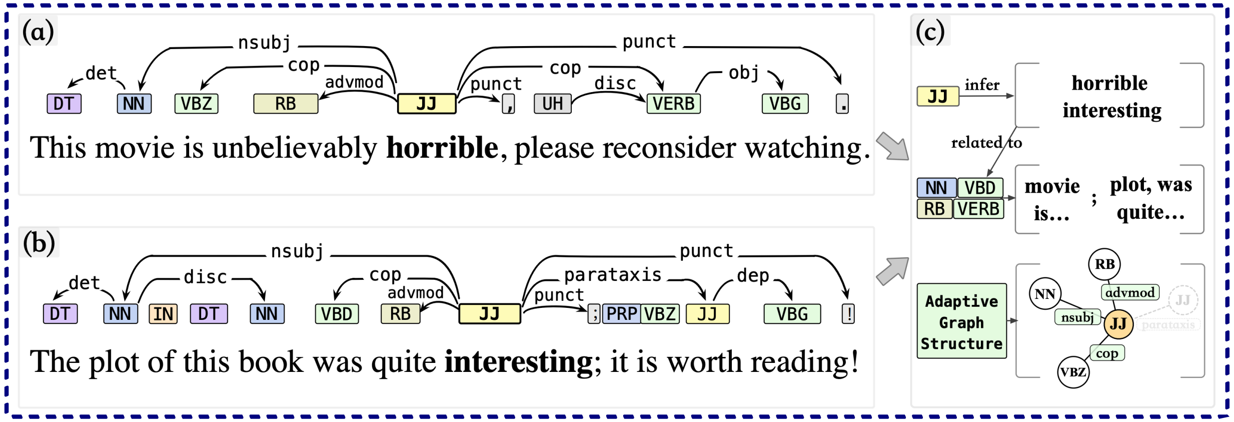
1. Sentiment words play a crucial role in CDSC，POS-tags can distinguish sentiment words (e.g., “horrible” and “interesting” in the Figure) via the POS-tag “JJ” in a natural way , i.e., the “JJ” label means the word is an adjective



The GAST Model

Motivation of our GAST model

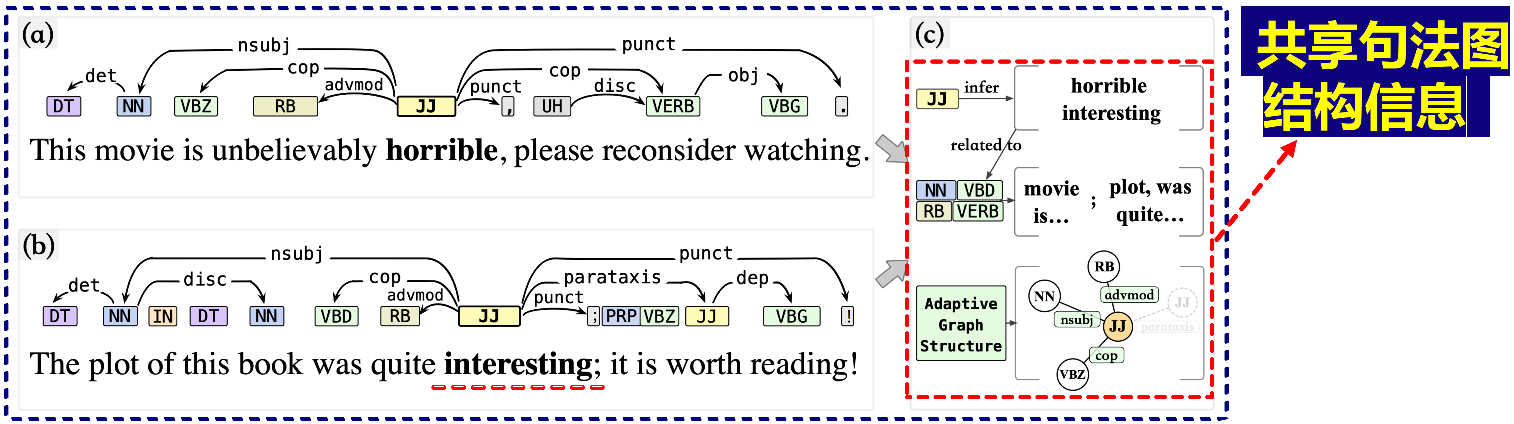
2. The sentiment polarity of reviews is largely influenced by the sentiment word's neighbors, whether they are in-domain or across-domain; Meanwhile, different neighbors' syntactic relations also have different influences for each sentiment word



