Structure-aware Generation Model for Cross-Domain Aspect-based Sentiment Classification

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Background

Cross Domain ABSC

"The **keyboard** feels cheap but the screen is good.

——A review from Laptop domain

(keyboard, negative)

(screen, positive)

?

"The **food** is cheap here but the waiting can be a nightmare.

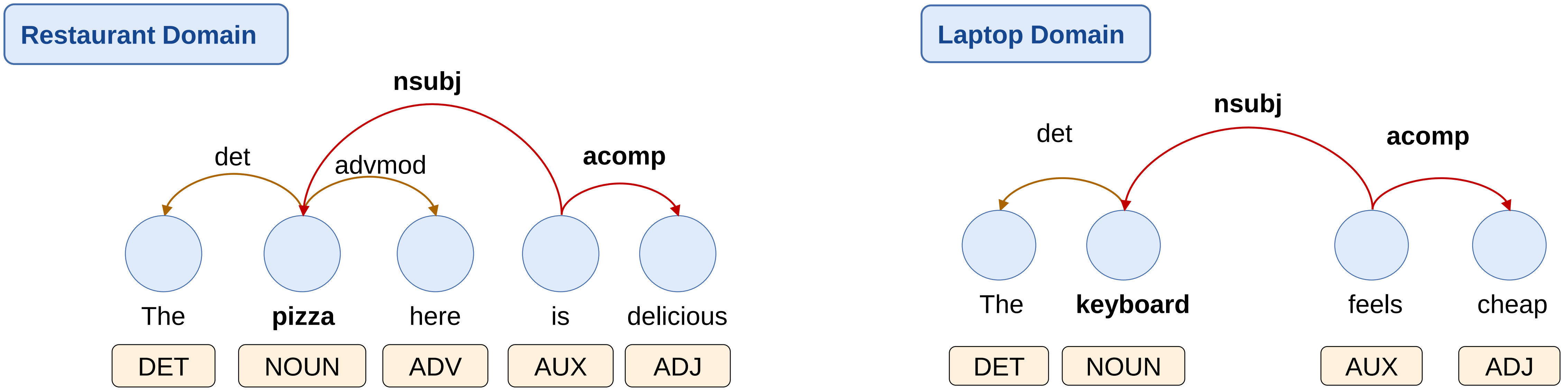
——A review from Restaurant domain

Background

Challenges

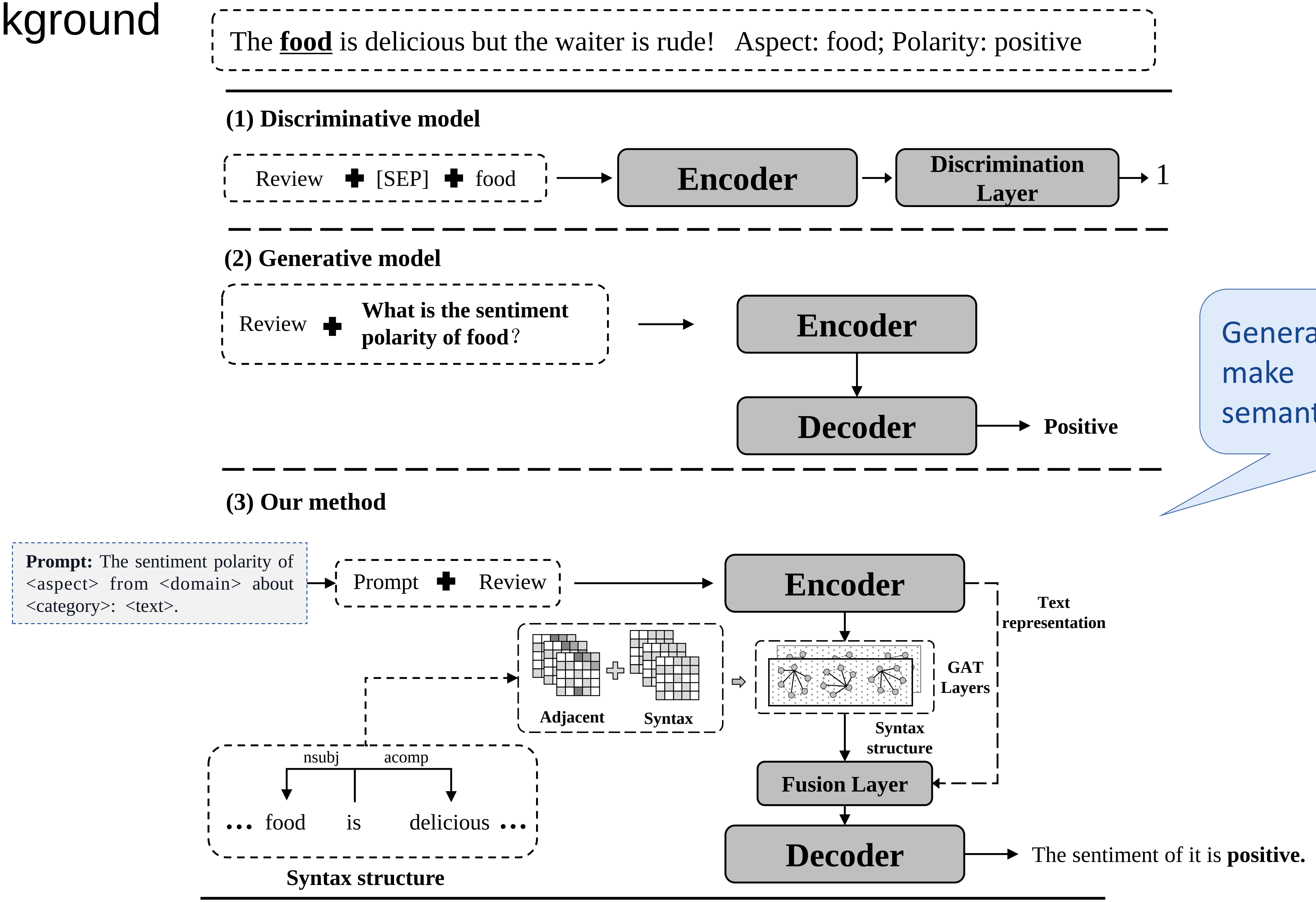
