Powering Comparative Classification with Sentiment Analysis via Domain Adaptive Knowledge Transfer

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1. Introduction

- Comparative Preference Classification (**CPC**) explores whether a preference comparison exists between **two entities** in a sentence.
- Example: ***Python*** *is better suited for data analysis than* ***MATLAB*** *due to the many available deep learning libraries.* We would like to know if there is a preference of Python over MATLAB.
- Existing work: (1) Some model CPC as a sentence classification task without highlighting the two entities; (2) The state-of-the-art ED-GAT (Ma et al., 2020) only considers syntactic information (dependency parsing) and ignores the critical semantic relations and the sentiments to the compared entities.
- Another challenge: dataset is small (CompSent-19 with 7.2k sentences).
- We propose Sentiment Analysis Enhanced COmparative Network **(SAECON)** which improves CPC accuracy with a ***sentiment analyzer*** that learns sentiments to individual entities via ***domain adaptive knowledge transfer***.

2. Architecture Intuition

- Semantics: Add a semantics module to understand the entire sentences.
- Incorporating more knowledge:
  - Aspect Based Sentiment Analysis (ABSA) tries to identify the fine-grained opinion polarity towards a specific aspect associated with a given target.
  - Use ABSA to identify the sentiment to each entity. The preferred entity usually gets a positive sentiment. Its rival gets a relatively negative one.
- How to?
  - Directly incorporating a trained sentiment analyzer would cause a performance degradation due to **domain shift** between the CPC & ABSA.
  - Incorporating the architecture only with untrained parameters and jointly optimize them with the CPC task closes domain shift via GRL.

3. SAECON

- CPC task:
  - Global Semantic Context (orange)

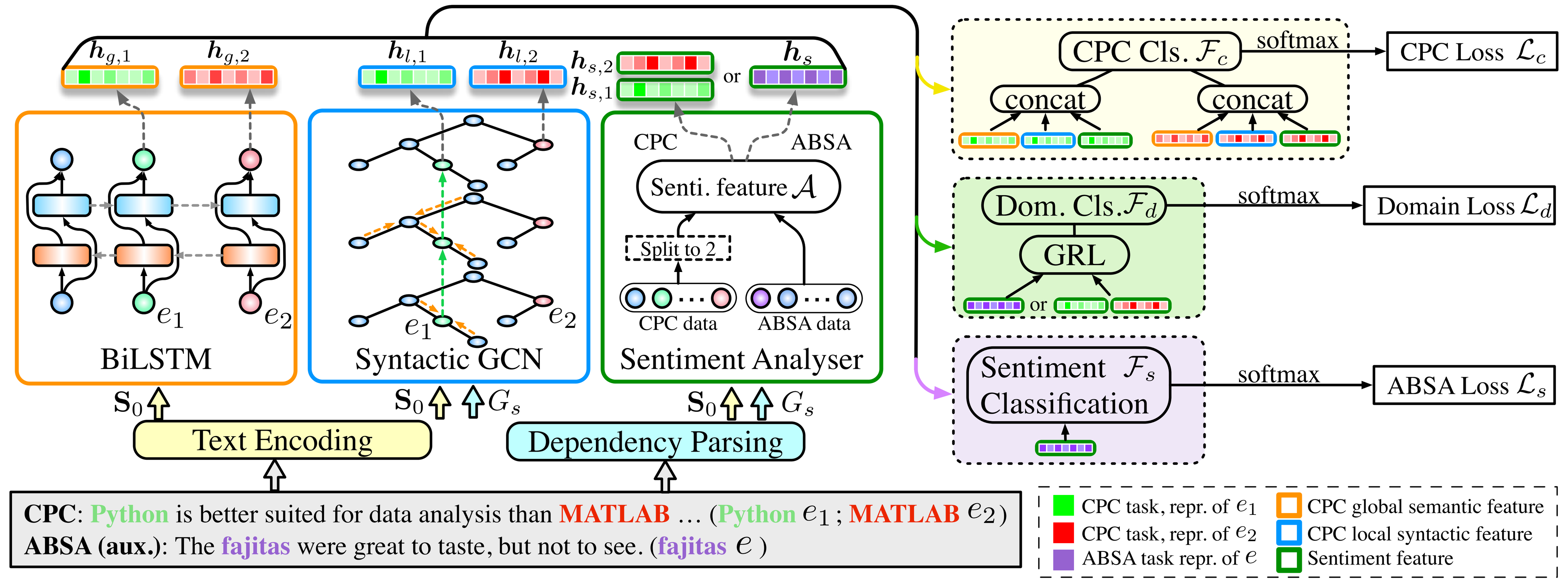
$$\overrightarrow{\boldsymbol{h}_{g,i}}, \overleftarrow{\boldsymbol{h}_{g,i}} = \mathrm{BiLSTM}(\mathbf{S}_0)[e_i.\mathrm{index}], \quad i = 1, 2$$

