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Self Question-answering: Aspect-based Sentiment Analysis by Role Flipped Machine Reading Comprehension

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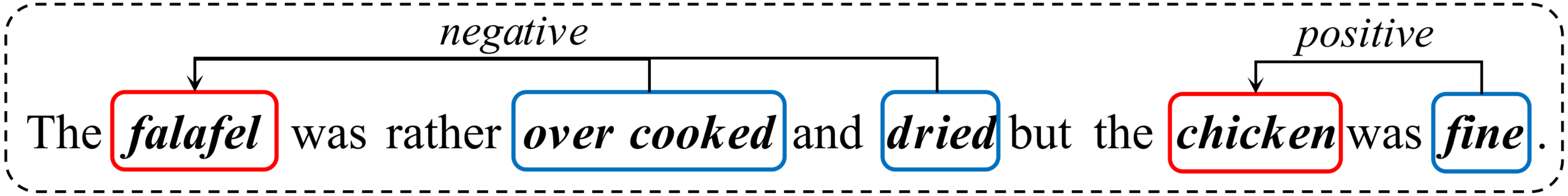
PART .01

INTRODUCTION

Unified Aspect-based Sentiment Analysis (ABSA)

ABSA generally consists of three sub-tasks, namely, Aspect Terms Extraction (ATE), Opinion Terms Extraction(OTE) and Aspect Sentiment Classification(ASC).

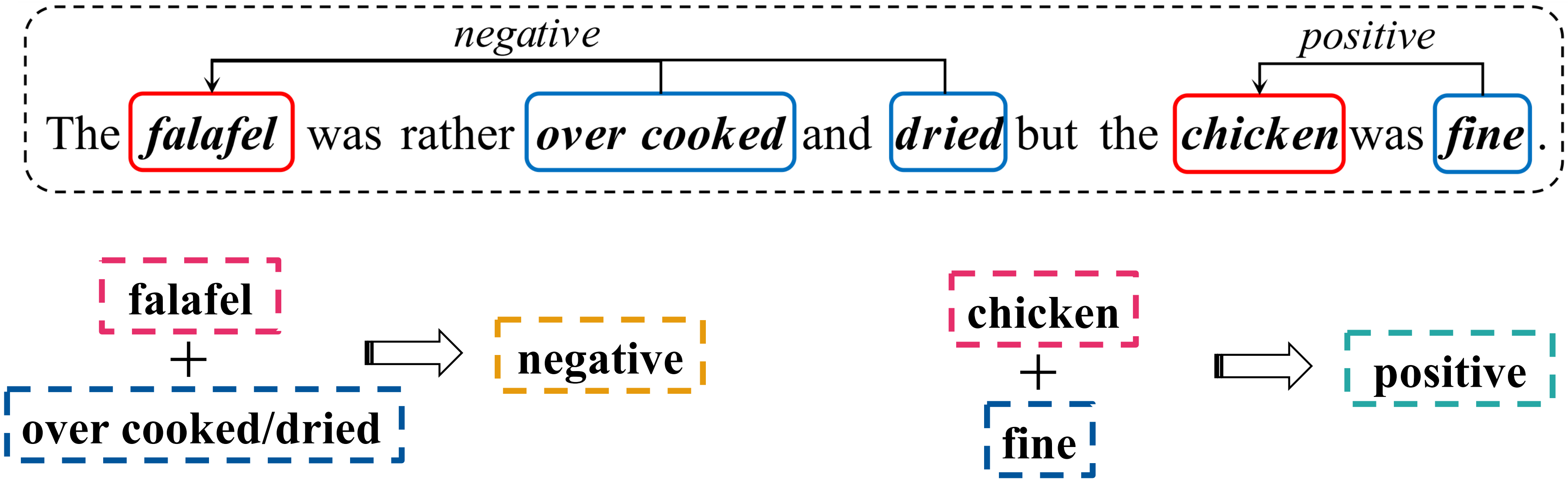


- **ATE** extracts the aspect terms with obvious emotion inclinations.
- **OTE** aims to extract the opinion terms that express emotions.
- **ASC** predicts the sentiment polarities of aspect terms in the given sentence.