The GAST Model

Motivation of our GAST model

3. As shown in Figure, the syntactic graph structures of sentences in different domains **are remarkably similar**, which means that the syntactic rules are **domain-invariant** and **can be naturally transferred across domains**

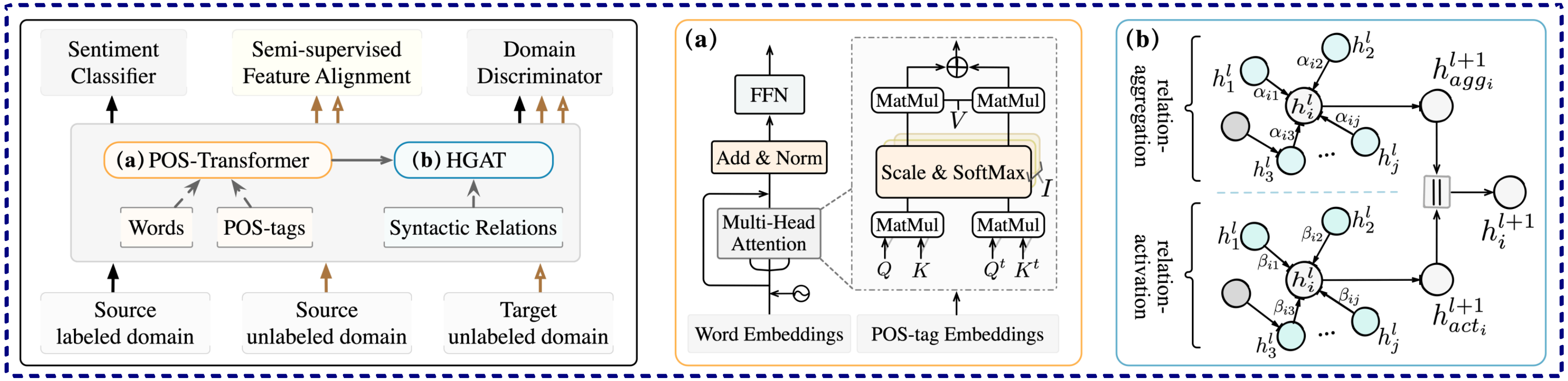


GAST: Graph Adaptive Semantic Transfer for Cross-domain Sentiment Classification

The GAST Model

Overall architecture of GAST

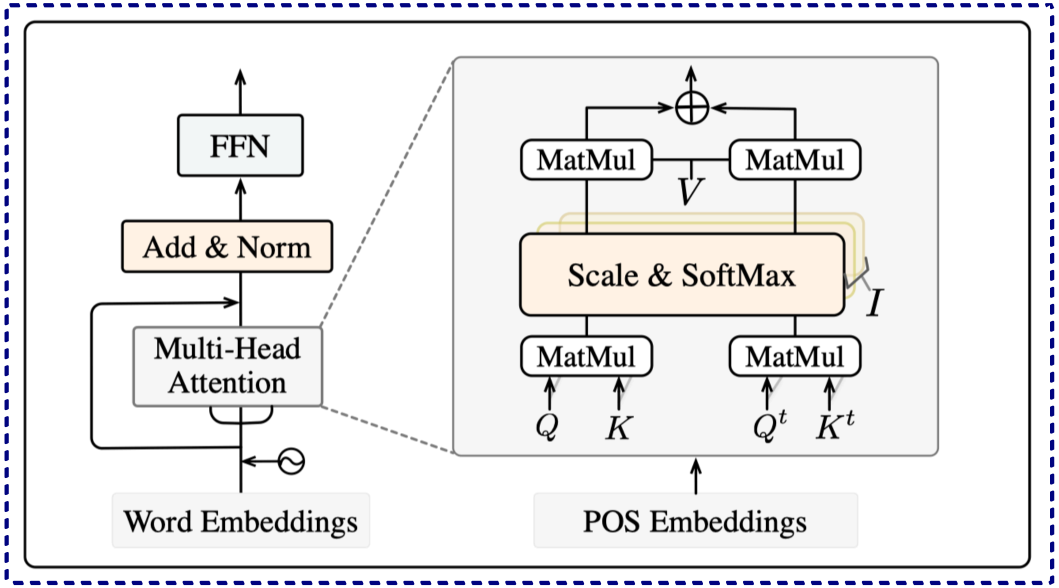
1. Generally, GAST improves the semantic representation and transferable knowledge between domains by **aggregating the information from both word sequences and syntactic graphs**
2. GAST mainly contains two modules to learn comprehensive semantics：
   - The first is **POS-based Transformer** (POS-Transformer, a in Figure)
   - The other is **Hybrid Graph Attention** (HGAT，b in Figure)



