Aspect-Based Sentiment Analysis

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Goals

1. 속성 기반 감성분석 내 여러 하위 과업들이 존재함을 확인한다
2. 속성 기반 감성분석의 네 가지 요소들에 대해서 이해한다
3. Aspect Sentiment Triplet Extraction 과업을 이해한다

Keywords: Aspect-Based Sentiment Analysis, Aspect Sentiment Triplet Extraction

1 Backgrounds

Aspect-Based Sentiment Analysis(ABSA)

김도윤 석박통합과정 PYSR 자료(ASGCN)
A Survey on Aspect-Based Sentiment Analysis: Tasks, Methods, and Challenges(Zhang et al., 2022)

- 무엇을(Aspect Terms, Category), 어떻게(Sentiment Polarity), 왜(Opinion) 그렇게 생각하는지 분석
  - 4개의 요소 : Aspect Term / Aspect Category / Opinion Term / Sentiment Polarity
  - 기본적으로 리뷰 단위로 진행
    : 한 리뷰 내 단일/복수 elements 존재 가능
  - Main Tasks
    1) Aspect Term Extraction
    2) Aspect Category Detection
    3) Opinion Term Extraction
    4) Aspect Sentiment Classification
  - **위의 과업 동시에 진행 가능**
    : Pair/Triplet/Quad Extraction

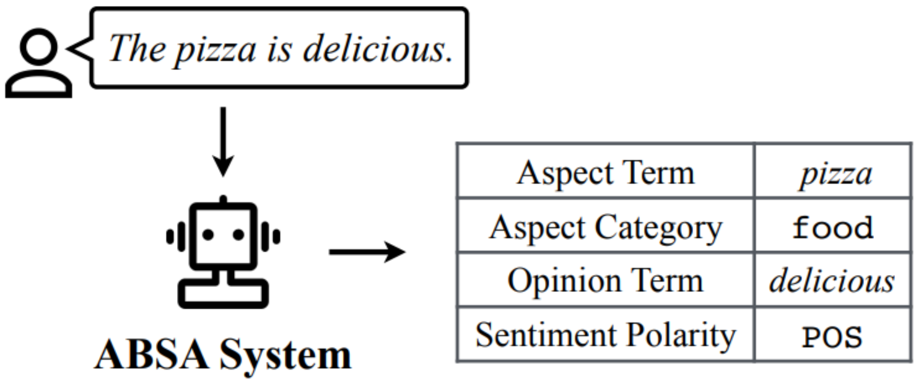

Fig. 1. An example of the four key sentiment elements of ABSA.

Aspect-Based Sentiment Analysis(ABSA)

- 각 Task 별 입력/출력 값 예시
  - sentence(s) : " The pizza is delicious, but the service is terrible "
  - a: aspect / c: category / o: opinion term / p: polarity

Task	Input	Example Input*	Output	Example Output
Aspect Term Extraction	s	sentence	$\{a\}$	{pizza, service}
Aspect Category Detection	s	sentence	$\{c\}$	{food, service}
Aspect Opinion Co-Extraction	s	sentence	$\{a\}, \{o\}$	{pizza, service}, {delicious, terrible}
Target-oriented Opinion Words Extraction	s, a_1	sentence, pizza	o_1	delicious
	s, a_2	sentence, service	o_2	terrible
Aspect Sentiment Classification	s, a_1	sentence, pizza	p_1	POS
	s, a_2	sentence, service	p_2	NEG
Aspect-Opinion Pair Extraction	s	sentence	$\{(a, o)\}$	(pizza, delicious), (service, terrible)
End-to-End ABSA	s	sentence	$\{(a, p)\}$	(pizza, POS), (service, NEG)
Aspect Category Sentiment Analysis	s	sentence	$\{(c, p)\}$	(food, POS), (service, NEG)
Aspect Sentiment Triplet Extraction	s	sentence	$\{(a, p, o)\}$	(pizza, POS, delicious), (service, NEG, terrible)
Aspect-Category-Sentiment Detection	s	sentence	$\{(c, a, p)\}$	(food, pizza, POS), (service, service, NEG)
Aspect Sentiment Quad Prediction	s	sentence	$\{(c, a, p, o)\}$	(food, pizza, POS, delicious), (service, service, NEG, terrible)

* We assume the concerned "*sentence*" for all example inputs is: "*The pizza is delicious, but the service is terrible*".

Aspect-Based Sentiment Analysis(ABSA)

김도윤 석박통합과정 PYSR 자료(ASGCN)
A Survey on Aspect-Based Sentiment Analysis: Tasks, Methods, and Challenges(Zhang et al., 2022)

- ABSA 내 하위 과업과 대표 방법론들

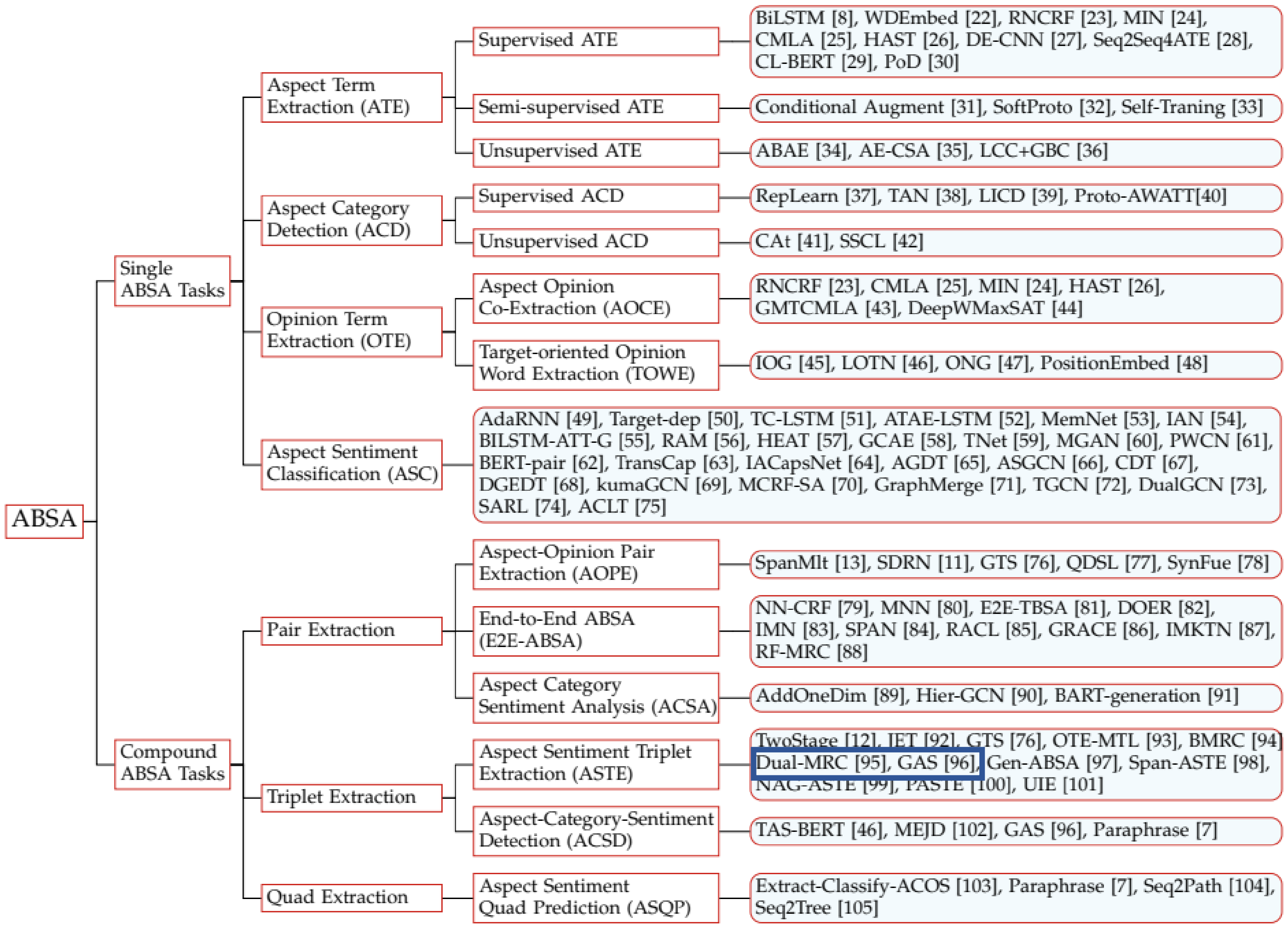

Fig. 2. Taxonomy of ABSA tasks, with representative methods of each task.

