Label-Driven Denoising Framework for Multi-Label Few-Shot Aspect Category Detection

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https://github.com/1429904852/LDF

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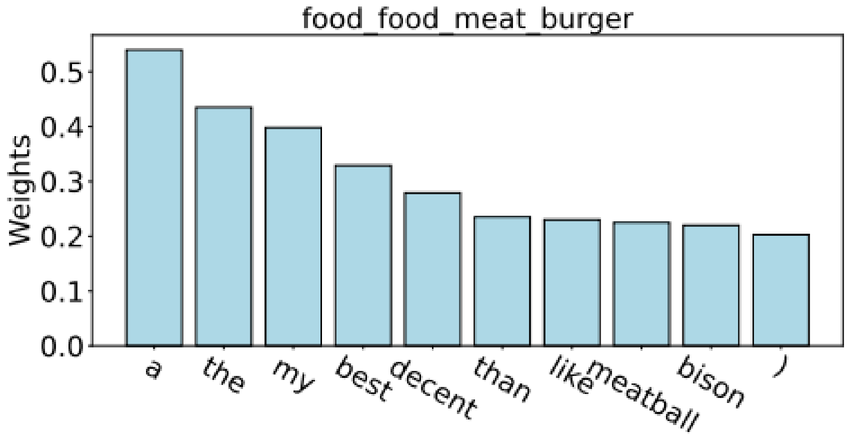
Reported by Dongdong Hu

Introduction

Support set	
Aspect Category	Sentences
(A) food_food_meat_burger	(1) *first time, burger was not fully cooked and my smash fries were cold.* (2) *food was over priced, but okay not great.*
(B) food_mealtype_lunch	(1) *my brother and i stopped in for lunch.* (2) *lunch has a great option of picking one or two food with rice.*
(C) restaurant_location	(1) *i prefer the other location to be honest.* (2) *there's a new standard in town.*
Query set	
Aspect Category	Sentences
(B)	(1) *went back today for lunch.*
(A) and (C)	(2) *food is whats to be expected at a neighborhood grill.*

Table 1: An example of 3-way 2-shot meta-task. A sentence (instance) may belong to multiple aspects.



(1) due to lack of sufficient supervised data, the previous methods easily catch noisy words irrelevant to the current aspect category, which largely affects the quality of the generated prototype;
(2) the semantically-close aspect categories usually generate similar prototypes, which are mutually noisy and confuse the classifier seriously.