The GAST Model

Detail of the GAST model

1. We project the word's embedding matrix E into the query, key, and value matrices
2. Apart from word's embeddings, we also map the whole tag embedding matrix



$$Z = concat(z_1, z_2, \ldots, z_I),$$

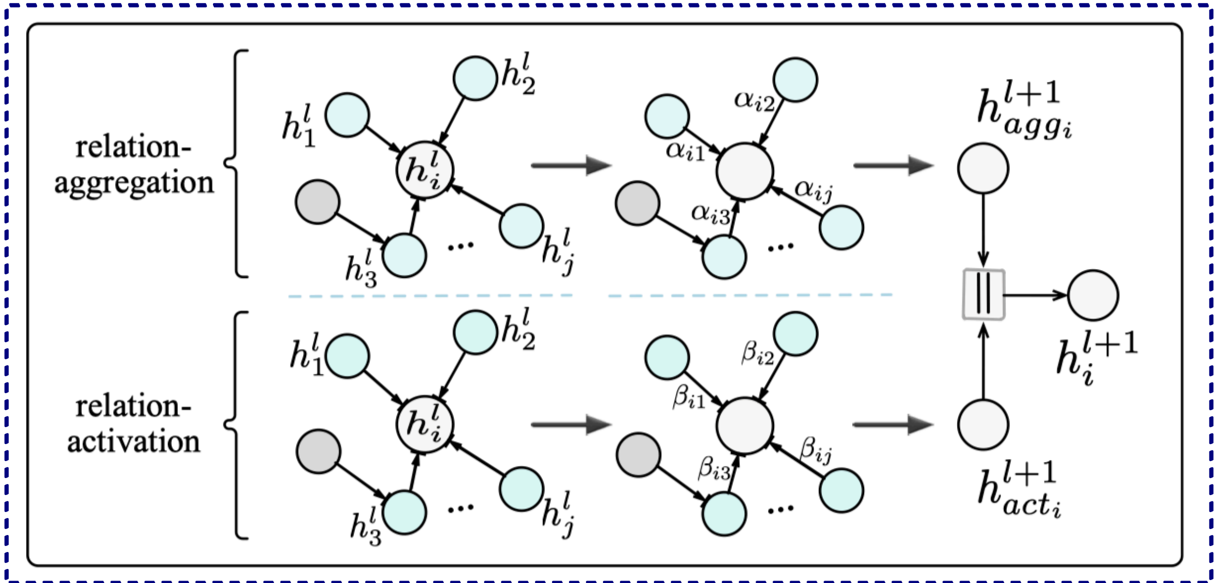
$$z_i = Att.(Q_i, K_i, V_i) + Att.(Q_i^t, K_i^t, V_i),$$

$$Att.(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d/I}}\right)V,$$

The GAST Model

Detail of the GAST model

1. **Contains two different calculation methods for better relation representation (i.e., relation-aggregation and relation-activation)**
2. **Through the above two relational functions, we can obtain two syntax-enhanced word representations**



$$h_{agg_i}^{l+1} = \|_{k=1}^{\bar{K}} \sigma\Big(\sum_{j \in \mathcal{N}_i} \alpha_{ij}^{lk} W_{lk} h_j^l\Big),$$

$$f_{ij}^{lk} = \sigma(a_{lk}^T [W_{lk} h_i^l \| W_{lk} h_j^l \| W_{lk} r_{ij}]),$$

$$\alpha_{ij}^{lk} = \frac{\exp\left(f_{ij}^{lk}\right)}{\sum_{j=1}^{\mathcal{N}_i} \exp\left(f_{ij}^{lk}\right)},$$