Aspect-Based Sentiment Analysis(ABSA)

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- Benchmark Datasets
  - SemEval-2014/2015/2016 내 competition
  - 한정적인 Domain, ABSA 연구 분야 한계점 중 하나

Dataset	Language	Major Domains*	Annotations	URL
SemEval-2014 [114]	English	Lap, Rest	a, c, p	https://alt.qcri.org/semeval2014/task4/
SemEval-2015 [115]	English	Lap, Rest	a, c, p	https://alt.qcri.org/semeval2015/task12/
SemEval-2016 [116]	multilingual	Elec, Hotel, Rest	a, c, p	https://alt.qcri.org/semeval2016/task5/
TOWE [45]	English	Lap, Rest	a, o	https://github.com/NJUNLP/TOWE
ASC-QA [117]	Chinese	Bag, Cos, Elec	a, c, p	https://github.com/jjwangnlp/ASC-QA
MAMS [118]	English	Rest	a, c, p	https://github.com/siat-nlp/MAMS-for-ABSA
ARTS [119]	English	Lap, Rest	a, p	https://github.com/zhijing-jin/ARTS_TestSet
ASTE-Data-V2 [92]	English	Lap, Rest	a, p, o	https://github.com/xuuuluuu/Position-Aware-Tagging-for-ASTE
ASAP [120]	Chinese	Rest	c, p	https://github.com/Meituan-Dianping/asap
ACOS [103]	English	Lap, Rest	a, c, p, o	https://github.com/NUSTM/ACOS
ABSA-QUAD [7]	English	Rest	a, c, p, o	https://github.com/IsakZhang/ABSA-QUAD

* domain abbreviations: Lap-laptops, Rest-restaurants, Elec-electronics, Cos-cosmetics

Aspect Sentiment Triplet Extraction

Knowing What, How and Why: A Near Complete Solution for Aspect-Based Sentiment Analysis(Peng et al., 2020)

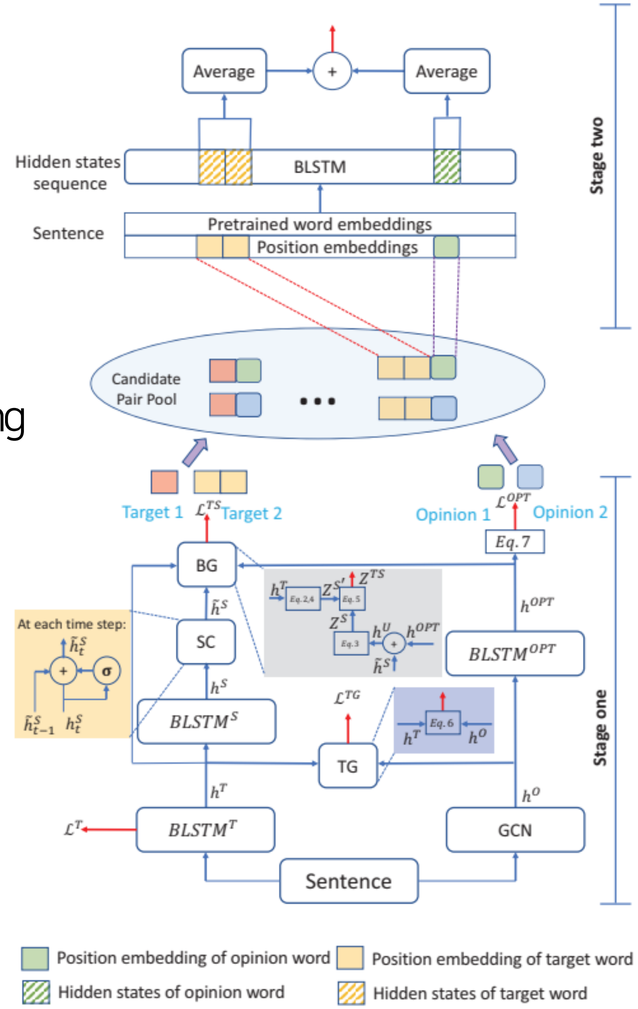
- 문장 내 포함되어 있는 Aspect Term, Opinion Term, Aspect Sentiment 순서 쌍 탐지 과업
  - 'Knowing What, How and Why: A Near Complete Solution for Aspect-Based Sentiment Analysis' 에서 처음 등장
  - What : Aspect Term / How : Polarity / Why : Opinion Term
  - 이전 연구들의 한계점

    1) 단일 요소 추출, 개별 과업으로 진행 후 compound task로 후처리 진행

    2) 두 가지 요소 추출 과업(co-extraction) 진행할 시 문장 내 다중 요소 고려 어려움
  - Two-stage 프레임워크 제시

    1) First Stage : Aspect Term + Sentiment 통합 BIO-Tagging , Opinion Term BIO-Tagging

    2) Second Stage : 추출 된 (Aspect Term, Opinion Term) 순서쌍 중 올바른 pair 찾기
  - 그러나, End-to-End 형식의 framework 아님



	Waiters	are	friendly	and	the	fugu	sashimi	is	out	of	the	world	.
Unified tag (aspect+sentiment)	B-POS	O	O	O	O	B-POS	E-POS	O	O	O	O	O	O
Opinion tag	O	O	S	O	O	O	O		B	I	I	E	O
(Aspect, Opinion) Term Pair	정답: (Waiters, friendly) / (fugu sashimi, out of the world) 오답: (Waiters, out of the world) / (fugu sashimi, friendly)												

Tagging & (Aspect,Opinion) Term pair 예시

Aspect Sentiment Triplet Extraction

- 문장 내 포함되어 있는 Aspect Term, Opinion Term, Aspect Sentiment 순서 쌍 탐지 과업
  - ASTE(Aspect Sentiment Triplet Extraction)의 특징 (발표자 견해)

    I. ABSA 과업들 중 가장 현실적인 과업

    : 사용자들의 관심 대상(aspect term), 이에 대한 견해(polarity)와 근거(opinion term) 탐색 과업

    : 現 LG 전자 소비자 리뷰 분석 프로젝트 주제와 상당 부분 유사, 그러나 Label 부재로 인해 적용 가능성 희박

    II. 특정 제품 및 서비스 사용자 후기 데이터에만 특화 됨

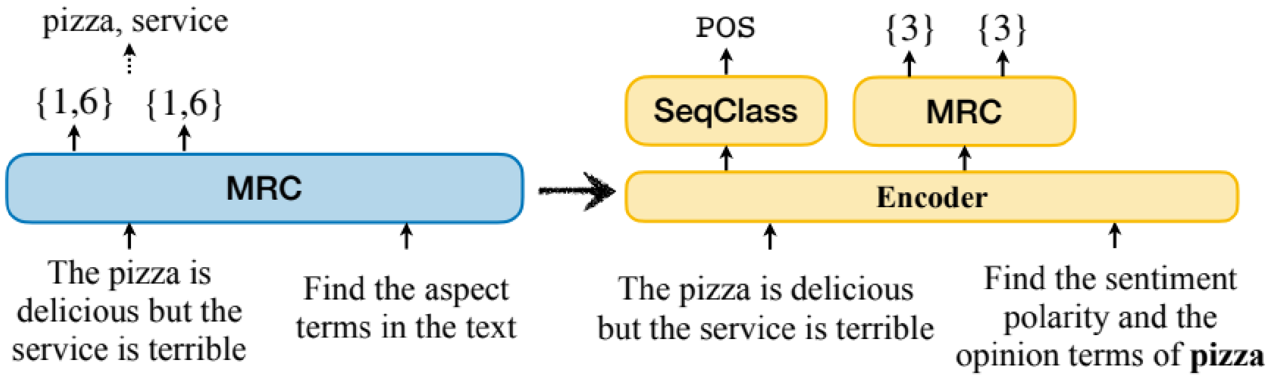
    : 적용 가능한 텍스트 종류 한정적

    : 벤치마크 데이터셋 종류 소수 존재

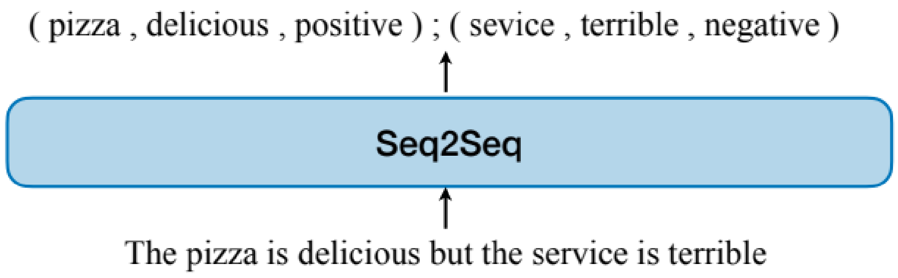
Aspect Sentiment Triplet Extraction

A Survey on Aspect-Based Sentiment Analysis: Tasks, Methods, and Challenges(Zhang et al., 2022)

- 문장 내 포함되어 있는 Aspect Term, Opinion Term, Aspect Sentiment 순서 쌍 탐지 과업
  - A Joint Training Dual-MRC Framework for Aspect Based Sentiment Analysis[Mao et al., 2021]
    : ASTE의 첫 End-to-end Framework
    : BERT 이용하여 기계독해(Machine Reading Comprehension) 문제로 변환
  - Towards Generative Aspect-Based Sentiment Analysis[Zhang et al., 2021]
    : Label(Aspect & Opinion Term)의 의미(semantic) 정보를 이용할 수 있는 생성 방식으로 문제 해결
    : Label을 서로 다른 두 가지 스타일로 구성할 때 성능 비교 - Annotation style, extraction style
    : T5 모델, backbone으로 이용