- Intractable to manually annotate data for training domain-specific models
- Discrepancy among different domains

Background



- ✓ Reviews from different domains share similar syntax structure
- ✓ Aspect and opinion terms from different domains share same syntax structure

Background



Generative models can make use of more label semantics

The proposed method

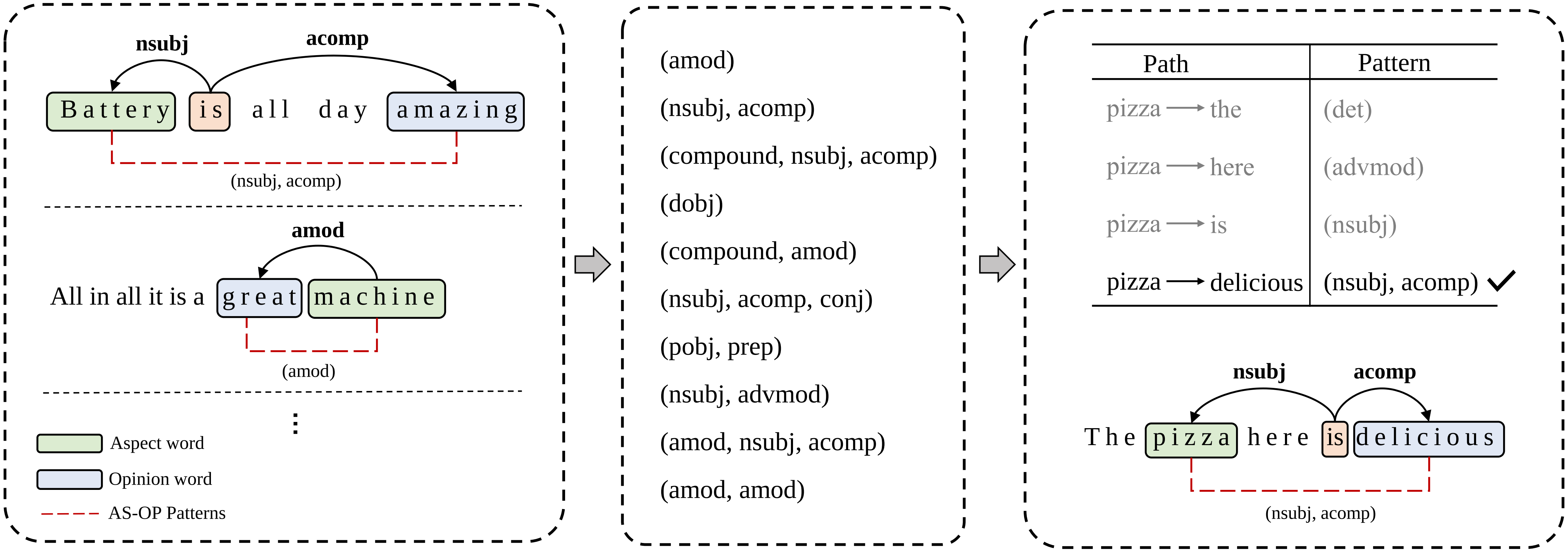
Investigating syntax structure for Cross-domain sentiment classification based on generative models

