Transferable End-to-End Aspect-based Sentiment Analysis with Selective Adversarial Learning

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Outline

- Background & Motivation
  - E2E-ABSA
  - Transferable E2E-ABSA
- Method
- Experiments
- Future Works

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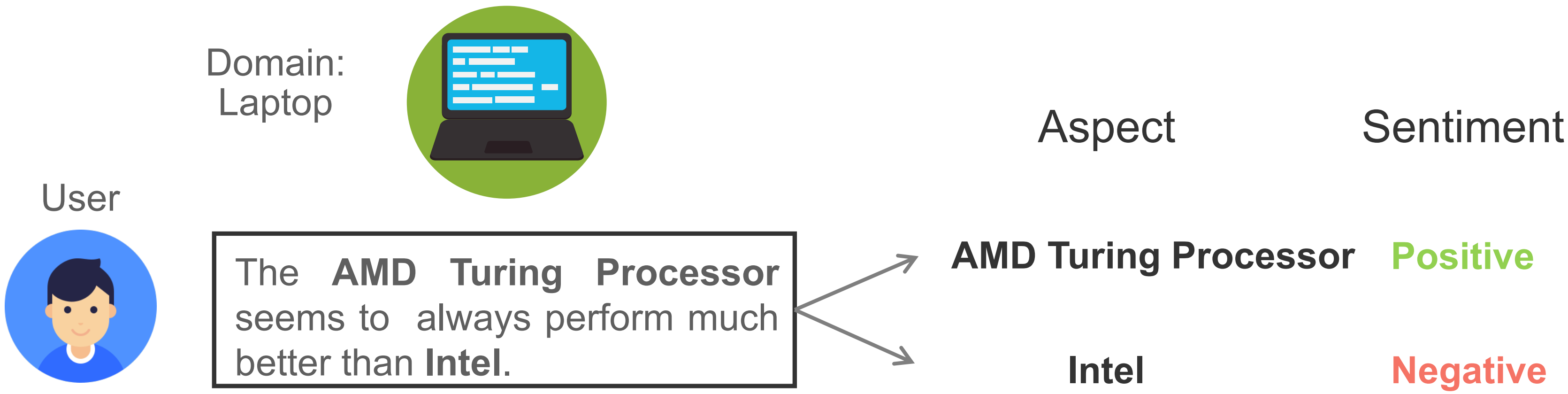
End-to-End Aspect-based Sentiment Analysis

E2E-ABSA: joint extraction of aspects and their sentiments from user reviews.



Two subtasks:

- Aspect detection (**AD**): extract the aspect terms from user reviews.
- Aspect sentiment (**AS**) classification: Given a review sentence and an aspect term, predict the sentiment towards the aspect.

Unified Formulation (single domain)

Formulation: coupling two subtasks as a unified sequence labeling problem.

- **Unified tag** = **aspect boundary tag** {B, I, E, O, S} + **sentiment tag** {POS, NEG, NEU}
- **NER tag** = **entity boundary tag** {B, I, E, O, S} + **entity type tag** {PER, ORG, LOC, …} (***Similar***)

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

Li et al., 2019 A unified model for opinion target extraction and target sentiment prediction AAAI

Pros:

- End-to-end manner
- Alleviate accumulated errors across two highly-correlative sub-tasks.

Cons:

- Lack of sufficient labeled data in a wide range of domains.
- Manual labeling for sequence data is expensive and time-consuming.

Transferable E2E-ABSA

Source domain
(Train): Laptop

User

The **[AMD Turing Processor]_POS** seems to always perform much better than **[Intel]_NEG**.

User

Target domain:
(**Test**) : Restaurant

Great salmon but the waitress is so rude.

Aspect

Sentiment

Cross-domain:

- leverage knowledge from a labeled source domain to improve the **sequence learning** (unified tag prediction) in an unlabeled target domain.

Unified Formulation (cross domain)

Input: a sequence of words $\mathbf{x} = \{w_1, w_2, ..., w_n\}$

Output: a unified tag sequence $\mathbf{y} = \{y_1, y_2, ..., y_n\}$

Source

$$D_s = \{(\mathbf{x}_s^i, \mathbf{y}_s^i)\}_{i=1}^{N_s}$$

Target

$$D_t = \{(\mathbf{x}_t^j)\}_{j=1}^{N_t}$$

Sequence Transfer Learning (unsupervised)

Challenges

What to transfer?

- There exists a **large domain shift** between domains since aspect terms in different domains are usually disjoint.

  e.g., “salmon” in the Restaurant domain and “mouse” in the Laptop domain.

How to transfer?

- Unlike domain adaptation in traditional sentiment classification that learns shared sentence or document representations, we need to learn **fine-grained** (word-level) representations to be domain-invariant for **sequence prediction**.

What to transfer?