Mao et al., 2021



Zhang et al., 2021

2 A Joint Training Dual-MRC Framework for Aspect Based Sentiment Analysis

A Joint Training Dual-MRC Framework for Aspect Based Sentiment Analysis

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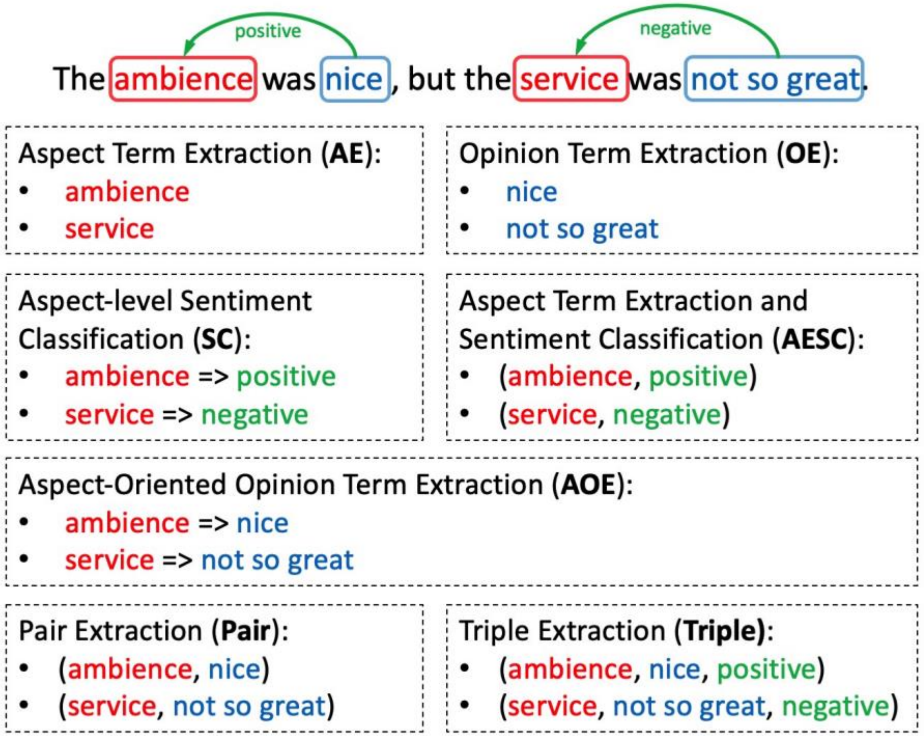
Introduction

- Dual-MRC Framework로 ABSA 내 다양한 하위 과업들(subtasks)을 모두 수행해보자
  - 2021 AAAI / 인용 횟수 : 111회 ('23. 8. 17. 기준)
  - Token이 아닌 span 기반의 추출 방식 채택
  - ASTE의 목적식을 AE, SC, AOE 과업의 각 목적식의 가중합으로 표현 가능

Subtasks	Left-MRC	Right-MRC	
	Extraction	Classification	Extraction
AE	√		
AOE			√
SC		√	
AESC	√	√	
Pair	√		√
Triple	√	√	√



Dual-MRC의 해결 가능 하위 과업들 구분 및 하위 과업 별 예시

Proposed Framework

- Joint Training for Triple Extractions
  - Notations

$D = \{(x_j, T_j)\}$ | Training set, $j \in |D|$

x_j = 최대 길이 n인 단일 문장

$T_j = \{(a, o, s)\}$ = 출력 값 | a = aspect, o = opinion, s = sentiment polarity where $s \in \{\text{Positive}, \text{Neutral}, \text{Negative}\}$

$$T_j|a = \{(o, s)\ where\ (a, o, s) \in T_j\}$$

$$k_{j,a} = |T_j|a| \in \mathbb{R}$$

  - Objective

: 문장 x_j 가 주어졌을 때 출력 값 $T_j(= (a, o, s)$)의 likelihood 를 최대화 하는 것

$$\text{Max}\ \ L(D) = \prod_{j=1}^{|D|} \prod_{(a,o,s)\in T_j} P((a, o, s)|x_j)$$

Proposed Framework

- Joint Training for Triple Extractions
  - Log-likelihood for x_j

$D = \{(x_j, T_j)\}$ | Training set, $j \in |D|$

x_j = 최대 길이 n인 단일 문장

$T_j = \{(a, o, s)\}$ = 출력 값 | a = aspect, o = opinion, s = sentiment polarity where $s \in \{\text{Positive}, \text{Neutral}, \text{Negative}\}$

$T_j|a = \{(o, s) \text{ where } (a, o, s) \in T_j\}$

$k_{j,a} = |T_j|a| \in \mathbb{R}$

✓ 이미 문장과 Aspect Term 만으로 polarity 판단 가능

✓ o,s 서로 독립

$$\therefore P((o,s)|x_j,a) = P(s|x_j,a) \cdot P(o|x_j,a)$$

$$\ell(x_j) = \sum_{(a,o,s)\in T_j} \log P((a,o,s)|x_j) = \sum_{a\in T_j} \sum_{(o,s)\in T_j|a} \log P(a|x_j) + \log P((o,s)|a,x_j)$$

$$= \sum_{a\in T_j}\left(\sum_{(o,s)\in T_j|a} \log P(a|x_j)\right) + \sum_{a\in T_j}\left(\sum_{(o,s)\in T_j|a} \log P(s|a,x_j) + \log P(o|a,x_j)\right)$$

$$= \sum_{a\in T_j} k_{j,a} \cdot \log P(a|x_j) + \sum_{a\in T_j}\left(k_{j,a} \cdot \log P(s|a,x_j) + \sum_{o\in T_j|a} \log P(o|a,x_j)\right)$$

∴ Aspect Term 추출 및 해당 Aspect Term 주어졌을 때 감성분석과 Opinion Term을 추출하는 과업을 함께 진행하는 목적식

Proposed Framework

$D = \{(x_j, T_j)\}$ | Training set, $j \in |D|$

x_j = 최대 길이 n인 단일 문장

$T_j = \{(a, o, s)\}$ = 출력 값 | a = aspect, o = opinion, s = sentiment polarity where $s \in \{\text{Positive}, \text{Neutral}, \text{Negative}\}$

$T_j|a = \{(o, s)\ where\ (a, o, s) \in T_j\}$

$k_{j,a} = |T_j|a| \in \mathbb{R}$

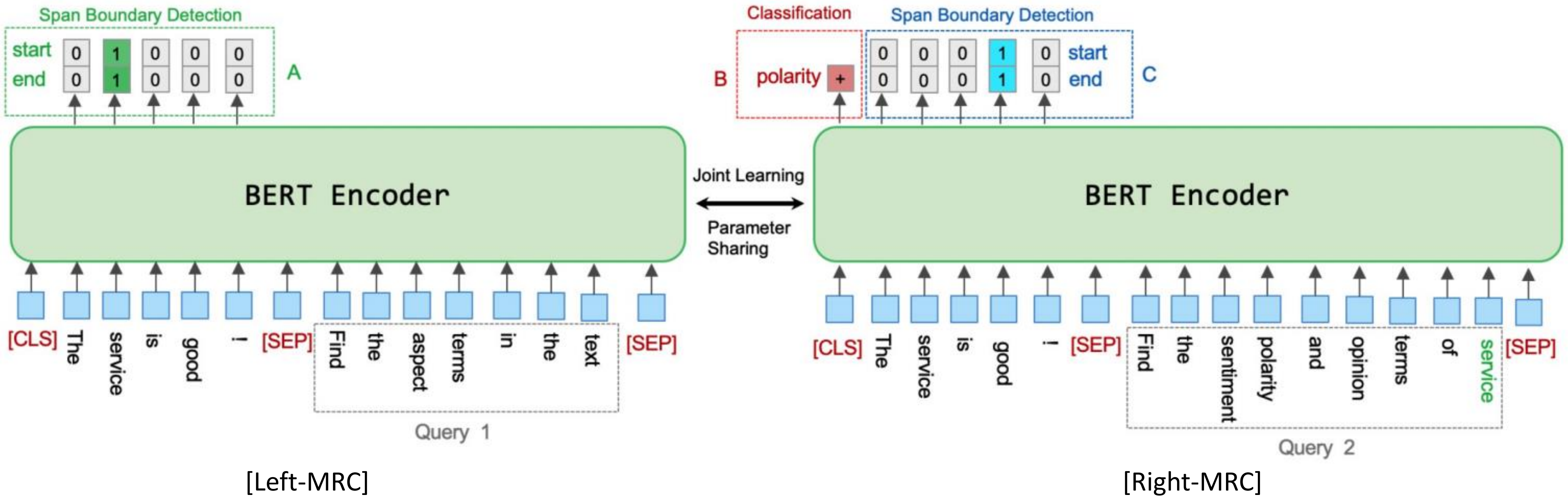
- Joint Training for Triple Extractions
  - Log-likelihood for D and normalization

$$\ell(D) = \underbrace{\alpha \cdot \sum_{j=1}^{|D|} \sum_{a \in T_j} \left(\sum_{a \in T_j} \log P(a|x_j) \right)}_{\text{Aspect term Extraction}} + \underbrace{\beta \cdot \sum_{j=1}^{|D|} \sum_{a \in T_j} \log P(s|a, x_j)}_{\text{Sentiment Classification}} + \underbrace{\gamma \cdot \sum_{j=1}^{|D|} \sum_{a \in T_j} \left(\sum_{o \in T_j|a} \log P(o|a, x_j) \right)}_{\text{Opinion term Extraction}} \text{ where } \alpha, \beta, \gamma \in [0,1]$$