In this work, we focus on solving three questions:

- How to alleviate the discrepancy among different domains with syntax structure
- How to effectively incorporate syntax structure into pretrained generative models
- How to construct prompt for better guidance of pretrained generative models

The proposed method

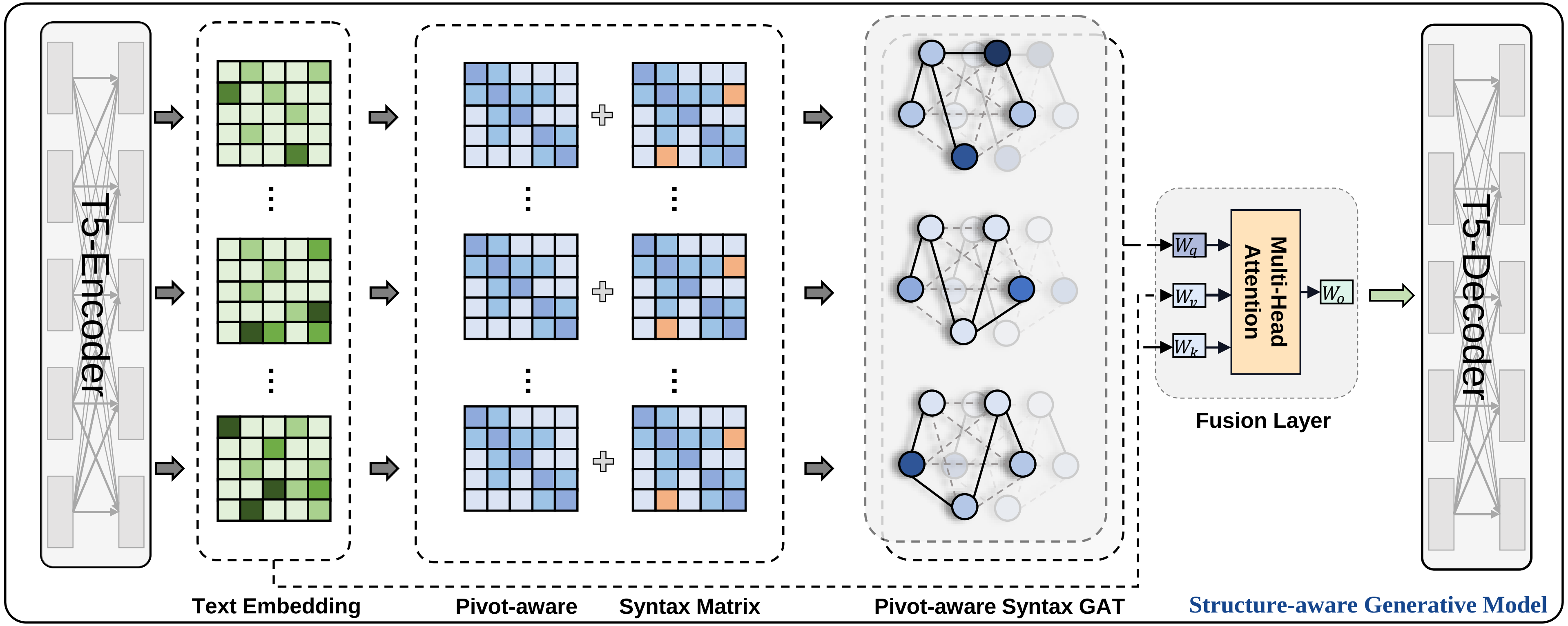
1. How to alleviate the discrepancy among different domains with syntax structure