$$\beta_{ij}^{lk} = \frac{\exp\left(F_{act.}(h_i^l, h_j^l)\right)}{\sum_{j=1}^{\mathcal{N}_i} \exp\left(F_{act.}(h_i^l, h_j^l)\right)},$$

$$F_{act.} = \frac{\left(W_Q^{lk} h_i^l\right)\left(W_K^{lk} h_j^l + W_{Kr}^l r_{ij}\right)^T}{\sqrt{d/\bar{K}}},$$

$$h_{act_i}^{l+1} = \|_{k=1}^{\bar{K}} \sigma\Big(\sum_{j \in \mathcal{N}_i} \beta_{ij}^{lk} (W_V^{lk} h_j^l + W_{Vr}^l r_{ij})\Big),$$

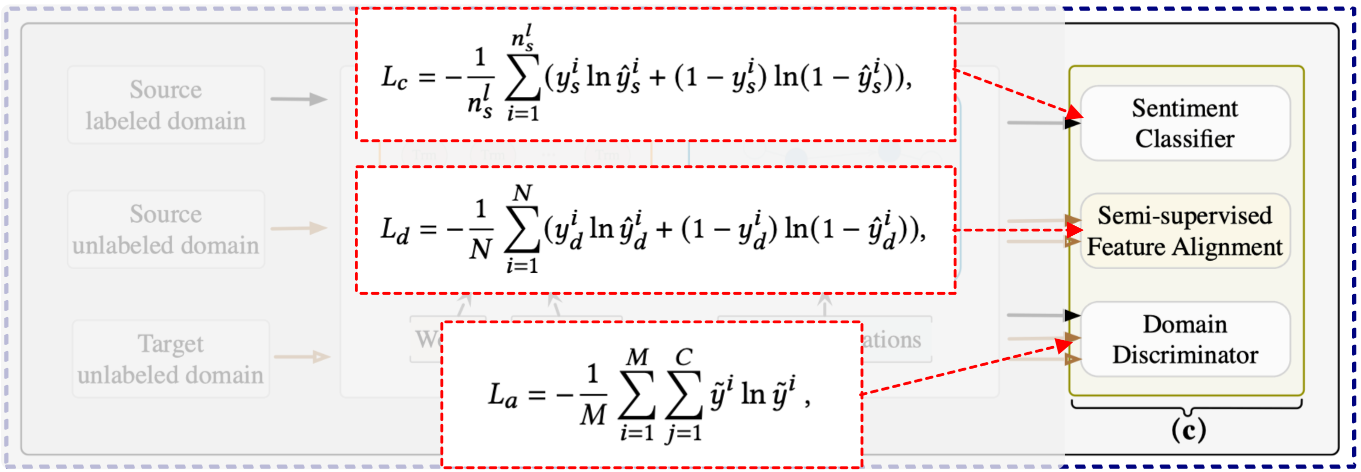
The GAST Model

Detail of the GAST model

Integrated Adaptive Strategy

As shown in Figure (c), the strategy includes three loss functions:

1. a **classifier loss** for sentiment knowledge learning
2. a **discriminator loss** for invariant feature extracting
3. a **feature alignment loss** for syntax-aware feature alignment



$$L_c = -\frac{1}{n_s^l}\sum_{i=1}^{n_s^l}(y_s^i \ln \hat{y}_s^i + (1-y_s^i)\ln(1-\hat{y}_s^i)),$$

$$L_d = -\frac{1}{N}\sum_{i=1}^{N}(y_d^i \ln \hat{y}_d^i + (1-y_d^i)\ln(1-\hat{y}_d^i)),$$

$$L_a = -\frac{1}{M}\sum_{i=1}^{M}\sum_{j=1}^{C}\tilde{y}^i \ln \tilde{y}^i ,$$

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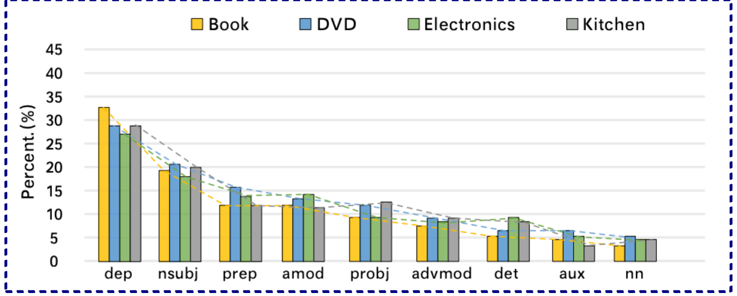
Experiment