* $\alpha = \beta = \gamma = 1/3$ 으로 설정

Proposed Framework

- Dual-MRC Framework
  - Left-MRC part : Extract all Aspect Terms
    Right-MRC part : Extract all Opinion Terms and find the sentiment polarity w.r.t a given specific aspect term
  - 'BERT-base-uncased' parameter sharing 진행 / 즉, 동일한 BERT 모델로 좌우측 과업 진행



Dual-MRC Framework

Open-Domain Targeted Sentiment Analysis via Span-Based Extraction and Classification(Hu et al., 2019)

Proposed Framework

- Dual-MRC Framework: Training
  - Total loss

$$\mathcal{J} = \frac{1}{3} \cdot \mathcal{J}_{AE} + \frac{1}{3} \cdot \mathcal{J}_{SC} + \frac{1}{3} \cdot \mathcal{J}_{AOE}$$

학습 시 데이터 입/출력 형태

Original training example:
- **input text**: The ambience was nice , but service was not so great.
- **annotations**: (ambience, nice, positive), (service, no so great, negative)

⇩

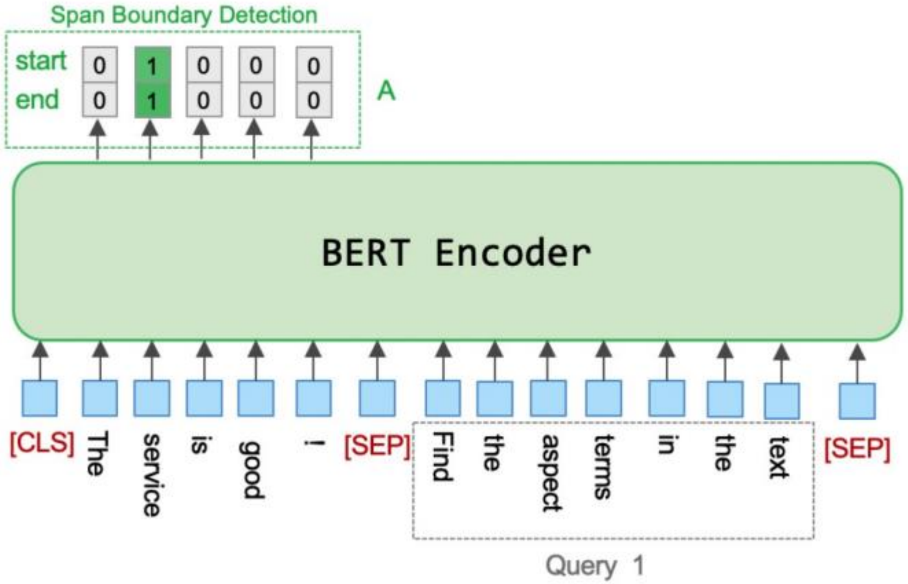
Converted training example 1:
- **query-1**: Find the *aspect terms* in the text.
- **answer-1**: ambience, service
- **query-2**: Find the *sentiment polarity* and *opinion terms* for ambience in the text.
- **answer-2**: (nice, positive)

Converted training example 2:
- **query-1**: Find the *aspect terms* in the text.
- **answer-1**: ambience, service
- **query-2**: Find the *sentiment polarity* and *opinion terms* for service in the text.
- **answer-2**: (not so great, negative)

Proposed Framework

Open-Domain Targeted Sentiment Analysis via Span-Based Extraction and Classification(Hu et al., 2019)

- Dual-MRC Framework: Left-MRC
  - Left-MRC part : Extract all Aspect Terms
  - $h^{l,s}$: Left-MRC의 마지막 layer의 hidden states 이며 Aspect Term의 start token 위치 탐색의 입력 값
    $h^{l,e}$: Left-MRC의 마지막 layer의 hidden states 이며 Aspect Term의 end token 위치 탐색의 입력 값
    Technically, $h^{l,s} = h^{l,e} \in \mathbb{R}^{(n+2)\times d}$ / n : 문장 최대 길이(토큰 개수) , 문장 전후로 [CLS], [SEP] 추가 / d : Hidden dimension
  - Hu et al., 2019 의 Span-Based Extraction(Multi-Target Extractor) 방법 활용 (cont')



[Left-MRC]

[Input 예시]

[CLS] The service is good ! [SEP] ***Find the aspect terms in the text*** *[SEP]*

$$g^{l,s} = W^{l,s}h^{l,s}, \qquad p^{l,s} = softmax(g^{l,s})$$
$$g^{l,e} = W^{l,e}h^{l,e}, \qquad p^{l,e} = softmax(g^{l,e})$$
$$W^{l,s}, W^{l,e} \in \mathbb{R}^{1\times d}$$

[Extraction Loss]

$$\mathcal{J}_{AE} = -\sum_i y_i^{l,s}\log(p_i^{l,s}) - \sum_i y_i^{l,e}\log(p_i^{l,e})$$

Open-Domain Targeted Sentiment Analysis via Span-Based Extraction and Classification(Hu et al., 2019)

Proposed Framework

- Dual-MRC Framework: Left-MRC
  - Multi-Target Extractor with Heuristic multi-span decoding
  - line2 : Top-M confidence 값의 각 시작/끝 위치 확인

    candidate span : $r_l = (s_i, e_j)$ / span length : $(e_j - s_i + 1)$
  - Heuristic regularized score : $u_l = g^s_{s_i} + g^e_{e_j} - (e_j - s_i + 1)$

    : Span의 시작/끝 위치의 confidence score와 길이의 차
  - line 9~14 : Non-Maximum suppression algorithm

    : 중복되는 span을 후보군에서 제거

    : l = 가장 큰 Heuristic regularized score의 인덱스
  - line 13: word-level(글자 단위의) F1-score 구함

    : r_l 과 하나라도 겹치는 글자가 있으면 후보군에서 제외
  - 후보군에 남은 후보가 없거나 top-K 개 선택 완료시 종료

Algorithm Heuristic multi-span decoding

Input: g^s, g^e, γ, K

g^s denotes the score of start positions
g^e denotes the score of end positions
γ is a minimum score threshold # hyperparameter
K is the maximum number of proposed targets # hyperparameter

1: **Initialize** $R, U, O = \{\ \}, \{\ \}, \{\ \}$
2: **Get** top-M indices S, E from g^s, g^e # M : hyperparameter
3: **for** s_i in S **do**
4:     **for** e_j in E **do**
5:         **if** $s_i \le e_j$ and $g^s_{s_i} + g^e_{e_j} \ge \gamma$ **then**
6:             $u_l = g^s_{s_i} + g^e_{e_j} - (e_j - s_i + 1)$
7:             $r_l = (s_i, e_j)$
8:             $R = R \cup \{r_l\},\ U = U \cup \{u_l\}$
9: **while** $R \ne \{\ \}$ and size(O)< K **do**
10:     $l = \arg\max U$
11:     $O = O \cup \{r_l\}$; R $= R - \{r_l\}$; $U = U - \{u_l\}$
12:     **for** r_k in R **do**
13:         **if** F1-score$(r_l, r_k) \ne 0$ **then**
14:             $R = R - \{r_k\}$; $U = U - \{u_k\}$

return O

Proposed Framework

Open-Domain Targeted Sentiment Analysis via Span-Based Extraction and Classification(Hu et al., 2019)

- Dual-MRC Framework: Right-MRC
  - Right-MRC part : Extract all Opinion Terms and find the sentiment polarity w.r.t a given specific Aspect Term
  - $h^{r,s}$: Right-MRC의 마지막 layer의 hidden states 이며 Opinion Term의 start token 위치 탐색의 입력 값

    $h^{r,e}$: Right-MRC의 마지막 layer의 hidden states 이며 Opinion Term의 end token 위치 탐색의 입력 값
  - 동일하게 Heuristic multi-span decoding 적용