Prior work: highly depends on common syntactic relations between aspect and opinion words

- manually-designed rules
- external linguistic resources (dependency parsers)

RuleID	Rule	Example
R1	$\texttt{O} \xrightarrow{amod} \texttt{T}$	They have nice dessert. (nice $\xrightarrow{amod}$ *dessert*)
R2	$\texttt{T} \xrightarrow{nsubj} \texttt{O}$	Its camera is great. (*camera* $\xrightarrow{nsubj}$ great)
R3	$\texttt{T} \xrightarrow{dobj} \texttt{O}$	I love their fries. (*fries* $\xrightarrow{dobj}$ love)
R4	$\texttt{T} \xrightarrow{nsubj} \texttt{H} \xleftarrow{amod} \texttt{O}$	iPhone is the best cellphone. (*iPhone* $\xrightarrow{nsubj}$ phone $\xleftarrow{amod}$ best)
ER1	$\texttt{W} \xrightarrow{amod} \texttt{T}$	I like Indian food. (*Indian* $\xrightarrow{amod}$ food)
ER2	$\texttt{W} \xrightarrow{nn} \texttt{T}$	Their spring roll is great. (*spring* $\xrightarrow{nn}$ roll)
ER3	$\texttt{W}_2 \xrightarrow{pobj} \texttt{W}_1 \xrightarrow{prep} \texttt{T}$	I like the design of iPhone. (*iPhone* $\xrightarrow{pobj}$ *of* $\xrightarrow{prep}$ design)

I love tuna sandwich very much.

I love the design of iPhone 7

Ding et al., 2017. Recurrent neural networks with auxiliary labels for cross-domain opinion target extraction. AAAI

Ours: automatically capture the latent relations among aspect and opinion words as transferable knowledge.

How to transfer?

straightforward solution: apply domain adaption methods to align all words within the sentence. (**no significant improvements**).

Reason: Only a small number of words are informative words that are not tagged with “O”.

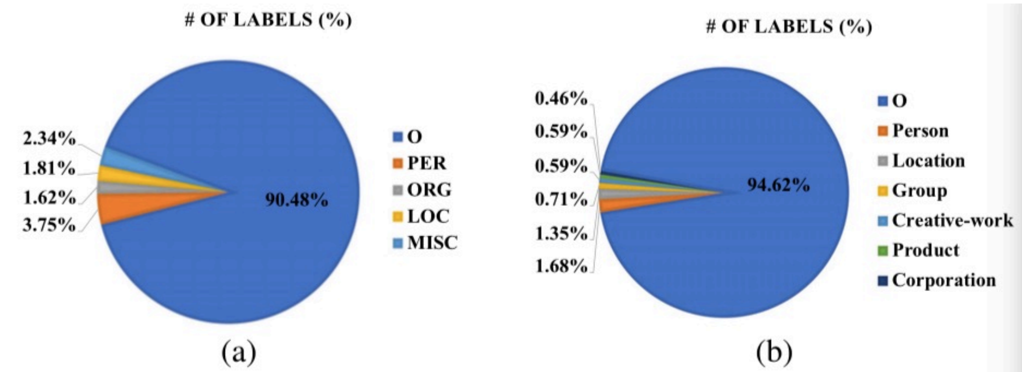


Fig. 2. Label statistics on CoNLL-2002 Dutch NER and WNUT-2017 English Twitter NER train set. The label type “O” is dominant in different data sets. (a) CoNLL-2002 Dutch. (b) WNUT-2017 English Twitter.

TABLE I

F1 SCORE OF BILSTM-CNNS-CRF MODEL ON WNUT-2017 DEVELOPMENT SET

Label Type	Precision (%)	Recall (%)	F1 Score (%)
O	95.56	99.46	97.47
Person	78.75	49.23	60.59
Location	51.02	46.73	48.78
Group	19.23	7.81	11.11
Creative-work	32.94	11.76	17.34
Product	33.33	7.69	12.50
Corporation	18.18	21.74	19.80

Zhou et al., Roseq: Robust sequence labeling. TNNLS 2019

Ours: selectively align the informative words within the sentence.