(a) Path Pattern Extraction **(b)** Top-10 Patterns **(c)** Pivot-Aware Syntax Tree Construction

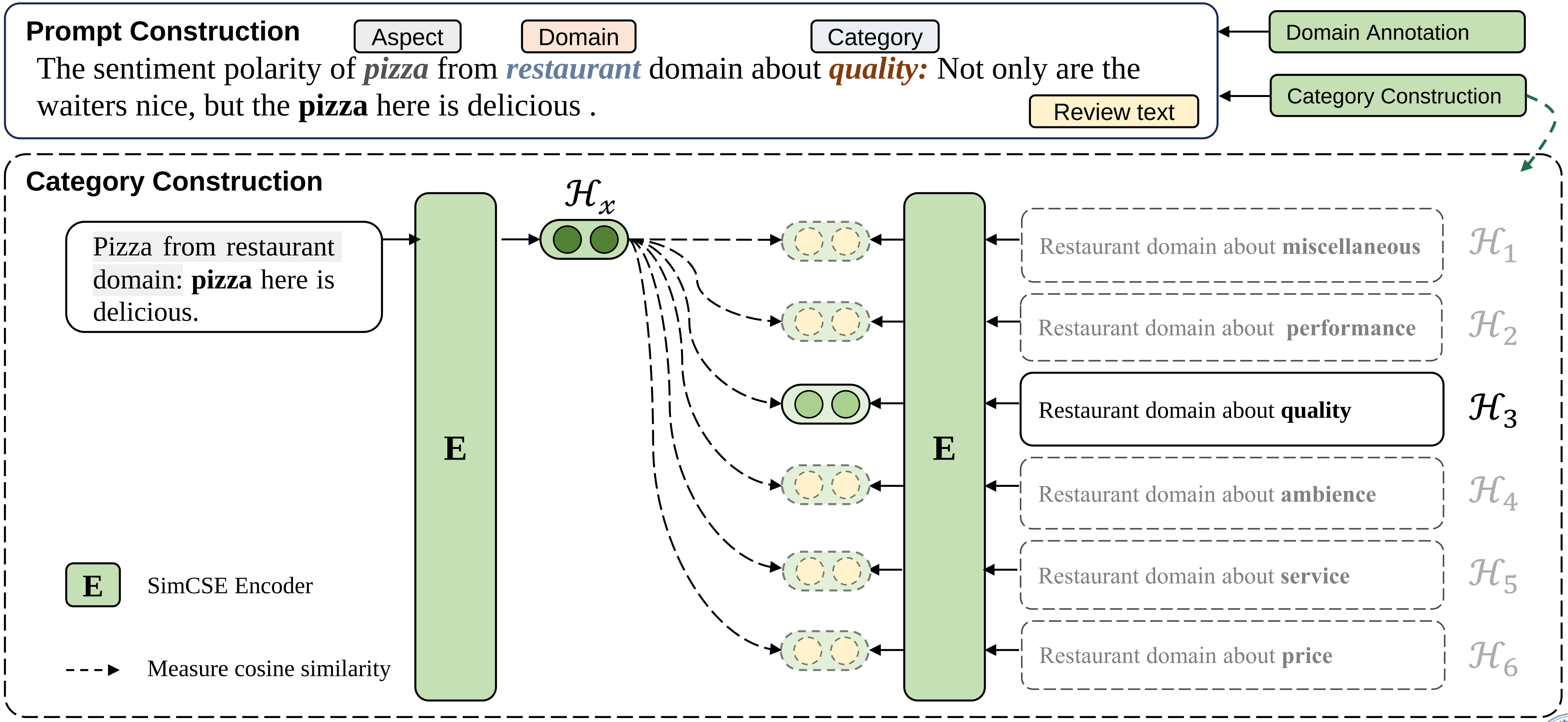
The proposed method

2. How to effectively incorporate syntax structure into pretrained generative models?

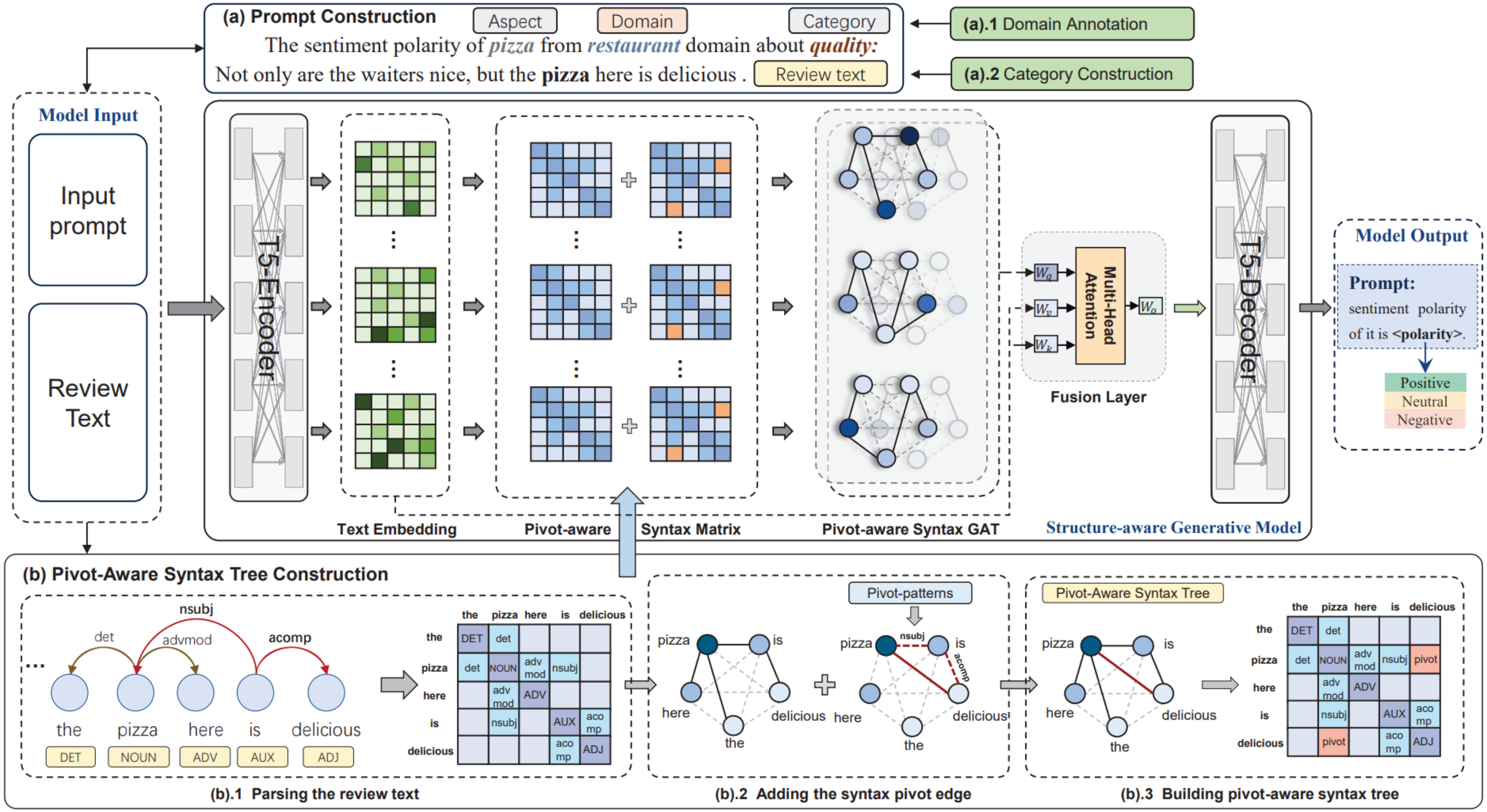


The proposed method

3. How to construct prompt for better guidance of pretrained generative models?



The proposed method



Experiments

a) BEAR Dataset

We evaluate our model on four aspect-based sentiment analysis datasets

Domains	Reviews	Training	Testing
Device	2,085	1,394	691
Laptop	2,928	2,297	631
Restaurant	6,536	4,284	2,252
Service	2,726	1,840	886

Experiments

b) Main results on dataset

Proposed model outperforms ChatGPT and LLaMA, whose parameters are much larger.