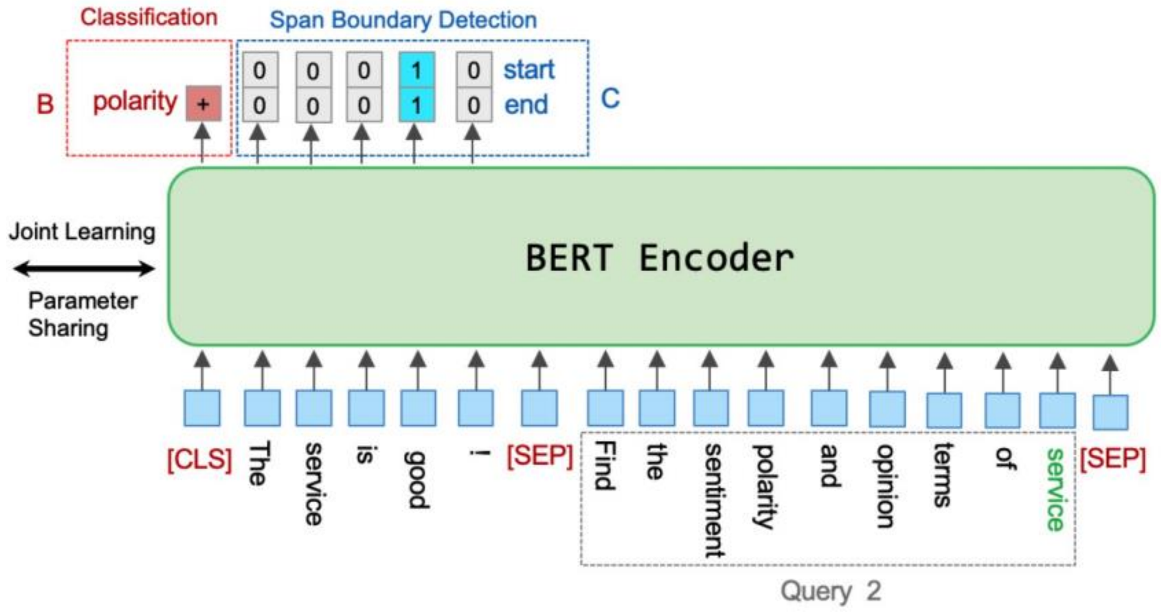
[Input 예시]

[CLS] The service is good ! [SEP] ***Find the sentiment polarity and opinion terms of service*** *[SEP]*

$$g^{r,s} = W^{r,s}h^{r,s}, \qquad p^{r,s} = softmax(g^{r,s})$$
$$g^{r,e} = W^{r,e}h^{r,e}, \qquad p^{r,e} = softmax(g^{r,e})$$
$$W^{r,s}, W^{r,e} \in \mathbb{R}^{1\times d}$$

[Extraction Loss]

$$\mathcal{J}_{AOE} = -\sum_i y_i^{r,s}\log(p_i^{r,s}) - \sum_i y_i^{r,e}\log(p_i^{r,e})$$



Open-Domain Targeted Sentiment Analysis via Span-Based Extraction and Classification(Hu et al., 2019)

Proposed Framework

- Dual-MRC Framework: Right-MRC
  - Right-MRC part : Extract all Opinion Terms and find the sentiment polarity w.r.t a given specific Aspect Term
  - $h^{r,s}$: Right-MRC의 마지막 layer의 hidden states 이며 Opinion Term의 start token 위치 탐색의 입력 값
    $h^{r,e}$: Right-MRC의 마지막 layer의 hidden states 이며 Opinion Term의 end token 위치 탐색의 입력 값
  - 동일하게 Heuristic multi-span decoding 적용

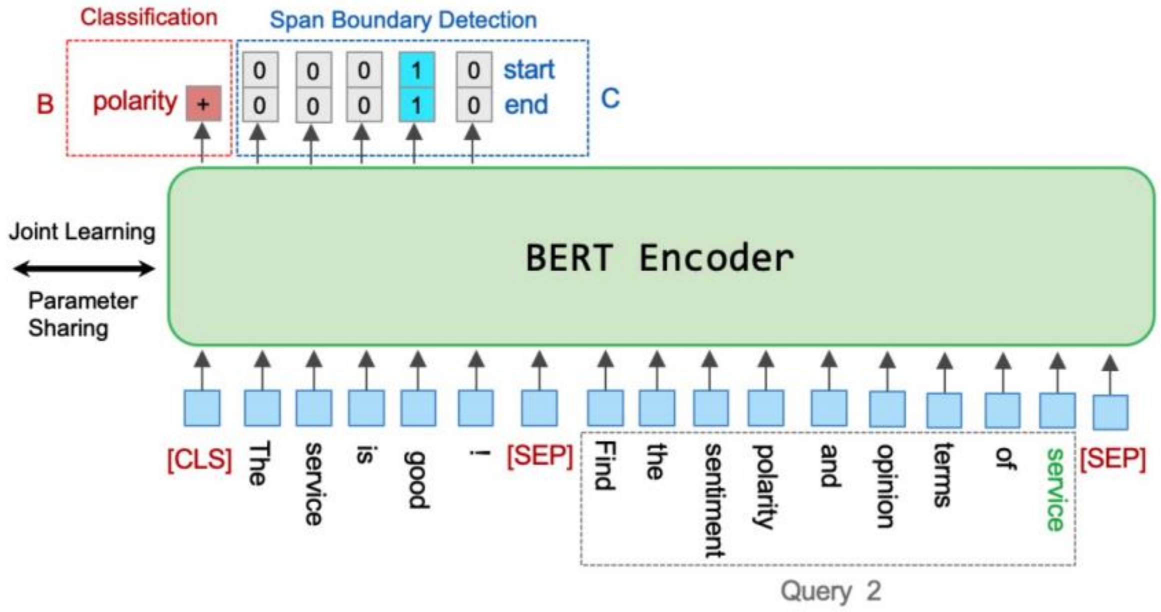
[Input 예시]

[CLS] The service is good ! [SEP] ***Find the sentiment polarity and opinion terms of service*** *[SEP]*

$$p^r_{cls} = softmax(W^r_{cls} h^r_{cls} + b^r_{cls})$$
$$W^r_{cls} \in \mathbb{R}^{3\times d}$$

[Classification Loss]

$$\mathcal{J}_{SC} = CrossEntropy(p^r_{cls}, y_{cls})$$
$$y_{cls} \in \mathbb{R}^3$$



Proposed Framework

- Dual-MRC Framework: Inference Process
  - 학습 시, Aspect Terms 모두 알고 있는 상황
  - 추론 시, Left-MRC의 결과 활용
  - Left-MRC의 결과(Aspect Terms)와 Right-MRC의 결과(Opinion Terms)의 모든 조합 고려
  - Aspect Triplet Extraction 외의 과업들 개별 진행/평가 가능

Algorithm 1: The inference Process for Triple Extraction of the Dual-MRC Framework

Input: sentence x

Output: $T = \{(a, o, s)\}$ triples

Initialize $T = \{\}$

Input x with the query "Find the aspect terms in the text" as the Left-MRC, and output the Aspect Term candidates A

If $A = \{\}$, return T

for $a_i \in A$ **do**

> Input x with the query "Find the sentiment polarity and opinion terms for a_i in the text" as the Right-MRC, and output the sentiment polarity s and Opinion Terms $\{o_j, j = 1,2, \dots\}$
>
> $T \leftarrow T \cup \{(a_i, o_j, s), j = 1,2, \dots\}$

end

Return T

Experiments

- Datasets, Subtasks and Baselines
  - Subtask 수행에 활용된 방법론들과 데이터셋 비교
  - 14/15/16 = SemEval 2014, 2015, 2016
    res = restaurant / lap = laptop

Tasks	Methods	Datasets	Baseline Results
Aspect terms Extraction (AE) Opinion terms Extraction (OE) Aspect Sentiment Classification (SC) Aspect terms Extraction & Sentiment Classification (AESC) - I	SPAN-BERT(Hu et al., 2019) IMN-BERT(He et al., 2019) RACL-BERT(Chen and Qian, 2020)	14res, 14lap, 15res (Wang et al., 2017)	Chen and Qian, 2020
Aspect-oriented Opinion terms Extraction (AOE)	IOG(Fan et al., 2019) LOTN(Wu et al., 2020)	14res, 14lap, 15res, 16res (Fan et al., 2019)	Wu et al., 2020
Aspect & Opinion terms pair extraction (Pair) Aspect Sentiment Triple Extraction (Triple) Aspect terms Extraction & Sentiment Classification (AESC) - II	RINANTE(Dai and Song, 2019) CMLA(Wang et al., 2017) Li-unified-R(Peng et al., 2020) Peng-two-stage(Peng et al., 2020)	14res, 14lap, 15res, 16res (Peng et al., 2020)	Peng et al., 2020

Experiments

- Model Settings
  - BERT-large-uncased : AE, OE, SC, AESC-1
    BERT-base-uncased : AOE, AESC-2, Pair, Triple
  - Optimizer : Adam / lr: $2e^{-5}$ / warmup : First 10% steps
  - Epochs : 3 / Batch size : 12
  - Dropout : 0.1
  - Tesla-V100 1장 활용

Experiments

- Results : AE, SC, AESC
  - Metric: F1-score
  - Validation set = Training set의 20% Random 설정 / 5번 실험 수행 후 평균 스코어 산출
  - AE: Left-MRC / SC: Right-MRC / AESC: Dual-MRC
  - OE는 Dual-MRC 특성상 수행 어려움(Aspect oriented Opinion terms Extraction만 가능)
  - 대 다수의 데이터셋과 Task에서 가장 좋은 성능 보임

	14res				14lap				15res			
	AE	OE	SC	AESC	AE	OE	SC	AESC	AE	OE	SC	AESC
SPAN-BERT	**86.71**	-	71.75	73.68	82.34	-	62.50	61.25	74.63	-	50.28	62.29
IMN-BERT	84.06	85.10	75.67	70.72	77.55	81.00	75.56	61.73	69.90	73.29	70.10	60.22
RACL-BERT	86.38	87.18	81.61	75.42	81.79	79.72	73.91	63.40	73.99	76.00	**74.91**	**66.05**
Dual-MRC	86.60	-	**82.04**	**75.95**	**82.51**	-	**75.97**	**65.94**	**75.08**	-	73.59	65.08

Table 2: Results for *AE*, *SC* and *AESC* on the datasets annotated by (Wang et al. 2017). *OE* is not applicable to our proposed framework. All tasks are evaluated with F1. Baseline results are directly taken from (Chen and Qian 2020). Our model is based on BERT-Large-Uncased. 20% of the data from the training set are randomly selected as the validation set. The results are the average scores of 5 runs with random initialization.