Outline

- Method
- Experiments
- Future Works

Framework

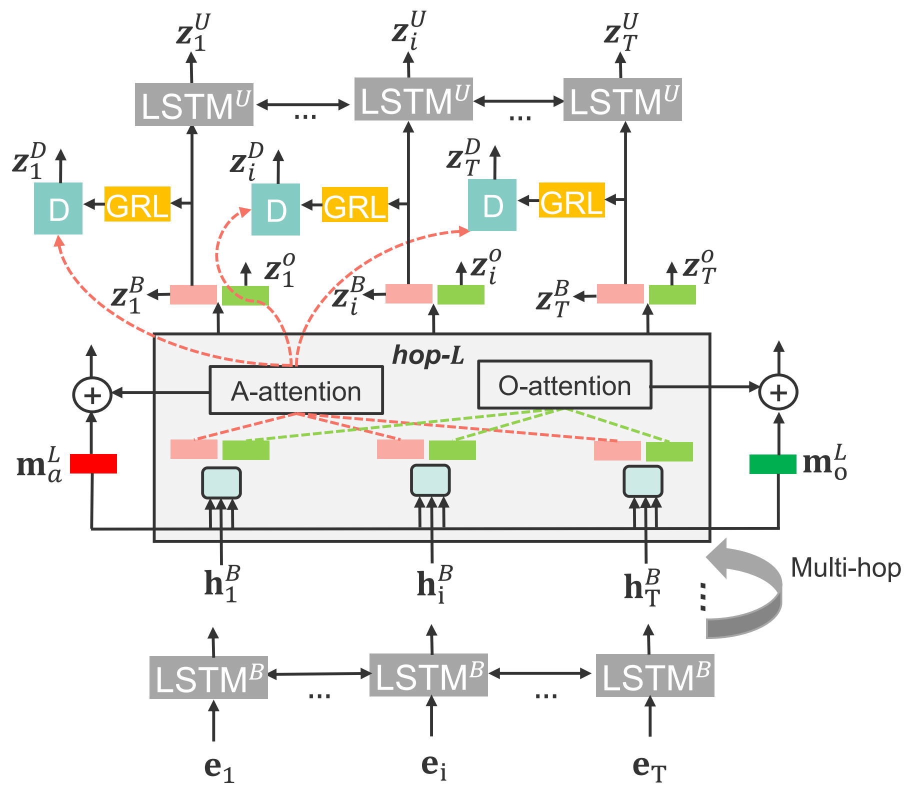
Aspect global memory

Opinion global memory

Dual Memory Interaction

D Domain discriminator

GRL Gradient Reversal Layer



Upper LSTM^U: *unified tag*

SAL: how to transfer

DMI: what to transfer

Lower LSTM^B: *aspect boundary tag*

Embedding layer

Base Model

Two stacked Bi-LSTMs:

- Aspect boundary information can be used as the guidance

$$
\begin{aligned}
\mathbf{h}_i^{\mathcal{B}} &= [\overrightarrow{\mathrm{LSTM}}^{\mathcal{B}}(\mathbf{e}_i); \overleftarrow{\mathrm{LSTM}}^{\mathcal{B}}(\mathbf{e}_i)],\\
\mathbf{h}_i^{\mathcal{U}} &= [\overrightarrow{\mathrm{LSTM}}^{\mathcal{U}}(\mathbf{h}_i^{\mathcal{B}}); \overleftarrow{\mathrm{LSTM}}^{\mathcal{U}}(\mathbf{h}_i^{\mathcal{B}})].
\end{aligned}
$$

Low-level AD

$$\mathbf{z}_i^{\mathcal{B}} = \mathrm{p}(\mathbf{y}_i^{\mathcal{B}}|\mathbf{h}_i^{\mathcal{B}}) = \mathrm{Softmax}(\mathbf{W}_{\mathcal{B}}\mathbf{h}_i^{\mathcal{B}} + \mathbf{b}_{\mathcal{B}}).$$

High-level ADS

$$\mathbf{z}_i^{\mathcal{U}} = \mathrm{p}(\mathbf{y}_i^{\mathcal{U}}|\mathbf{h}_i^{\mathcal{U}}) = \mathrm{Softmax}(\mathbf{W}_{\mathcal{U}}\mathbf{h}_i^{\mathcal{U}} + \mathbf{b}_{\mathcal{U}}).$$

Primary loss:

$$\mathcal{L}_{\mathcal{M}} = \sum_{D_s} \sum_{\mathcal{Q}\in\{\mathcal{B},\mathcal{U}\}} \sum_{i=1}^{T} \ell(\mathbf{z}_i^{\mathcal{Q}}, \mathbf{y}_i^{\mathcal{Q}}).$$

AD: Aspect Detection (aspect boundary tags)

ADS: Aspect Detection and Sentiment Classification (unified tags)

What to transfer: Global-Local Memory Interaction (GLMI)

GLMI: basic operation for computing the correlations between two objects (local & global memory).

$$\textbf{GLMI}: f(\overbrace{\mathbf{h}_i^{\mathcal{B}}}^{\text{Local Memory: LSTM hidden states}}, \underbrace{\mathbf{m}}_{\text{Global Memory: commonly-used in memory networks}}; \boldsymbol{\Theta}, \mathbf{G})$$

1) Residual transformation

$$\tilde{\mathbf{h}}_i^{\mathcal{B}} = \mathbf{h}_i^{\mathcal{B}} + \mathrm{ReLU}(\mathbf{W}[\mathbf{h}_\mathbf{i}^{\mathcal{B}} : \mathbf{m}] + \mathbf{b}),$$

2) Multi-dimensional Bilinear Transformation

$$\mathbf{r}_i = \mathbf{m}^T \mathbf{G} \tilde{\mathbf{h}}_i^{\mathcal{B}}$$

$\mathbf{G} \in \mathbb{R}^{K \times \dim_h^{\mathcal{B}} \times \dim_h^{\mathcal{B}}}$ models K kinds of latent relations

What to transfer: Dual Memory Interaction (DMI)