$$\boldsymbol{h}_{g,i} = \frac{1}{2}\left(\overrightarrow{\boldsymbol{h}_{g,i}} + \overleftarrow{\boldsymbol{h}_{g,i}}\right), \boldsymbol{h}_{g,i} \in \mathbb{R}^{d_g}.$$

  - Local Syntactic Context (Syntactic GCN, blue)

$$g_{uv}^{(j)} = \sigma\left(\boldsymbol{h}_u^{(j)} \cdot \boldsymbol{\beta}_{d_{uv}}^{(j)} + \gamma_{l_{uv}}^{(j)}\right), \quad g_{uv}^{(j)} \in \mathbb{R},$$

$$\boldsymbol{h}_v^{(j+1)} = \rho\left(\sum_{u \in \mathcal{N}(v)} g_{uv}^{(j)} \left(\mathbf{W}_{d_{uv}}^{(j)} \boldsymbol{h}_u^{(j)} + \boldsymbol{b}_{l_{uv}}^{(j)}\right)\right)$$



3. SAECON (cont'd)

- Sentiment Analyzing representation for each entity (green)

$$\mathcal{A}(\mathbf{S}_0, G_s, E) = \begin{cases} \boldsymbol{h}_{s,1}, \boldsymbol{h}_{s,2} & \text{if } s \in D_c, \text{ For CPC task/input, with CPC labels} \\ \boldsymbol{h}_s & \text{if } s \in D_s. \text{ For ABSA task/input, with ABSA labels} \end{cases}$$

- Domain shift via Gradient Reversal Layer (GRL) $\frac{\partial \mathrm{GRL}_\alpha}{\partial \boldsymbol{x}} = -\alpha \mathbf{I}.$
- Objective and Optimization

$$\hat{y}_c = \delta(\mathcal{F}_c([\mathcal{F}(\boldsymbol{h}_{e_1}); \mathcal{F}(\boldsymbol{h}_{e_2})])) \qquad \text{(CPC only)},$$

$$\hat{y}_s = \delta(\mathcal{F}_s(\boldsymbol{h}_s)) \qquad \text{(ABSA only)},$$

$$\hat{y}_d = \delta(\mathcal{F}_d(\mathrm{GRL}(\mathcal{A}(\mathbf{S}_0, G_s, E)))) \qquad \text{(Both tasks)},$$

4. CompSent-19 Dataset

- Statistics (see right)
- Imbalanced Data
  - Flipping labels
  - Upsampling
  - Weighted loss

Dataset	Better	Worse	None	Total
Train	872 (19%)	379 (8%)	3,355 (73%)	4,606
Development	219 (19%)	95 (8%)	839 (73%)	1,153
Test	273 (19%)	119 (8%)	1,048 (73%)	1,440
Total	1,346 (19%)	593 (8%)	5,242 (73%)	7,199
Flipping labels	1,251 (21%)	1,251 (21%)	3,355 (58%)	5,857
Upsampling	3,355 (33%)	3,355 (33%)	3,355 (33%)	10,065

5. Experiments

- Dataset: CompSent-19 (see above)
- ABSA dataset: SemEval 14 to 16
- Evaluation Metric:
  - F1 score of each label (Better, Worse, None)
  - Micro-averaging F1 score