Experiments

- Results : AOE
  - LOTN(Latent Opinions Transfer Network, 2020)

    : Bi-LSTM 모델로 단순 리뷰 감성분석 과업으로 사전학습 후 Attention을 이용하여 BIO-Tagging으로 Opinion Term 추출
  - 16res 데이터셋 제외 나머지 데이터셋에서 가장 높은 F1 스코어 보임

	14res			14lap			15res			16res		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
IOG	82.38	78.25	80.23	73.43	68.74	70.99	72.19	71.76	71.91	84.36	79.08	81.60
LOTN	84.00	**80.52**	82.21	77.08	67.62	72.02	76.61	70.29	73.29	**86.57**	**80.89**	**83.62**
Dual-MRC	**89.79**	78.43	**83.73**	**78.21**	**81.66**	**79.90**	**77.19**	**71.98**	**74.50**	86.07	80.77	83.33

Table 3: Results for *AOE* on the datasets annotated by (Fan et al. 2019). Baseline results are directly taken from (Wu et al. 2020). Our model is based on BERT-Base-Uncased.

Experiments

- Results : AESC-2, Pair, Triple
  - Pair : (Aspect Term, Opinion Term) 추출 / Triple : (Aspect Term, Opinion Term, Sentiment Polarity) 추출
  - Li-unified-R, Peng-two-stage : Unified Tagging(S-POS,E-POS,S-NEG,E-NEG,...) 사용
  - Unified Tagging 보다 Span 기반 방법론 우수 : 토큰 별 tag 확인보다 시작/끝 위치 파악 더 용이

		14res			14lap			15res			16res		
		P	R	F1	P	R	F1	P	R	F1	P	R	F1
AESC	RINANTE	48.97	47.36	48.15	41.20	33.20	36.70	46.20	37.40	41.30	49.40	36.70	42.10
	CMLA	67.80	73.69	70.62	54.70	59.20	56.90	49.90	58.00	53.60	58.90	63.60	61.20
	Li-unified-R	73.15	74.44	73.79	66.28	60.71	63.38	64.95	**64.95**	64.95	66.33	**74.55**	70.20
	Peng-two-stage	74.41	73.97	74.19	63.15	61.55	62.34	**67.65**	64.02	**65.79**	**71.18**	72.30	**71.73**
	Dual-MRC	**76.84**	**76.31**	**76.57**	**67.45**	**61.96**	**64.59**	66.84	63.52	65.14	69.18	72.59	70.84
Pair	RINANTE	42.32	51.08	46.29	34.40	26.20	29.70	37.10	33.90	35.40	35.70	27.00	30.70
	CMLA	45.17	53.42	48.95	42.10	46.30	44.10	42.70	46.70	44.60	52.50	47.90	50.00
	Li-unified-R	44.37	73.67	55.34	52.29	52.94	52.56	52.75	61.75	56.85	46.11	64.55	53.75
	Peng-two-stage	47.76	68.10	56.10	50.00	58.47	53.85	49.22	**65.70**	56.23	52.35	70.50	60.04
	Dual-MRC	**76.23**	**73.67**	**74.93**	**65.43**	**61.43**	**63.37**	**72.43**	58.90	**64.97**	**77.06**	**74.41**	**75.71**
Triple	RINANTE	31.07	37.63	34.03	23.10	17.60	20.00	29.40	26.90	28.00	27.10	20.50	23.30
	CMLA	40.11	46.63	43.12	31.40	34.60	32.90	34.40	37.60	35.90	43.60	39.80	41.60
	Li-unified-R	41.44	68.79	51.68	42.25	42.78	42.47	43.34	50.73	46.69	38.19	53.47	44.51
	Peng-two-stage	44.18	62.99	51.89	40.40	47.24	43.50	40.97	**54.68**	46.79	46.76	62.97	53.62
	Dual-MRC	**71.55**	**69.14**	**70.32**	**57.39**	**53.88**	**55.58**	**63.78**	51.87	**57.21**	**68.60**	**66.24**	**67.40**

Table 4: Results for *AESC*, *Pair* and *Triple* on the datasets annotated by (Peng et al. 2020). Baseline results are directly taken from (Peng et al. 2020). Our model is based on BERT-Base-Uncased.

Experiments

- Analysis on Joint Learning(Ablation Study)
  - Loss 구성(목적식)에 따른 각 task 별 성능 비교
    : √ 표시 된 것을 loss에 반영
  - [AT,OT] 추출(pair)의 경우, 감성분류 목적식 추가 시 성능 하락
    : 감성분석이 Opinion Terms 추출에 악영향
  - AE의 경우, AOE와 SC 목적식 추가 시 성능 하락
    : 단순한 task에 목적식에 불필요한 정보 추가 (발표자 의견)
  - 모든 요소 목적식에 포함할 시 성능 유지한채 다양한 Task 한 번에 다룰 수 있음 (저자 의견)
  - 목적식 내 각 요소별 가중치(α, β, γ) 적절한 조합 파악 시 모든 요소를 고려하는 것이 항상 높은 성능 보일 수 있을 듯(발표자 의견)

Task	Left	Right		14res	14lap	15res	16res
	e	c	e				
AESC	√	√		76.31	63.95	65.43	69.48
	√	√	√	76.57	64.59	65.14	70.84
Pair	√		√	76.33	65.26	65.21	76.61
	√	√	√	74.93	63.37	64.97	75.71
AE	√			82.80	78.35	78.22	82.16
	√	√	√	82.93	77.31	76.08	81.20

Table 6: Results on the analysis of joint learning for *AESC* and *Pair* on the dataset from (Peng et al. 2020). In the table, the letter e stands for extraction and the letter c stands for classification.

Experiments

- Case Study
  - 입력 문장과 Right-MRC에 활용되는 query (“Find the sentiment polarity and opinion terms for *AT* in the text) Self-Attention score 비교

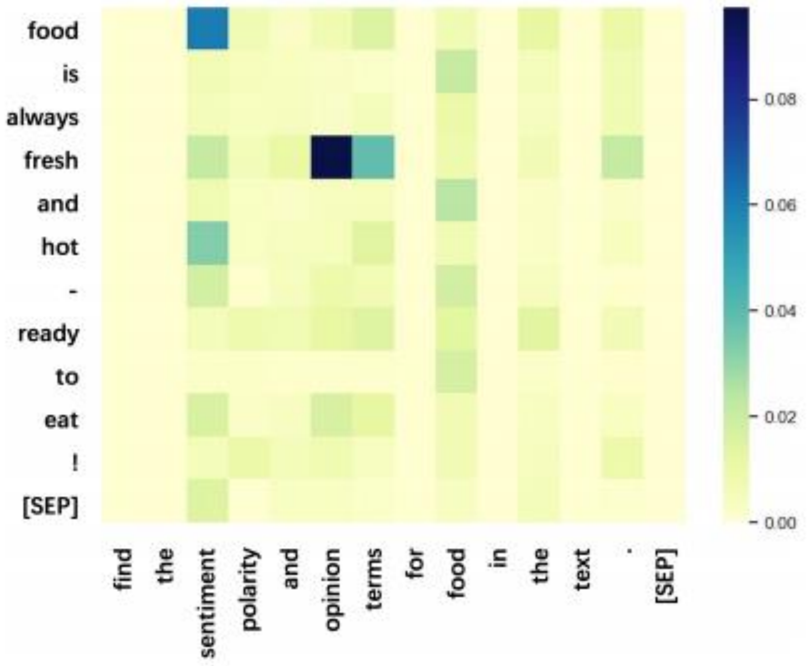


Figure 4: An example of attention matrices for the input text and query.