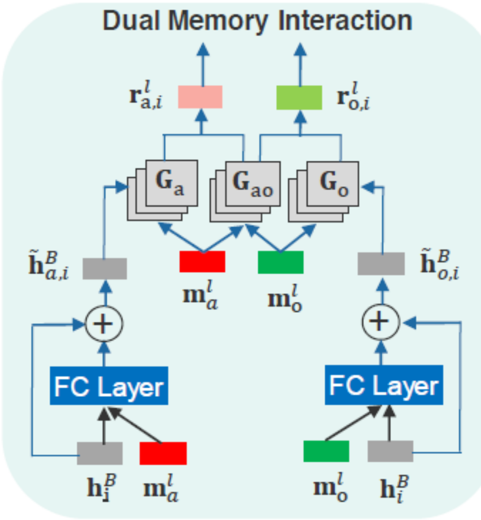
DMI: models the correlations between **a**spect and **o**pinions for aspect and opinion co-detection.

$$\text{aspect}\quad \mathbf{r}^l_{a,i} = [\overbrace{f(\mathbf{h}^{\mathcal{B}}_i, \mathbf{m}^l_a; \boldsymbol{\Theta}_a, \mathbf{G}_a)}^{\textbf{a \& a}} : \overbrace{f(\mathbf{h}^{\mathcal{B}}_i, \mathbf{m}^l_o; \boldsymbol{\Theta}_o, \mathbf{G}_{ao})}^{\textbf{a \& o}}],$$

$$\text{opinion}\quad \mathbf{r}^l_{o,i} = [\underbrace{f(\mathbf{h}^{\mathcal{B}}_i, \mathbf{m}^l_o; \boldsymbol{\Theta}_o, \mathbf{G}_o)}_{\textbf{o \& o}} : \underbrace{f(\mathbf{h}^{\mathcal{B}}_i, \mathbf{m}^l_a; \boldsymbol{\Theta}_a, \mathbf{G}^T_{ao})}_{\textbf{o \& a}}],$$

opinion detection is used as a auxiliary task to link the different aspect across domains.

$$\mathcal{L}_{\mathcal{O}} = \sum_{D_s \cup D_t} \ell(\mathbf{z}^{\mathcal{O}}_i, \mathbf{y}^{\mathcal{O}}_i)$$



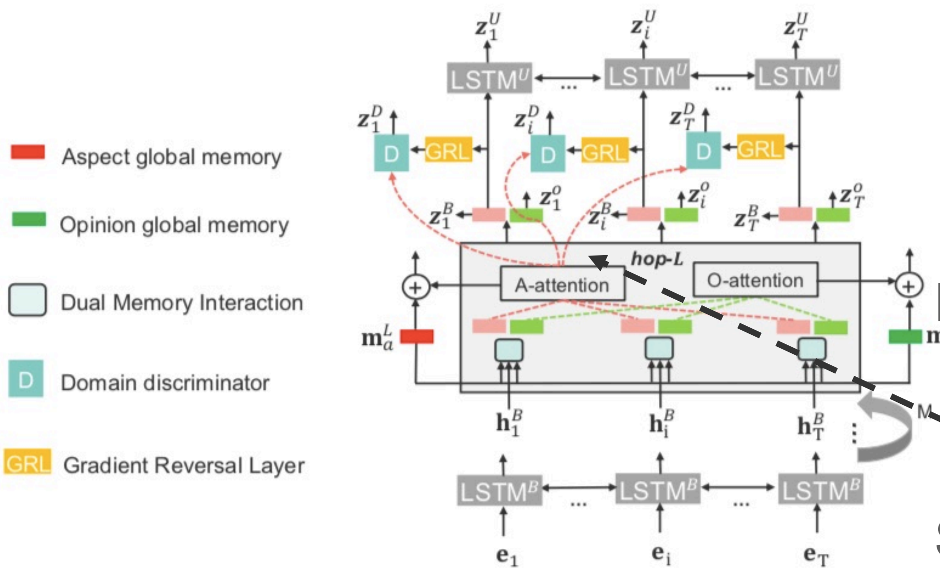
global aspect memory

global opinion memory

A-attention (aspect) & O-attention (opinion)

$$\alpha^l_{p,i} = \frac{\exp(\mathbf{u}_p \mathbf{r}^l_{p,i})}{\sum_{j=1}^{T} \exp(\mathbf{u}_p \mathbf{r}^l_{p,j})}. \qquad p \in \{a, o\}$$

How to transfer: Selective Adversarial Learning (SAL)



Gradient Reversal Layer: (Ganin et al., 2016)

$$R_\lambda(\mathbf{x}) = \mathbf{x}$$

$$\frac{\partial R_\lambda(\mathbf{x})}{\partial \mathbf{x}} = -\lambda I$$

Domain discriminator

$$\mathbf{z}_i^{\mathcal{D}} = \mathbf{p}(\mathbf{y}_i^{\mathcal{D}} | \mathbf{r}_{a,i}^L) = \mathrm{Softmax}(\mathbf{W}_{\mathcal{D}} R_\lambda(\mathbf{r}_{a,i}^L) + \mathbf{b}_{\mathcal{D}})$$