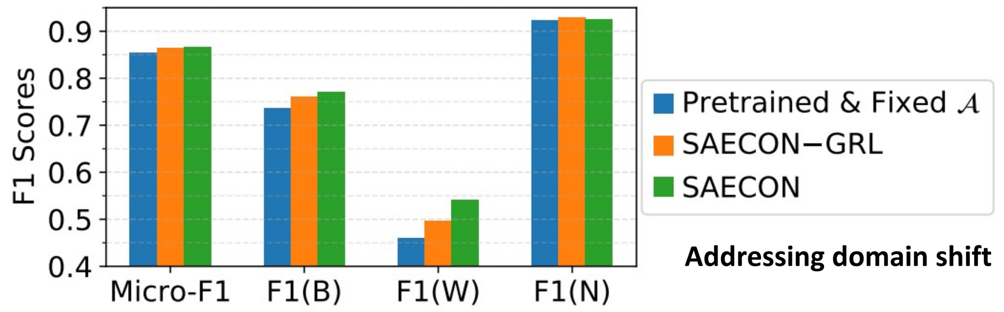
5. Experiments (cont'd)

- Experimental results demonstrate an increase in CPC task performance.
- Our ablation study suggests the effectiveness of our modules.
- Our techniques in addressing domain shift improve all F1 scores.
- Weighted loss proves to be the most effective technique in addressing data imbalance.

Model	Micro.	F1(B)	F1(W)	F1(N)
Majority	68.95	0.0	0.0	81.62
SE-Lin	79.31	62.71	37.61	88.42
SE-XGB	85.00	75.00	43.00	92.00
SVM-Tree	68.12	53.35	13.90	78.13
BERT-CLS	83.12	69.62	50.37	89.84
AvgWE-G	76.32	48.28	20.12	86.34
AvgWE-B	77.64	53.94	26.88	87.47
ED-GAT-G	82.73	70.23	43.30	89.84
ED-GAT-B	85.42	71.65	47.29	92.34
SAECON-G	83.78	71.06	45.90	91.05
SAECON-B	**86.74**	**77.10**	**54.08**	**92.64**

Variants	Micro.	F1(B)	F1(W)	F1(N)
SAECON	**86.74**	**77.10**	**54.08**	92.64
−BiLSTM	85.21	72.94	43.86	92.63
−SGCN	86.53	76.22	51.38	92.24
−GRL	86.53	76.16	49.77	**92.93**
−($\mathcal{A}$+GRL)	85.97	74.82	52.44	92.45

Methods	Micro.	F1(B)	F1(W)	F1(N)
Weighted loss (WL)	**86.74**	**77.10**	**54.08**	92.64
Original (OR)	85.97	73.80	46.15	92.90
Flipping labels (FL)	84.93	73.07	42.45	91.99
Upsampling (UP)	85.83	73.11	46.36	**92.95**



Addressing domain shift

Directed	Gating	Micro.	F1(B)	F1(W)	F1(N)
✓	✓	**86.74**	**77.10**	**54.08**	92.64
✗	✓	86.18	75.72	49.78	92.40
✓	✗	85.35	74.03	43.27	92.34
✗	✗	85.35	73.39	35.78	**93.04**

CPC sentences with sentiment predictions by $\mathcal{A}$	Label	Δ
S1: This is all done via the gigabit [**Ethernet**:POS] interface, rather than the much slower [**USB**:NEG] interface.	Better	+2
S2: Also, [**Bash**:NEG] may not be the best language to do arithmetic heavy operations in something like [**Python**:NEU] might be a better choice.	Worse	−1
S3: It shows how [**JavaScript**:POS] and [**PHP**:POS] can be used in tandem to make a user's experience faster and more pleasant.	None	0
S4: He broke his hand against [**Georgia Tech**:NEU] and made it worse playing against [**Virginia Tech**:NEU].	None	0

Supplementary CPC sentences with sentiment predictions by $\mathcal{A}$	Label	Δ
S1: [**Ruby**:NEU] wasn't designed to "exemplify best practices", it was to be a better [**Perl**:NEG].	Better	+1
S2: And from my experience the ticks are much worse in [**Mid Missouri**:NEG] than they are in [**South Georgia**:POS] which is much warmer year round.	Worse	−2
S3: As an industry rule, [**hockey**:NEG] and [**basketball**:NEG] sell comparatively poorly everywhere.	None	0
S4: [**Milk**:NEG], [**juice**:NEG] and soda make it ten times worse.	None	0

***Open Source:** https://github.com/zyli93/SAECON