Conclusions

- Joint training Dual-MRC Framework
  - 하나의 모델로 여러가지 ABSA의 하위 과업들을 모두 수행할 수 있음
  - ASTE 과업 수행 위한 목적식 설정, 수학적으로 개별 과업의 목적식의 가중합으로 나타내었음
  - 치밀하게 구성된 논문 X, 그러나 부족함 없이 잘 설명되어 있음

3 Towards Generative Aspect-Based Sentiment Analysis

Towards Generative Aspect-Based Sentiment Analysis*

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Introduction

- ABSA 내 여러 과업을 분류(classification) 문제가 아닌 생성(generative) 문제로 접근해보자
  - 2021 ACL-IJCNLP Short Papers / 인용 횟수 : 99회 ('23. 8. 17. 기준)
  - 대부분의 ABSA 과업들, token/span 단위의 분류 문제
  - 분류 문제, 각 단어의 의미 고려하지 않은 채 인덱스 화 진행

    : 사람에게 (AT,OT) 쌍 추출 어렵지 않은 이유 : 단어들의 의미와 연관성 직관적으로 파악 가능
  - 생성 문제로 변환 시 task에 맞는 모델 구조 변경 불필요
  - Keywords: Prediction Normalization, Annotation-style, Extraction-style

Introduction

- ABSA with Generative Paradigm
  - Unified ABSA : (Aspect Term, Sentiment Polarity) 동시 추출 과업
  - Target Aspect Sentiment Detection(TASD) : (Aspect Term, Aspect Category, Sentiment Polarity) 동시 추출 과업
  - Input : *"Salads were fantastic, our server was also very helpful."*

* 붉은 색은 이해를 돕기 위함

Task	Style	Target Sequence Examples
Pair	Annotation	[Salads | fantastic] were fantastic here, our [server | helpful] was also very helpful.
	Extraction	(Salads, fantastic), (server, helpful)
Unified ABSA	Annotation	[Salads | positive] were fantastic here, our [server | positive] was also very helpful.
	Extraction	(Salads, positive), (server, positive)
TASD	Annotation	[Salads | food quality | positive] were fantastic here, our [server | service | positive] was also very helpful.
	Extraction	(Salads, food quality, positive), (server, service, positive)
ASTE	Annotation	[Salads | fantastic | positive] were fantastic here, our [server | helpful | positive] was also very helpful.
	Extraction	(Salads, fantastic, positive), (server, helpful, positive)

Methodology

- Generation Model
  - $\boldsymbol{x}$: Input sentence / $\boldsymbol{s}$: true pairs or triples / $\boldsymbol{y}'$: Target sequence
  - $f(\cdot)$: Text generation model = T5
  - Post process to extract words
    1) Annotation style : '[]' 안의 텍스트 추출 후 '| ' 기준으로 구분
       만약, 생성이 잘 못되어 '|'의 개수가 너무 많거나, '[]' 안에 단어 없을 시 해당 예측 결과 무시(ignore)
    2) Extraction style : '()'안에 콤마(,) 기준으로 구분
       Annotation style과 같이 생성에 오류 있을 시 무시
  - 입력 값에 별 다른 prompt 추가하지 않음

Methodology

- Prediction Normalization
  - 생성된 y' 에 온전한 단어 형태의 텍스트 존재하지 않을 가능성 높음 (= 토큰 형태로 존재)
    ∴ 정제(refine) 과정 필요
  - 각 요소(AT, OT, Category, Sentiment Polarity)의 단어 집합(vocabulary) 형성 : $\boldsymbol{v_a, v_o, v_c, v_s}$
    1) $v_a = v_o$: 데이터셋 내 모든 문장 구성 단어 집합
    2) v_c : 데이터셋 내 모든 카테고리 집합 / ex) {Food Quality, Service …}
    3) v_s : {positive, neutral, negative}
  - 후처리 규칙에 따라 추출된 각 텍스트가 해당 요소의 단어 집합에 없는 경우
    : 단어 집합 내 단어 중 <u>Levenshtein distance</u> 가장 작은 단어로 선택

Methodology

- Prediction Normalization
  - Levenshtein distance(레벤슈타인 거리, 편집거리) / $lev(a,b), lev_{a,b}$

    : 문자열 a 가 문자열 b 와 동일해지기까지 필요한 최소 편집(변경, 삽입, 삭제) 횟수

    : 두 문자열의 유사도 측정 지표 중 하나

$$lev_{a,b}(i,j) = \begin{cases} \max(i,j), & if\ \min(i,j) = 0 \\ \min \begin{cases} lev_{a,b}(i-1,j)+1 \\ lev_{a,b}(i,j-1)+1 \\ lev_{a,b}(i-1,j-1)+1_{a_i \neq b_j} \end{cases}, & otherwise \end{cases}$$

$$where\ i \in len(a), j \in len(b)$$

Get lev(m,n) where m = len(a) , n=len(b)

Initialize
first column and first row with indices
lev(0,0) = 0

for i in 1 to m
  for j in 1 to n
    if a_i=b_j
      lev(i,j) = lev(i-1,j-1)
    else
      diagonal = lev(i-1,j-1) + 1
      left = lev(i,j-1)+1
      up = lev(i-1,j)+1
      lev(i,j) = Min(diagonal, left, up)

return lev(m,n)

[출처]: 후니의 컴퓨터 레벤슈타인 거리

Methodology

- Prediction Normalization
  - Levenshtein distance(레벤슈타인 거리, 편집거리)

    [Example]

    a: RELEVANT / b: ELEPHANT

i \ j		0	1	2	3	4	5	6	7	8
			E	L	E	P	H	A	N	T
0		0	1	2	3	4	5	6	7	8
1	R	1	1							
2	E	2								
3	L	3								
4	E	4								
5	V	5								
6	A	6								
7	N	7								
8	T	8								?

Get lev(1,1)

a_1=R , b_1=E

if $a_1 = b_1$

lev(1,1) = lev(0,0)

else

diagon = lev(0,0) + 1 # which is 1

left = lev(1,0)+1 # which is 1

up = lev(0,1)+1 # which is 1

lev(1,1) = Min(diagon, left, up) # Min(1,1,1)

return lev(1,1) # lev(1,1) =1

Get lev(m,n) where m = len(a) , n=len(b)

Initialize
first column and first row with indices
lev(0,0) = 0

for i in 1 to m

for j in 1 to n

if a_i=b_j

lev(i,j) = lev(i-1,j-1)

else

diagonal = lev(i-1,j-1) + 1

left = lev(i,j-1)+1

up = lev(i-1,j)+1

lev(i,j) = Min(diagonal, left, up)

return lev(m,n)

Methodology

[출처]: 후니의 컴퓨터 레벤슈타인 거리

- Prediction Normalization
  - Levenshtein distance(레벤슈타인 거리, 편집거리)

    [Example]

    a: RELEVANT / b: ELEPHANT

i \ j		0	1	2	3	4	5	6	7	8
			E	L	E	P	H	A	N	T
0		0	1	2	3	4	5	6	7	8
1	R	1	1							
2	E	2	1							
3	L	3								
4	E	4								
5	V	5								
6	A	6								
7	N	7								
8	T	8								?

Get lev(2,1)

a_2=E , b_1=E

if $a_2 = b_1$

lev(2,1) = lev(1,0) # lev(1,0) =1

else

diagon = lev(1,0) + 1

left = lev(2,0)+1

up = lev(1,1)+1

lev(2,1) = Min(diagon, left, up)

return lev(2,1)

Get lev(m,n) where m = len(a) , n=len(b)

Initialize
first column and first row with indices
lev(0,0) = 0

for i in 1 to m

for j in 1 to n

if $a_i = b_j$

lev(i,j) = lev(i-1,j-1)

else

diagonal = lev(i-1,j-1) + 1

left = lev(i,j-1)+1

up = lev(i-1,j)+1

lev(i,j) = Min(diagonal, left, up)

return lev(m,n)

Methodology

[출처]: 후니의 컴퓨터 레벤슈타인 거리

- Prediction Normalization
  - Levenshtein distance(레벤슈타인 거리, 편집거리)

    [Example]

    a: RELEVANT / b: ELEPHANT

    ∴ lev(RELEVANT, ELEPHANT) =3

i \ j		0	1	2	3	4	5	6	7	8
			E	L	E	P	H	A	N	T
0		0	1	2	3	4	5	6	7	8
1	R	1	1	2	3	4	5	6	7	8
2	E	2	1	2	2	3	4	5	6	7
3	L	3	2	1	2	3	4	5	6	7
4	E	4	3	2	1	2	3	4	5	6
5	V	5	4	3	2	2	3	4	5	6
6	A	6	5	4	3	3	3	3	4	5
7	N	7	6	5	4	4	4	4	3	4
8	T	8	7	6	5	5	5	5	4	3

```
def leven(aText,bText):
    aLen = len(aText)+1
    bLen = len(bText)+1
    array = [ [] for a in range(aLen) ]
    for i in range(aLen):
        array[i] = [0 for a in range(bLen)]
    for i in range(bLen):
        array[0][i] = i
    for i in range(aLen):
        array[i][0] = i
    cost = 0
    for i in range(1,aLen):
        for j in range(1,bLen):
            if aText[i-1] != bText[j-1]:
                cost = 1
            else :
                cost = 0
            addNum = array[i-1][j] + 1 #추가
            minusNum = array[i][j-1] + 1 #감소
            modiNum = array[i-1][j-1]+cost # 변경
            minNum = min([addNum,minusNum,modiNum])
            array[i][j] = minNum

    return array[aLen-1][bLen-1]
```