	BERT	BART	T5	ChatGPT	LLaMA	ADSPT	PADA	ACSC	Ours
D → L	67.83	69.10	70.68	**79.23**	70.40	70.05	71.36	68.94	71.32
D → R	80.37	82.33	81.79	**86.32**	81.86	82.86	83.28	82.19	84.28
D → S	85.21	86.46	87.58	83.63	87.91	87.13	87.23	86.57	**89.28**
L → D	89.58	89.29	92.19	90.30	91.91	92.04	90.40	91.17	**94.21**
L → R	81.13	82.73	79.53	**86.32**	81.04	84.81	84.66	83.57	86.15
L → S	81.94	86.00	85.33	83.63	86.97	83.30	85.20	84.54	**87.02**
R → D	88.28	90.16	93.92	90.30	92.03	91.17	91.10	89.44	**94.65**
R → L	77.81	77.50	78.29	79.23	74.81	78.45	78.34	75.75	**81.30**
R → S	84.54	86.68	87.02	83.63	86.57	83.86	87.79	85.97	**88.49**
S → D	90.74	91.03	93.49	90.30	92.76	91.46	93.04	91.75	**94.79**
S → L	69.73	70.84	70.36	**79.23**	73.18	71.47	69.78	71.16	75.91
S → R	79.75	81.35	81.17	**86.32**	81.43	82.37	82.93	82.28	83.39
Average	81.41	82.79	83.45	84.87	83.40	83.25	83.76	82.94	**85.90**

Experiments

c) Ablation study

The impact of different factors

Method	Accuracy
Ours	85.90
-Prompt	85.21
-Tree	84.40
-Prompt -Tree	83.45

Analysis

a) Effect of prompt design

All the prompt design strategies are beneficial to capture the cross-domain knowledge in both the input and output sides.

	Prompt	Accuracy
Ours	**Input**: The sentiment polarity of <aspect> from <domain> about <category>: sentence + <aspect> **Output**: Sentiment polarity of it is <polarity>	85.90
w/o input instruction	**Input**: sentence + <aspect> **Output**: Sentiment polarity of it is <polarity>	85.23
w/o domain instruction	**input**: The sentiment polarity of <aspect> about <category>: sentence + <aspect> **output**: Sentiment polarity of it is <polarity>	85.52
w/o category instruction	**input**: The sentiment polarity of <aspect> from <domain>: sentence + <aspect> **output**: Sentiment polarity of it is <polarity>	85.68
w/o output instruction	**input**: The sentiment polarity of <aspect> from <domain> about <category>: sentence + <aspect> **output**: <polarity>	85.78