PART .01 **INTRODUCTION**

The Heart of Unified ABSA

The heart of ABSA is to capture the connection between aspect terms and their respective opinion terms, which might make it easier to predict the sentiment polarities.



PART .02

METHOD

Machine Reading Comprehension in NLP

Many tasks in natural language processing can be transformed into a question answering problem. Question-Answering aims to extract answer spans from a passage through a question.

C = The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called “showers”.

Q = Where do water droplets collide with ice crystals to form precipitation?

A = within a cloud

PART .02

METHOD

Transform ABSA into A MRC Problem

In this paper, we examine the unified ABSA from a perspective of Machine Reading Comprehension (MRC).

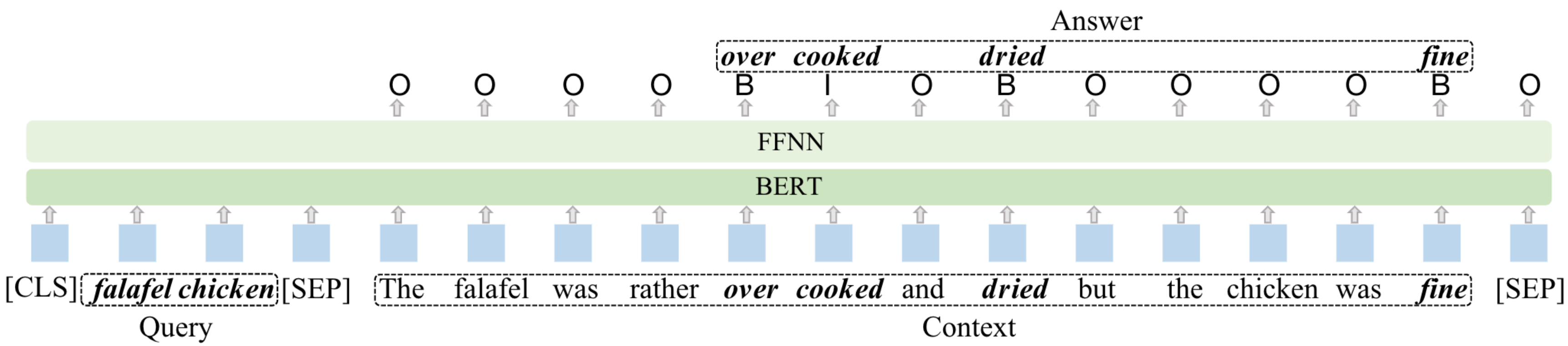


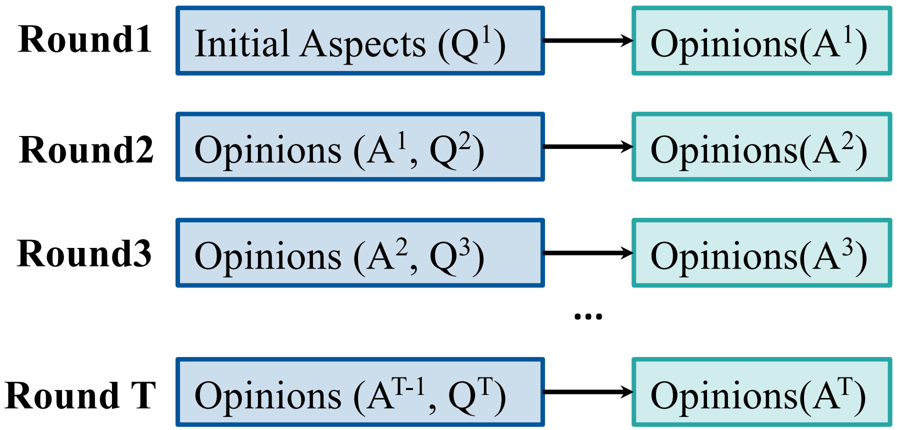
Figure 2: An example to examine the unified ABSA from a perspective of MRC.