Dataset Setup & Data Analysis

1. We evaluate GAST on four widely-used Amazon datasets, i.e., DVD ($\boldsymbol{D}$), Book ($\boldsymbol{B}$), Electronics ($\boldsymbol{E}$) and Kitchen ($\boldsymbol{K}$)
2. We count the ratio of different syntactic relationships as shown in Figure. The proportions between various domains are close, meaning each sentence's components might be remarkably similar, even in different domains

Domains	Testing set percentage			
	#Train	#Vali.	#Test	#Unlabel
Books	1,600	400	2,000	4,000
DVD	1,600	400	2,000	4,000
Electronics	1,600	400	2,000	4,000
Kitchen	1,600	400	2,000	4,000



Experiment

Experimental & Ablation Results

Our proposed model (BERT-GAST) gets further improvement and achieves a new SOTA. The reason is that GAST is able to consider the sequential information and syntactic structures jointly

Baselines	*DVD (D)*			*Book (B)*			*Electronics (E)*			*Kitchen (K)*		
	$D \mapsto B$	$D \mapsto E$	$D \mapsto K$	$B \mapsto D$	$B \mapsto E$	$B \mapsto K$	$E \mapsto D$	$E \mapsto B$	$E \mapsto K$	$K \mapsto D$	$K \mapsto B$	$K \mapsto E$
SCL	77.8	75.2	75.5	80.4	76.5	77.1	74.5	71.6	81.7	75.2	71.3	78.8
SFA	78.8	75.8	75.7	81.3	75.6	76.9	75.4	72.4	82.6	74.7	72.4	80.7
DANN	80.5	77.6	78.8	83.2	76.4	77.2	77.6	73.5	84.2	75.1	74.3	82.2
AMN	84.5	81.2	82.7	85.6	82.4	81.7	81.7	76.6	85.7	81.5	80.9	86.1
HATN	86.6	86.3	87.4	86.5	85.7	86.8	84.3	81.5	87.9	84.7	84.1	87.0
IATN	87.0	86.9	85.8	86.8	86.5	85.9	84.1	81.8	88.7	84.4	84.7	87.6
BERT-DAAT	90.8	89.3	90.5	89.7	89.5	90.7	90.1	88.9	93.1	88.8	87.9	91.7
LSTM	75.6	73.4	-	78.6	75.2	-	72.2	69.6	-	-	-	-
TextGCN	80.8	77.6	79.2	85.3	81.1	79.7	82.6	78.2	82.3	83.3	84.1	81.7
FastGCN	81.6	80.6	81.1	86.0	82.7	82.0	83.5	78.7	84.5	84.2	85.7	83.4
GAST	87.9	87.3	89.1	88.2	86.2	87.4	85.6	83.4	89.3	87.7	87.5	89.4
BERT-GAST	**91.1**	**90.7**	**92.1**	**90.4**	**91.2**	**91.5**	**90.7**	**89.4**	**93.5**	**89.7**	**89.2**	**92.6**
G_Non_Pos-Tran.	85.9	84.7	87.6	86.8	83.4	85.5	84.2	80.4	87.8	85.8	85.5	87.4
G_Non_HGAT	86.6	85.9	88.1	87.4	85.0	86.1	84.5	81.3	88.2	86.4	86.7	88.2
G_Non_IDS	87.2	86.6	87.9	87.6	85.8	86.7	85.0	82.6	88.5	85.9	86.2	87.7
G_Non_agg	87.5	86.7	88.9	88.0	85.9	86.9	85.2	82.6	89.0	87.3	87.2	89.1
G_Non_act	87.3	86.3	88.7	87.7	85.3	86.2	84.8	81.8	88.7	86.9	87.1	88.7