Experiments

- Experimental Setup
  - 5번의 random seed 설정 후 F1 스코어 평균 구함
  - T5 base model 활용
  - AdamW(lr:3e-4) / Batch size: 16(Accum steps: 2 Batch) / 30 Epochs(TASD), 20 Epochs(Others)

Tasks	Methods	Datasets
Aspect & Opinion terms Pair Extraction (AOPE)	SpanMlt(Zhao et al., 2020) SDRN(Chen et al., 2020)	14res, 14lap, 15res, 16res (Fan et al., 2019)
Aspect terms Extraction & Sentiment Classification (Unified ABSA)	BERT+GRU(Li et al., 2019) SPAN-BERT(Hu et al., 2019) IMN-BERT(He et al., 2019) RACL(Chen and Qian, 2020) Dual-MRC(Mao et al., 2021)	14res, 14lap, 15res, 16res (Li et al., 2019)
Aspect Sentiment Triple Extraction (ASTE)	CMLA+(Wang et al., 2017) Li-unified-R(Peng et al., 2020) Peng-two-stage(Peng et al., 2020) Jet/Jet+BERT(Xu et al., 2020)	14res, 14lap, 15res, 16res (Xu et al., 2020)
Target Aspect Sentiment Detection (TASD)	Baseline(Brun and Nikoulina, 2018) TAS(Wan et al., 2020)	15res, 16res (Wan et al., 2020)

Experiments

- Results
  - '~ R' : 제안방법론에서 Refinement 과정 생략 했을 경우

Main results of AOPE task

	Lap14	Res14	Res15	Res16
HAST+TOWE	53.41	62.39	58.12	63.84
JERE-MHS	52.34	66.02	59.64	67.65
SpanMlt	68.66	**75.60**	64.68	71.78
SDRN	66.18	73.30	65.75	73.67
GAS-ANNOTATION-R	<u>68.74</u>	72.66	65.03	73.75
GAS-EXTRACTION-R	67.58	73.22	65.83	74.12
GAS-ANNOTATION	**69.55**	<u>75.15</u>	**67.93**	**75.42**
GAS-EXTRACTION	68.08	74.12	<u>67.19</u>	<u>74.54</u>

Main results of UABSA task

	Lap14	Res14	Res15	Res16
BERT+GRU	61.12	73.17	59.60	70.21
SPAN-BERT	61.25	73.68	62.29	-
IMN-BERT	61.73	70.72	60.22	-
RACL	63.40	75.42	<u>66.05</u>	-
Dual-MRC	65.94	75.95	65.08	-
GAS-ANNOTATION-R	67.37	75.77	65.75	71.87
GAS-EXTRACTION-R	66.71	76.30	64.00	72.39
GAS-ANNOTATION	**68.64**	<u>76.58</u>	**66.78**	<u>73.21</u>
GAS-EXTRACTION	<u>68.06</u>	**77.13**	65.96	**73.64**

Experiments

- Results
  - '~ R' : 제안방법론에서 Refinement 과정 생략 했을 경우

Main results of ASTE task

	Lap14	Res14	Res15	Res16
CMLA+	33.16	42.79	37.01	41.72
LI-unified-R	42.34	51.00	47.82	44.31
Pipeline	42.87	51.46	52.32	54.21
Jet	43.34	58.14	52.50	63.21
Jet+BERT	51.04	62.40	57.53	63.83
GAS-ANNOTATION-R	52.80	67.35	56.95	67.43
GAS-EXTRACTION-R	<u>58.19</u>	<u>70.52</u>	60.23	<u>69.05</u>
GAS-ANNOTATION	54.31	69.30	<u>61.02</u>	68.65
GAS-EXTRACTION	**60.78**	**72.16**	**62.10**	**70.10**

Main results of TASD task

	Res15	Res16
Baseline	-	38.10
TAS-LPM-CRF	54.76	64.66
TAS-SW-CRF	57.51	65.89
TAS-SW-TO	58.09	65.44
GAS-ANNOTATION-R	59.27	66.54
GAS-EXTRACTION-R	<u>60.63</u>	<u>68.31</u>
GAS-ANNOTATION	60.06	67.70
GAS-EXTRACTION	**61.47**	**69.42**

Experiments

- Results
  - 비교적 간단한 AOPE, Annotation >> Extraction 성능 우수
  - 여러 요소 확인 필요한 ASTE & TASD , Extraction >> Annotation 성능 우수

    : ASTE & TASD 학습 시, Annotation 방식의 경우 과다한(too much) 정보 입력 필요
  - Prediction Normalization 미적용시 성능 하락

    : Prediction Normalization 효과 확인

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Experiments

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  - 여러 요소 확인 필요한 ASTE & TASD , Extraction >> Annotation 성능 우수
    : ASTE & TASD 학습 시, Annotation 방식의 경우 과다한(too much) 정보 입력 필요
  - Prediction Normalization 미적용시 성능 하락
    : Prediction Normalization 효과 확인

Example cases of the prediction normalization

Before	After	Label
Bbq rib	BBQ rib	BBQ rib
repeat	repeats	repeats
chicken peas	chickpeas	chickpeas
bodys	bodies	None
cafe	coffee	coffee
vegetarian	vegan	vegetarian
salmon	not	spinach
flight cookie	might cookie	fortune cookie

Morphology shift (minor lexical differences) 보정
: 소/대문자 보정, 복수형 표현

존재하는 단어로 보정

유사한 의미의 단어지만 입력 문장 내 단어로 보정

Conclusions

- Generative Aspect-Based Sentiment Analysis
  - Encoder-Decoder 구조의 T5 이용하여 최초로 생성방식으로 접근한 방법론
    : 간단하고 효과적인 아이디어
  - (Aspect, Opinion), (Aspect, Sentiment), (Aspect, Opinion, Category), (Aspect, Opinion, Sentiment) 등 원하는 조합의 요소 추출할 수 있는 통합 pipeline
  - 비록 Prediction Normalization 과정 있지만 생각보다 온전한 단어로 생성되기 어려울 듯 (발표자 견해)

4 Conclusions

Aspect-Based Sentiment Analysis

- 무엇을(Aspect Terms, Category), 어떻게(Sentiment Polarity), 왜(Opinion) 그렇게 생각하는지 분석
  - 탐색하고자 하는 요소의 조합에 따라 여러 하위 과업들로 구분
  - 현재, 하나의 모델/framework/pipeline 으로 여러 하위 과업들을 진행할 수 있도록 발전

Task	Input	Example Input*	Output	Example Output
Aspect Term Extraction	s	sentence	$\{a\}$	{pizza, service}
Aspect Category Detection	s	sentence	$\{c\}$	{food, service}
Aspect Opinion Co-Extraction	s	sentence	$\{a\}, \{o\}$	{pizza, service}, {delicious, terrible}
Target-oriented Opinion Words Extraction	s, a_1	sentence, pizza	o_1	delicious
	s, a_2	sentence, service	o_2	terrible
Aspect Sentiment Classification	s, a_1	sentence, pizza	p_1	POS
	s, a_2	sentence, service	p_2	NEG
Aspect-Opinion Pair Extraction	s	sentence	$\{(a, o)\}$	(pizza, delicious), (service, terrible)
End-to-End ABSA	s	sentence	$\{(a, p)\}$	(pizza, POS), (service, NEG)
Aspect Category Sentiment Analysis	s	sentence	$\{(c, p)\}$	(food, POS), (service, NEG)
Aspect Sentiment Triplet Extraction	s	sentence	$\{(a, p, o)\}$	(pizza, POS, delicious), (service, NEG, terrible)
Aspect-Category-Sentiment Detection	s	sentence	$\{(c, a, p)\}$	(food, pizza, POS), (service, service, NEG)
Aspect Sentiment Quad Prediction	s	sentence	$\{(c, a, p, o)\}$	(food, pizza, POS, delicious), (service, service, NEG, terrible)

* We assume the concerned "*sentence*" for all example inputs is: "*The pizza is delicious, but the service is terrible*".

Aspect-Based Sentiment Analysis

- 무엇을(Aspect Terms, Category), 어떻게(Sentiment Polarity), 왜(Opinion) 그렇게 생각하는지 분석
  - ABSA 연구 분야 계속해서 발전할 것으로 예상됨
    : 사람들의 생각/의견을 직접적으로 분석할 수 있는 좋은 연구 분야
    : 수많은 기업에서 고객의 소리(Voice Of Customers, VOC) 분석/파악 하는 것에 큰 노력
  - 최근, Aspect-Category-Opinion-Sentiment (ACOS) Quadruple Extraction 방법론 연구 진행 중(Cai et al., 2021)
  - 마땅한 한국어 데이터 부족한 점, 큰 한계점 중 하나

감사합니다.