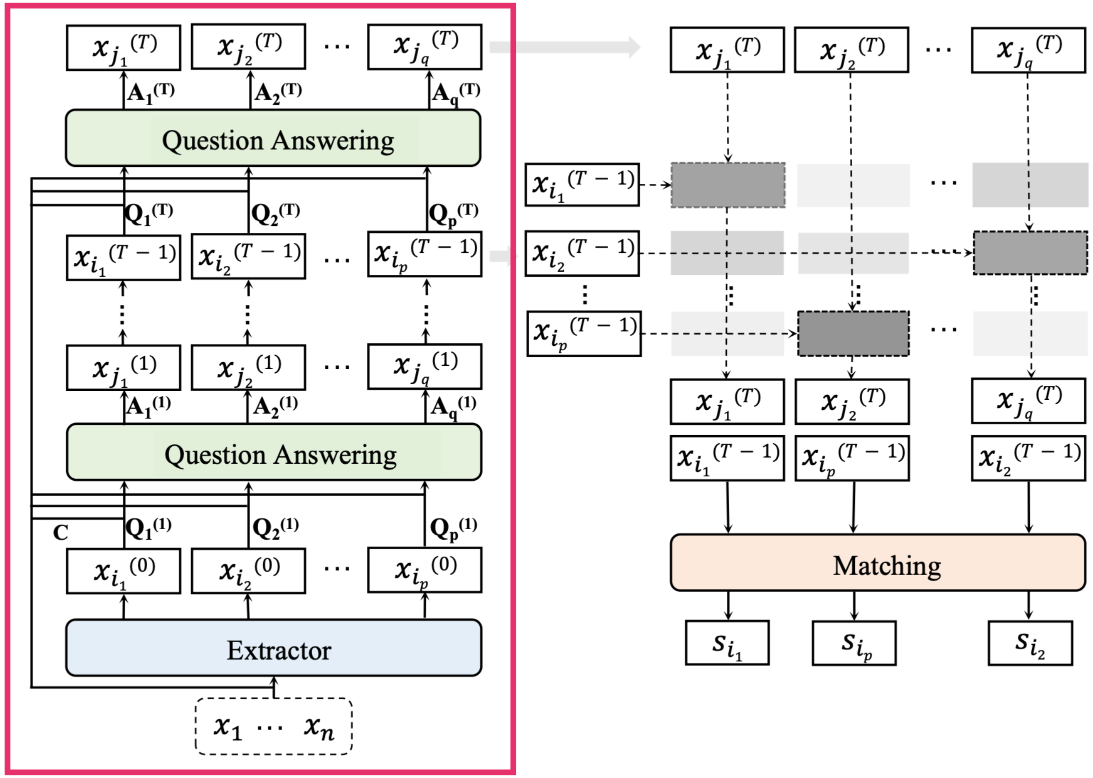
PART .02

METHOD

Role Flipped Module

Based on the initial extraction results, we devise a ***role flipped module*** to grasp the connection between aspect terms and relevant opinion terms in-side the sentence