Analysis

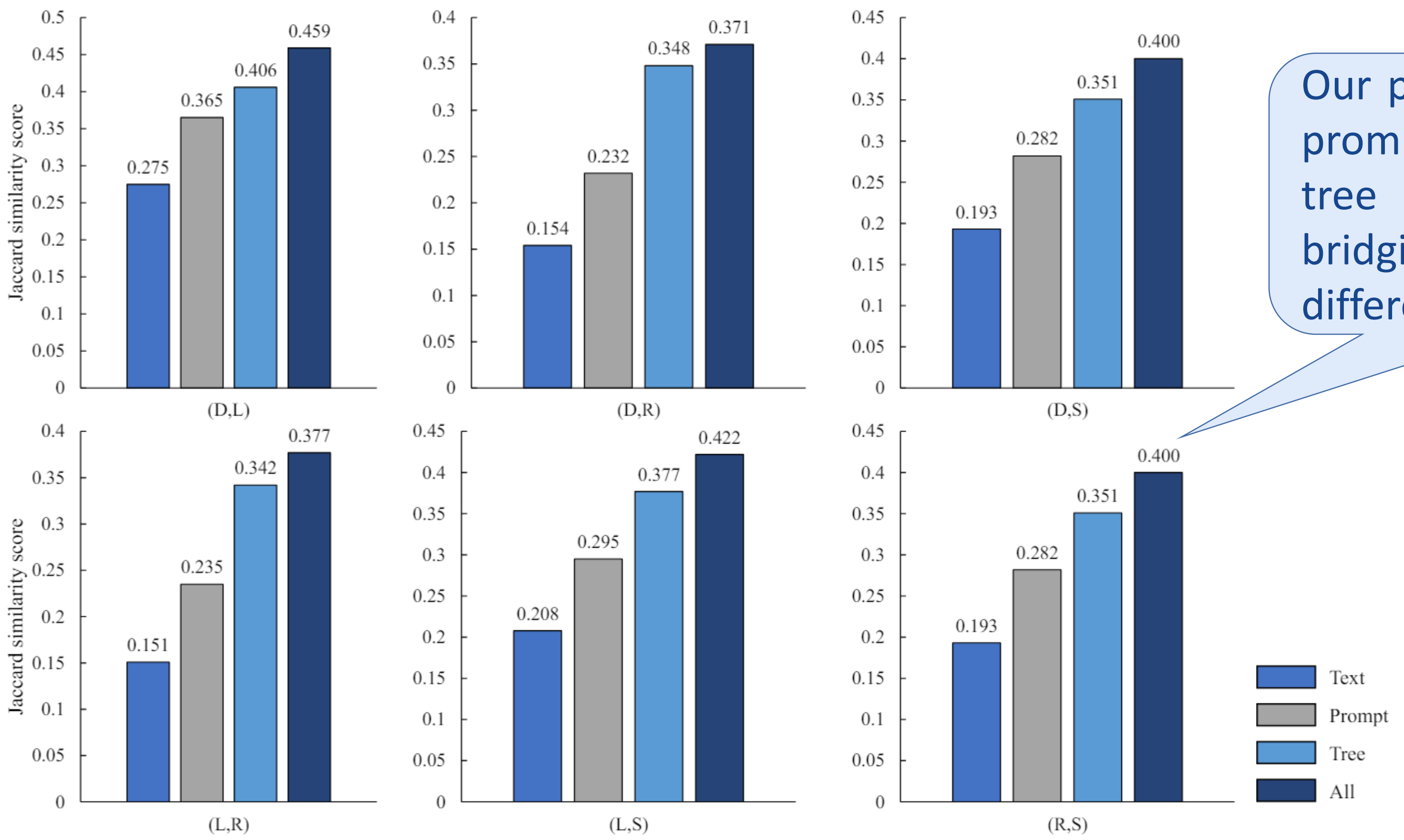
b) Influence of syntax tree

All the models with syntax tree perform better than T5.

Method	Accuracy
T5	83.45
Ours (Original)	85.49
Ours (Pivot-Aware)	85.90
Linearization (Original)	83.81
Linearization (Pivot-Aware)	83.86