Experiment

Case Study & Hyper-parameter Study

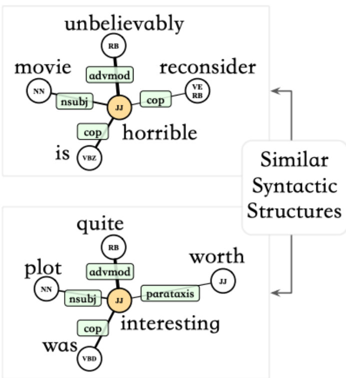
1. the vanilla transformer **makes extra decisions on some unrelated word** (e.g., "this", "please") and pays much attention to these uncritical words
2. On the contrary, POS-transformer can alleviate this problem by revising attention scores **with the help of POS tags**
3. HGAT could **deal with the problem more appropriately** through the domain-invariant syntactic relations between words

	This	movie	is	unbelievably	**horrible**,	please	reconsider	watching.
(1) Transformer	0.08	0.11	0.09	0.16	0.15	0.19	0.13	0.09
(2) Pos-Transformer	0.02	0.17	0.11	0.21	0.18	0.06	0.15	0.10
(3) Hybrid GAT	0.00	0.22	0.12	0.26	0.21	0.00	0.19	0.00

(a) Case Example 1: The attention values related to the word "horrible".

	The	plot	of	this	book	was	quite	**interesting**;	it	is	worth	reading!
(1) Transformer	0.05	0.08	0.03	0.06	0.14	0.07	0.13	0.18	0.05	0.03	0.14	0.04
(2) Pos-Transformer	0.03	0.09	0.02	0.02	0.12	0.07	0.17	0.21	0.02	0.05	0.12	0.08
(3) Hybrid GAT	0.00	0.16	0.00	0.00	0.00	0.21	0.28	0.24	0.00	0.00	0.11	0.00

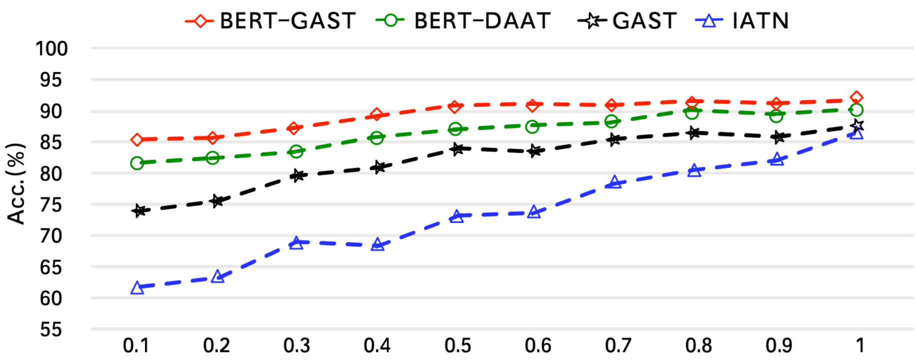
(b) Case Example 2: The attention values related to the word "interesting".



Experiment

Adaptive Efficiency & Adaptive Graph

The GAST model with 40% samples even performs better than IATN with 80% samples, which proves that GAST gains an advanced adaptive ability and efficiency in CDSC



Syntax Parser	$D \mapsto B$	$D \mapsto E$	$D \mapsto K$
(1) Without Graph	86.6	85.9	88.1
(2) Stanford Graph	**87.1**	**86.6**	**88.6**
+compare with (1)	**(+0.5)**	**(+0.7)**	**(+0.5)**
(3) Biaffine Graph	**87.9**	**87.3**	**89.1**
+compare with (1)	**(+1.3)**	**(+1.4)**	**(+1.0)**
+compare with (2)	**(+0.8)**	**(+0.7)**	**(+0.5)**

The quality of the syntactic graph affect the final results, which shows the effectiveness of syntactic features for CDSC research

Outline

Conclusion

In this Work

- **Learn what ?**
  - ✓ **Adaptive Graph Features （pos-tags & dependency relations ）**
- **How to learn ?**
  - ✓ **Graph Adaptive Semantic Transfer (GAST) model**
- **Experimental analysis**

In the Feature

- **Further characterization of graph structural information**
- **Dynamic semantic change & dynamic graph learning**

See more details in our paper:

Graph Adaptive Semantic Transfer for Cross-domain Sentiment Classification

http://home.ustc.edu.cn/~sa517494/files/sigir22.pdf

T & Q !