PART .02

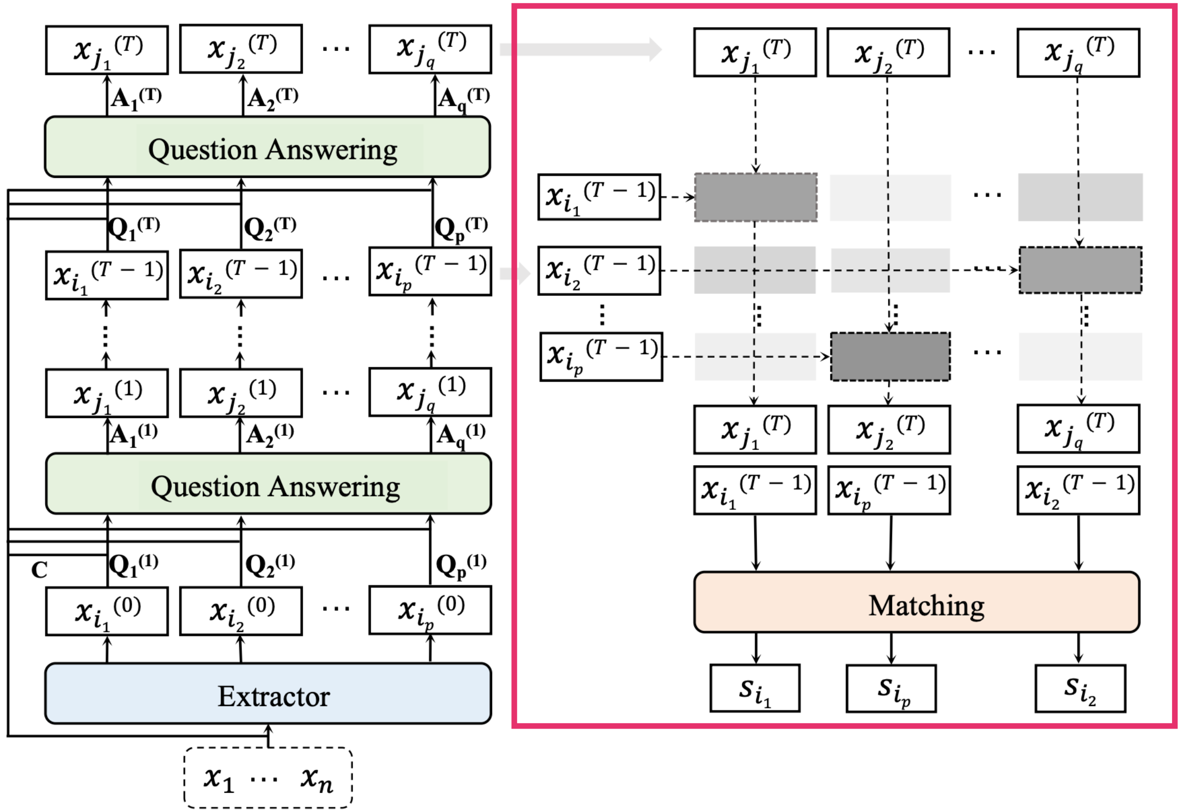
METHOD

Transform ABSA into A MRC Problem

Finally, we design ***a matching mechanis*** We apply an attention mechanism to compute the correspondence between aspects and opinions and select a best opinion for aspect to get the final sentiment.

$$score_{ij}^{(i\neq j)} = (\mathrm{H}_i^{(T)})^{\mathsf{T}}\mathrm{H}_j^{(T)},$$

$$\mathrm{A}_{ij} = \frac{\exp(score_{ij})}{\sum_{k=1}^{n}\exp(score_{ik})},$$



PART .02

METHOD

Loss in Training

Then we use the cross-entropy to compute the losses of three sub-tasks:

$$(\mathcal{L}^A)^{(t)} = -\frac{1}{N}\sum_{i=1}^{N}\frac{1}{n_i}\sum_{j=1}^{n_i}(y_{ij}^A \cdot \log(\hat{y}_{ij}^A)),$$

$$(\mathcal{L}^O)^{(t)} = -\frac{1}{N}\sum_{i=1}^{N}\frac{1}{n_i}\sum_{j=1}^{n_i}(y_{ij}^O \cdot \log(\hat{y}_{ij}^O)),$$

$$\mathcal{L}^S = -\frac{1}{N}\sum_{i=1}^{N}\frac{1}{n_i}\sum_{j=1}^{n_i}(y_{ij}^S \cdot \log(\hat{y}_{ij}^S)).$$