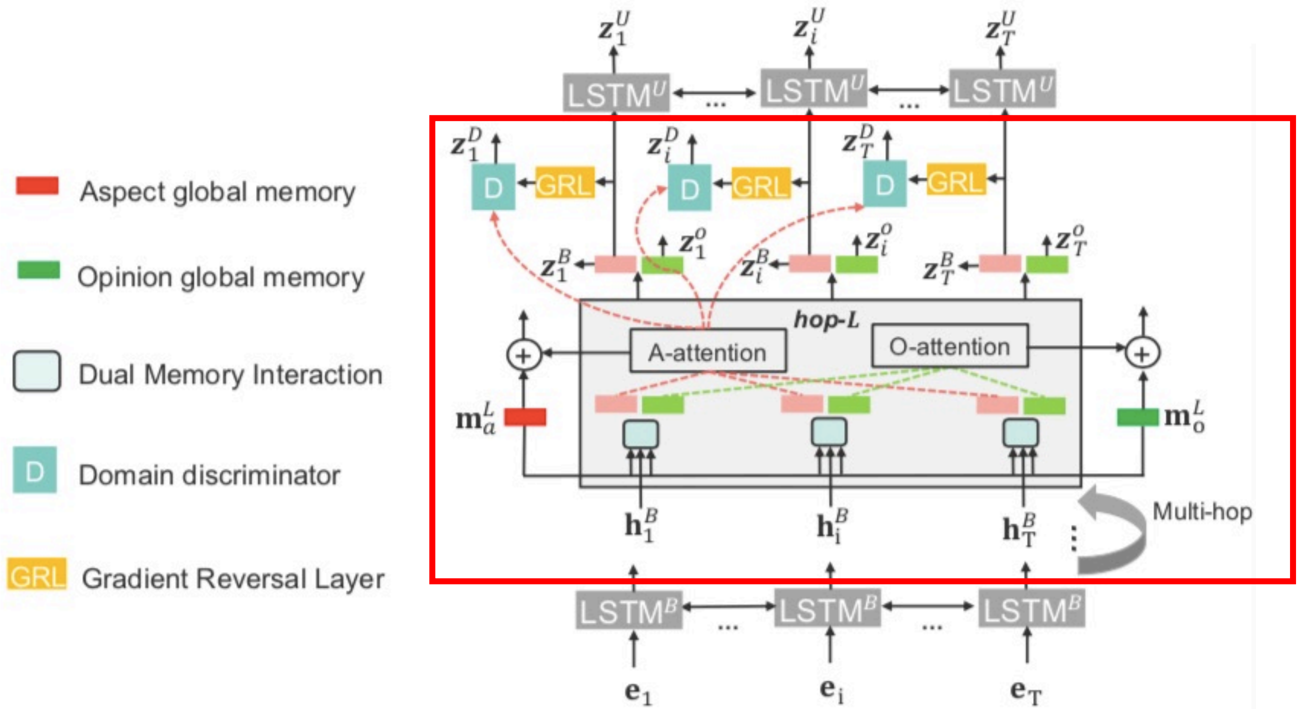
Selective adversarial loss:

$$\mathcal{L}_{\mathcal{D}} = \sum_{D_s \cup D_t} \sum_{i=1}^{T} \underbrace{\alpha_{a,i}^L}_{} \ell(\mathbf{z}_i^{\mathcal{D}}, \mathbf{y}_i^{\mathcal{D}}).$$

A-attention dynamically controls the selectivity

How to transfer: Selective Adversarial Learning (SAL)

- Why do we choose low-level neural layer features (e.g., SAL on the low-level AD task) for transfer?



Existing studies (Yosinski et al., 2014; Mou et al., 2016) have already shown some evidence that low-level neural layer features (i.e., low-level task) are more easily transferred to different tasks or domains.

Training Strategy

Joint training: (unstable, too many objectives)

$$E = \mathcal{L}_{\mathcal{M}} + \rho\mathcal{L}_{\mathcal{O}} + \gamma\mathcal{L}_{\mathcal{D}}$$

Alternating training: (more stable, two-stage optimization)

$$\mathcal{L}_{\mathcal{M}} + \rho\mathcal{L}_{\mathcal{O}}$$

$$\mathcal{L}_{\mathcal{D}}$$

iterative

$$(\hat{\boldsymbol{\theta}}_f^{(1)}, \hat{\boldsymbol{\theta}}_w) = \arg\min_{\boldsymbol{\theta}_f, \boldsymbol{\theta}_w} \mathcal{L}_{\mathcal{M}} + \rho\mathcal{L}_{\mathcal{O}}$$

discriminative stage

$$(\hat{\boldsymbol{\theta}}_f^{(2)}, \hat{\boldsymbol{\theta}}_d) = \arg\min_{\boldsymbol{\theta}_d} \max_{\boldsymbol{\theta}_f} \mathcal{L}_{\mathcal{D}}.$$

domain-invariant stage

$\boldsymbol{\theta}_f, \ \boldsymbol{\theta}_w, \ \boldsymbol{\theta}_d$ The parameters for feature learning of each word, word predictions for AD, ADS and opinion detection tasks, and domain classification, respectively.