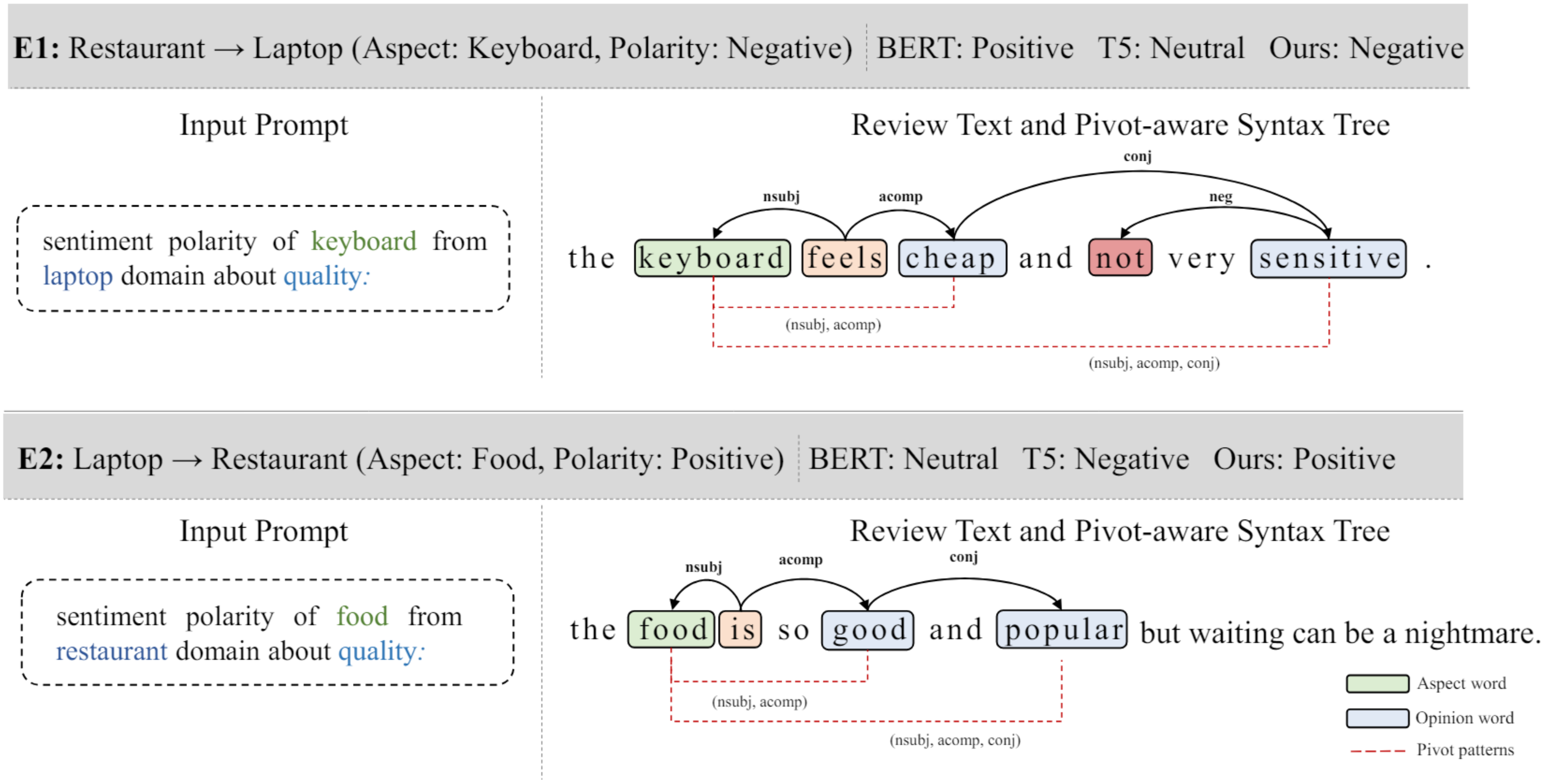
Analysis

c) Analysis of similarity between domains



Our proposed model with prompt design and syntax tree is truly useful for bridging the gap between different domains.

Case study


E1: Restaurant → Laptop (Aspect: Keyboard, Polarity: Negative) | BERT: Positive T5: Neutral Ours: Negative
Input Prompt
sentiment polarity of keyboard from laptop domain about quality:
Review Text and Pivot-aware Syntax Tree
conj
nsubj
acomp
neg
the keyboard feels cheap and not very sensitive .
(nsubj, acomp)
(nsubj, acomp, conj)
E2: Laptop → Restaurant (Aspect: Food, Polarity: Positive) | BERT: Neutral T5: Negative Ours: Positive
Input Prompt
sentiment polarity of food from restaurant domain about quality:
Review Text and Pivot-aware Syntax Tree
nsubj
acomp
conj
the food is so good and popular but waiting can be a nightmare.
(nsubj, acomp)
(nsubj, acomp, conj)
Aspect word
Opinion word
Pivot patterns

Conclusion

We employ syntax structure with generative model for cross-domain sentiment classification.

- ✓ We propose a novel structure-aware generation model to explicitly and implicitly encode the pivot-aware syntactic structure into the pre-trained generation model.
- ✓ We further design specific prompt to guide the pre-trained generation model for cross-domain aspect based sentiment analysis.
- ✓ Experimental results indicate that the proposed structure-aware generation model can effectively capture syntactic structure.

Thanks!

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