PART .03

EXPERIMENT

	Model	Restaurant14				Laptop14				Restaurant15			
		AE-F1	OE-F1	AS-F1	Overall-F1	AE-F1	OE-F1	AS-F1	Overall-F1	AE-F1	OE-F1	AS-F1	Overall-F1
M_1	CMLA+TNet	81.91	83.84	69.69	64.49	77.49	76.06	68.30	55.94	67.73	70.56	62.27	55.00
M_2	CMLA+TCap	81.91	83.84	71.32	65.68	77.49	76.06	69.49	56.30	67.73	70.56	63.32	55.47
M_3	DECNN+TNet	82.79	–	70.45	65.80	79.38	–	68.69	57.39	68.52	–	62.41	55.69
M_4	DECNN+TCap	82.79	–	71.77	66.84	79.38	–	69.61	57.71	68.52	–	63.60	56.22
M_5	MNN	83.05	84.55	68.45	63.87	76.94	77.77	65.98	53.80	70.24	69.38	57.90	56.57
M_6	E2E-TBSA	83.92	84.97	68.38	66.60	77.34	76.62	68.24	55.88	69.40	71.43	58.81	57.38
M_7	DOER	84.63	–	64.50	68.55	80.21	–	60.18	56.71	67.47	–	36.76	50.31
M_8	SPAN	86.71	–	71.75	73.68	82.34	–	62.50	61.25	74.63	–	50.28	62.29
M_9	IMN	84.06	85.10	75.67	70.72	77.55	**81.00**	75.56	61.73	69.90	73.29	70.10	60.22
M_{10}	RACL	86.38	**87.18**	**81.61**	75.42	81.79	79.72	73.91	63.40	73.99	76.00	74.91	66.05
M_{11}	RF-MRC	**88.22**	86.62	81.28	**76.87**	**82.44**	80.52	**76.05**	**65.31**	**75.57**	**78.60**	**75.79**	**67.86**

Table 2: Comparison results. The best scores are in bold face and the second best ones are underlined. The scores for models from M_1 to M_{10} are taken from Chen and Qian (2020). Models from M_1 to M_7 are based double embeddings (Xu et al., 2018), while M_8 to M_{11} used BERT$_{large}$ as a backbone. '-' denotes the method does not have the metric OE-F1.

PART .03

EXPERIMENT

01

Model	AE-F1	AS-F1	Overall-F1
SPAN	73.90	82.51	61.51
IMN	73.03	84.29	61.68
RACL	75.14	83.63	63.03
RF-MRC	**76.00**	**84.71**	**64.53**

Table 3: Auxiliary results in MAMS.

02

Model	Restaurant14	Laptop14	Restaurant15
w/o A2O	74.01	63.62	67.77
w/o O2A	75.21	64.22	67.38
Full Model	**76.87**	**65.31**	**67.86**

Table 4: Ablation Test. “w/o” denotes without.

03

Case	IMN	RACL	MCQA
The **(outdoor patio)** $_{pos}$ is really nice in good weather, but what **(ambience)** $_{neu}$ the indoors possesses is negated by the noise and the crowds.	**(outdoor patio)** $_{pos}$ **(crowds)** $_{neg}$ ✗	**(outdoor patio)** $_{pos}$ **(null)**✗	**(outdoor patio)** $_{pos}$ **(ambience)** $_{neu}$
The **(food)** $_{pos}$ is pretty good, but after 2 or 3 bad experiences at the restaurant (consistently rude, late with RSVP’d **(seating)** $_{neu}$), I decided I would only order **(delivery)** $_{neu}$.	**(food)** $_{pos}$ **(seating)** $_{neg}$ **(null)**✗	**(food)** $_{pos}$ **(seating)** $_{neg}$✗ **(delivery)** $_{neu}$	**(food)** $_{pos}$ **(seating)** $_{neu}$, **(delivery)** $_{neu}$
(Dinner) $_{neu}$ is okay not many vegetarian options and the **(portions)** $_{neg}$ are small.	**(Dinner)** $_{pos}$✗ **(portions)** $_{neg}$	**(Dinner)** $_{pos}$✗ **(vegetarian options)** $_{neg}$✗ **(portions)** $_{neg}$	**(Dinner)** $_{pos}$✗ **(vegetarian options)** $_{neg}$✗ **(portions)** $_{neg}$

Table 6: Case Study. The abbreviations pos, neu and neg on the table represent positive, neutral and negative sentiments, respectively. The sentiment polarities are demonstrated as the subscripts of aspect terms. “null” denotes that there is an aspect which is not extracted.

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THANK YOU

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