Outline

Method

Experiments

Future Works

Experiment Setup

Datasets

- **L**: Laptop domain (Pontiki et al., 2014)
- **R**: Restaurant domain (Pontiki et al., 2014,2015,2016)
- **D**: Device domain (Hu and Liu, 2004)
- **S**: Service domain (Toprak et al., 2010)

L and **R** are from SemEval ABSA challenge 2014, 2015, 2016

Dataset	Domain	Sentences	Training	Testing
$\mathbb{L}$	Laptop	1,869	1,458	411
$\mathbb{R}$	Restaurant	3,900	2,481	1,419
$\mathbb{D}$	Device	1,437	954	483
$\mathbb{S}$	Service	2,153	1,433	720

Experiment Setup

Setting

4 different domains, 10 transfer pairs (without two easy pairs L→D, D→L)

For each pair e.g., **source** A-> **target** B:

Training: Labeled training data from A, unlabeled training data from B

Validation: testing data from A

Testing: testing data from B

Baselines

- **TCRF**: (Jakob and Gurevych, 2010): Transferable CRF
- **RAP**: (Li et al., 2012): cross-domain Relational Adaptive Bootstrapping
- **Hier-Joint**: (Ding et al., 2017): RNN with manually designed rule-based auxiliary tasks based on common syntactic relations
- **RNSCN**: (Wang and Pan, 2018): a recursive neural structural correspondence network

Extended versions:

- **Hier-Joint+** & **RNSCN+**: original version with the proposed stacking architecture

Main Results

Transfer Pair	TCRF		RAP		Hier-Joint		Hier-Joint$^+$		RNSCN		RNSCN$^+$		**Ours**	
	AD	ADS	AD	ADS	AD	ADS	AD	ADS	AD	ADS	AD	ADS	AD	ADS
$\mathbb{S}\rightarrow\mathbb{R}$	-	14.84	-	25.41	-	32.81	46.39	31.10	-	30.56	48.89	33.21	**52.05**	**41.03**
$\mathbb{L}\rightarrow\mathbb{R}$	-	16.06	-	31.05	-	31.90	48.61	33.54	-	31.85	52.19	35.65	**56.12**	**43.04**
$\mathbb{D}\rightarrow\mathbb{R}$	-	17.05	-	28.37	-	30.03	42.96	32.87	-	31.41	50.39	34.60	**51.55**	**41.01**
$\mathbb{R}\rightarrow\mathbb{S}$	-	15.20	-	13.17	-	15.20	27.18	15.56	-	23.31	30.41	20.04	**39.02**	**28.01**
$\mathbb{L}\rightarrow\mathbb{S}$	-	12.34	-	13.72	-	15.33	25.22	13.90	-	16.73	31.21	16.59	**38.26**	**27.20**
$\mathbb{D}\rightarrow\mathbb{S}$	-	13.49	-	16.80	-	18.74	29.28	19.04	-	18.93	35.50	20.03	**36.11**	**26.62**
$\mathbb{R}\rightarrow\mathbb{L}$	-	14.59	-	15.69	-	19.17	34.11	20.72	-	25.54	**47.23**	26.63	45.01	**34.13**
$\mathbb{S}\rightarrow\mathbb{L}$	-	9.56	-	12.38	-	21.80	33.02	22.65	-	19.15	34.03	18.87	**35.99**	**27.04**
$\mathbb{R}\rightarrow\mathbb{D}$	-	19.84	-	17.50	-	22.91	34.81	24.53	-	32.43	**46.16**	33.26	43.76	**35.44**
$\mathbb{S}\rightarrow\mathbb{D}$	-	13.43	-	15.74	-	20.04	35.00	23.24	-	19.98	32.41	22.00	**41.21**	**33.56**
Average	-	14.64	-	18.98	-	22.79	35.66	23.72	-	24.99	40.84	26.09	**43.91**†	**33.71**†
(Δ)	-	(19.07)	-	(14.73)	-	(10.92)	(8.25)	(9.99)	-	(8.72)	(3.07)	(7.62)	-	-

Table 2: Main results (%). Δ refers to the improvements of the full model over baseline methods. The marker † means that our model significantly outperforms the best baseline **RNSCN**$^+$ with p-value < 0.01.

Ablation Study

Ablation Variants

What to transfer

- **Base Model (SO / TO):** two stacked Bi-LSTMs. SO (Source Only) and TO (Target Only). We usually refer to them as a lower bound and a upper bound, respectively.
- **Base Model + DMI:** two stacked Bi-LSTMs with a DMI between them.

How to transfer

- **AD-AL:** pure adversarial learning (removing the selective weight from the adversarial loss) for the low-level AD task .
- **ADS-SAL:** selective adversarial learning on each word representations for the high-level ADS task.
- **AD-SAL (Full model):** selective adversarial learning for the low-level AD task .

Note: The backbones of the **AD-AL ADS-SAL** and **AD-SAL** are all based on the **Base Model +DMI**

No DMI v.s. DMI

No DMI | DMI

Transfer Pair	Lower bound		Ablation Models						Full Model		Upper bound	
	Base Model (SO)		Base Model+DMI		AD-AL		ADS-SAL		AD-SAL		Base Model (TO)	
	AD	ADS	AD	ADS	AD	ADS	AD	ADS	AD	ADS	AD	ADS
$\mathbb{S}\rightarrow\mathbb{R}$	30.32	19.74	45.68	37.10	48.28	37.65	51.29	41.03	**52.05**	**41.03**		
$\mathbb{L}\rightarrow\mathbb{R}$	33.99	28.34	46.25	36.49	51.79	38.63	55.50	42.00	**56.12**	**43.04**	81.84	67.26
$\mathbb{D}\rightarrow\mathbb{R}$	31.59	27.25	46.56	36.89	46.39	37.34	46.43	38.35	**51.55**	**41.01**		
$\mathbb{R}\rightarrow\mathbb{S}$	15.63	8.61	21.88	16.85	25.13	18.61	37.11	25.84	**39.02**	**28.01**		
$\mathbb{L}\rightarrow\mathbb{S}$	22.45	16.07	28.67	21.53	28.18	20.74	30.35	23.73	**38.26**	**27.20**	68.28	41.12
$\mathbb{D}\rightarrow\mathbb{S}$	16.79	9.49	31.91	22.14	32.88	24.89	32.51	21.45	**36.11**	**26.62**		
$\mathbb{R}\rightarrow\mathbb{L}$	38.45	23.40	42.27	30.52	40.52	28.77	44.56	33.34	**45.01**	**34.13**	75.95	52.62
$\mathbb{S}\rightarrow\mathbb{L}$	24.69	14.48	36.38	27.48	32.96	25.16	33.87	24.22	**35.99**	**27.04**		
$\mathbb{R}\rightarrow\mathbb{D}$	34.87	25.79	36.90	27.71	41.61	31.88	**43.97**	34.50	43.76	**35.44**	70.37	57.62
$\mathbb{S}\rightarrow\mathbb{D}$	27.73	17.73	38.03	31.21	39.54	32.28	40.40	33.26	**41.21**	**33.56**		
Average (Δ)	27.65 (16.26)	19.09 (14.62)	37.45 (6.46)	28.79 (4.92)	38.73 (5.18)	29.60 (4.11)	41.60 (2.31)	31.77 (1.94)	**43.91**† -	**33.71**† -	74.11 -	54.66 -

Table 3: Ablation results (%). Δ refers to the improvements of the full model over ablation methods. The marker † means that the full model significantly outperforms the best ablation model **ADS-SAL** with p-value < 0.01.

No SAL v.s. SAL

No SAL

SAL

Transfer Pair	Lower bound		Ablation Models						Full Model		Upper bound	
	Base Model (SO)		Base Model+DMI		AD-AL		ADS-SAL		AD-SAL		Base Model (TO)	
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Average (Δ)	27.65 (16.26)	19.09 (14.62)	37.45 (6.46)	28.79 (4.92)	38.73 (5.18)	29.60 (4.11)	41.60 (2.31)	31.77 (1.94)	**43.91**† -	**33.71**† -	74.11 -	54.66 -

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No Selectivity v.s. Selectivity

No Selectivity Selectivity

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$\mathbb{S}\rightarrow\mathbb{L}$	24.69	14.48	36.38	27.48	32.96	25.16	33.87	24.22	**35.99**	**27.04**		
$\mathbb{R}\rightarrow\mathbb{D}$	34.87	25.79	36.90	27.71	41.61	31.88	**43.97**	34.50	43.76	**35.44**	70.37	57.62
$\mathbb{S}\rightarrow\mathbb{D}$	27.73	17.73	38.03	31.21	39.54	32.28	40.40	33.26	**41.21**	**33.56**		
Average (Δ)	27.65 (16.26)	19.09 (14.62)	37.45 (6.46)	28.79 (4.92)	38.73 (5.18)	29.60 (4.11)	41.60 (2.31)	31.77 (1.94)	**43.91**† -	**33.71**† -	74.11 -	54.66 -

Table 3: Ablation results (%). Δ refers to the improvements of the full model over ablation methods. The marker † means that the full model significantly outperforms the best ablation model **ADS-SAL** with p-value < 0.01.

Low-level v.s. High-level

High-level Low-level

Transfer Pair	Lower bound		Ablation Models						Full Model		Upper bound	
	Base Model (SO)		Base Model+DMI		AD-AL		ADS-SAL		AD-SAL		Base Model (TO)	
	AD	ADS	AD	ADS	AD	ADS	AD	ADS	AD	ADS	AD	ADS
$\mathbb{S}\to\mathbb{R}$	30.32	19.74	45.68	37.10	48.28	37.65	51.29	41.03	**52.05**	**41.03**	81.84	67.26
$\mathbb{L}\to\mathbb{R}$	33.99	28.34	46.25	36.49	51.79	38.63	55.50	42.00	**56.12**	**43.04**		
$\mathbb{D}\to\mathbb{R}$	31.59	27.25	46.56	36.89	46.39	37.34	46.43	38.35	**51.55**	**41.01**		
$\mathbb{R}\to\mathbb{S}$	15.63	8.61	21.88	16.85	25.13	18.61	37.11	25.84	**39.02**	**28.01**	68.28	41.12
$\mathbb{L}\to\mathbb{S}$	22.45	16.07	28.67	21.53	28.18	20.74	30.35	23.73	**38.26**	**27.20**		
$\mathbb{D}\to\mathbb{S}$	16.79	9.49	31.91	22.14	32.88	24.89	32.51	21.45	**36.11**	**26.62**		
$\mathbb{R}\to\mathbb{L}$	38.45	23.40	42.27	30.52	40.52	28.77	44.56	33.34	**45.01**	**34.13**	75.95	52.62
$\mathbb{S}\to\mathbb{L}$	24.69	14.48	36.38	27.48	32.96	25.16	33.87	24.22	**35.99**	**27.04**		
$\mathbb{R}\to\mathbb{D}$	34.87	25.79	36.90	27.71	41.61	31.88	**43.97**	34.50	43.76	**35.44**	70.37	57.62
$\mathbb{S}\to\mathbb{D}$	27.73	17.73	38.03	31.21	39.54	32.28	40.40	33.26	**41.21**	**33.56**		
Average	27.65	19.09	37.45	28.79	38.73	29.60	41.60	31.77	**43.91**†	**33.71**†	74.11	54.66
(Δ)	(16.26)	(14.62)	(6.46)	(4.92)	(5.18)	(4.11)	(2.31)	(1.94)	-	-	-	-

Table 3: Ablation results (%). Δ refers to the improvements of the full model over ablation methods. The marker † means that the full model significantly outperforms the best ablation model **ADS-SAL** with p-value < 0.01.

Case studies

No Adaptation | Adversarial | Selective Adversarial

Input: (Target domain 𝕃)	Base model+DMI		AD-AL		AD-SAL	
	AD	ADS	AD	ADS	AD	ADS
1. This laptop has only 2 [*usb ports*]$_{NEG}$, and they are both on the same side .	*ports*(✗), *side* (✗)	NONE(✗)	NONE(✗)	NONE(✗)	*usb ports*	[*usb ports*]$_{NEG}$
2. It is very easy to integrate [*bluetooth devices*]$_{POS}$, and [*usb devices*]$_{POS}$ are recognized almost instantly .	*devices* (✗), *devices* (✗)	[*devices*]$_{POS}$ (✗), [*devices*]$_{POS}$ (✗)	NONE(✗)	NONE(✗)	*bluetooth devices*, *usb devices*	[*bluetooth devices*]$_{POS}$, [*usb devices*]$_{POS}$
3. I also wanted [*windows 7*]$_{POS}$, which this one has .	NONE(✗)	NONE(✗)	NONE(✗)	NONE(✗)	*windows 7*	[*windows 7*]$_{POS}$
4. The [*speed*]$_{POS}$, the [*simplicity*]$_{POS}$, the [*design*]$_{POS}$ it is lightyears ahead of any pc i have ever owned .	*speed*, *design*	[*speed*]$_{POS}$, [*design*]$_{POS}$	*speed*, *design*, *pc* (✗)	[*speed*]$_{POS}$, [*design*]$_{POS}$, [*pc*]$_{POS}$ (✗)	*speed*, *design*, *simplicity*	[*speed*]$_{POS}$, [*design*]$_{POS}$, [*simplicity*]$_{POS}$
6. The [*battery life*]$_{POS}$ is excellent , the [*display*]$_{POS}$ is excellent and [*downloading apps*]$_{POS}$ is a breeze .	*battery* (✗), *display*, *apps* (✗)	[*battery*]$_{POS}$ (✗), [*display*]$_{POS}$, [*apps*]$_{POS}$ (✗)	*battery* (✗), *display*, *apps* (✗)	[*battery*]$_{POS}$ (✗), [*display*]$_{POS}$, [*apps*]$_{POS}$ (✗)	*battery life*, *display*, *downloading apps*	[*battery life*]$_{POS}$, [*display*]$_{POS}$, [*downloading apps*]$_{POS}$

Table 4: Case analysis for the ℝ→𝕃 pair. Note that we only show the sentiment part of the unified labels (i.e., POS, NEG, and NEU) and use brackets to indicate the boundary. The marker ✗ denotes an incorrect prediction.

Outline

Method

Experiments

Future Works

Future Works

- Potentially, extend the proposed SAL method to other domain adaptation methods.
- Apply the SAL on more general sequence labeling tasks including NER, POS, Chunking and so on.

Thank You!

Questions?

- Our code is open source and publicly available at the github: https://github.com/hsqmlzno1/Transferable-E2E-ABSA

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