Method

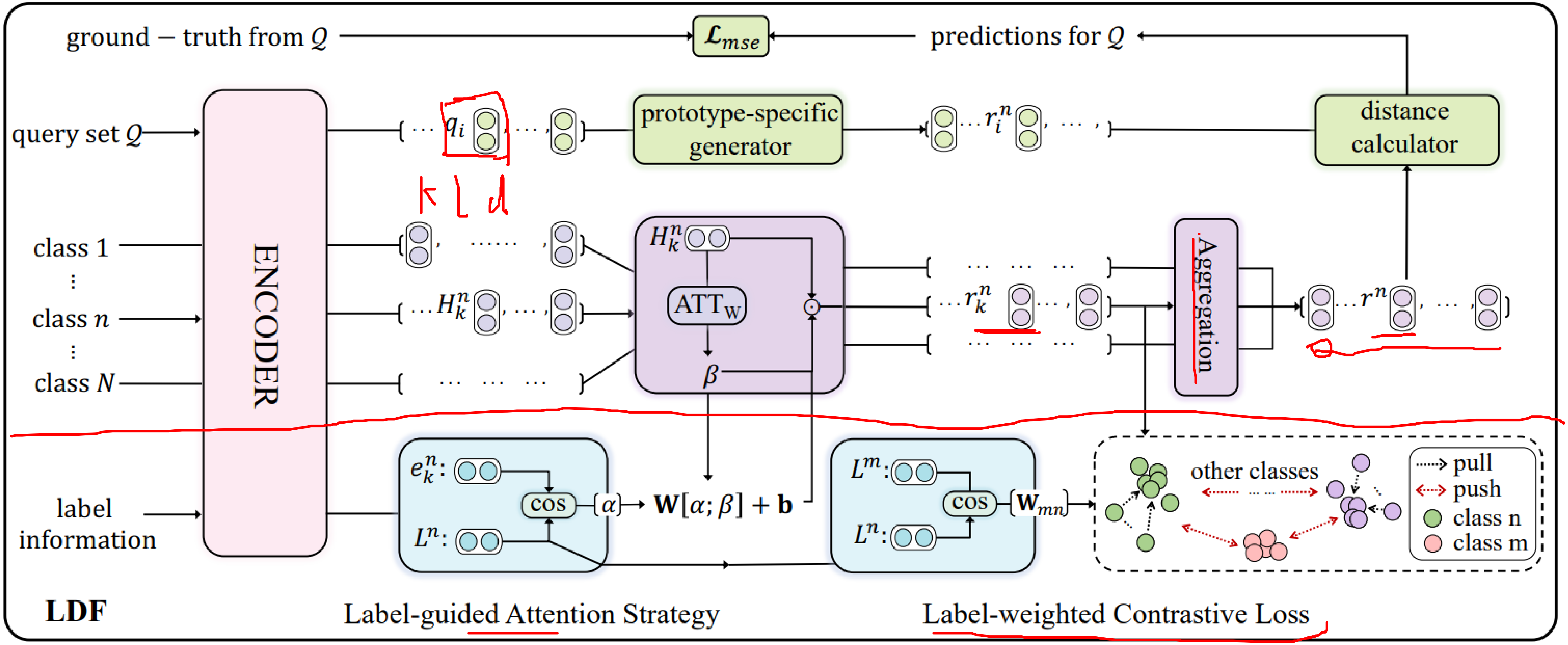


Figure 2: The overview of our proposed LDF framework.

Method

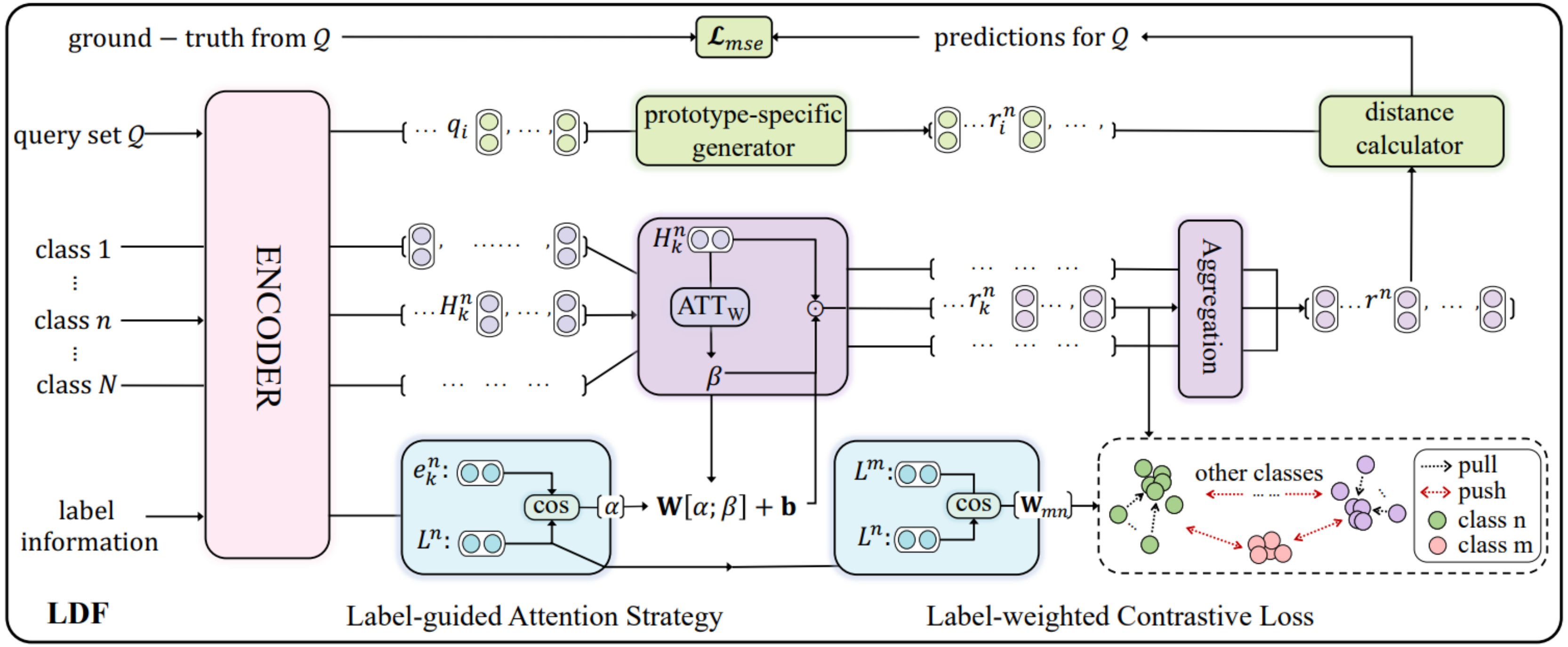


Figure 2: The overview of our proposed LDF framework.

$$s_k^n = \{w_1, w_2, ..., w_l\}$$

$$e_k^n = \{e_1, e_2, ..., e_l\}$$

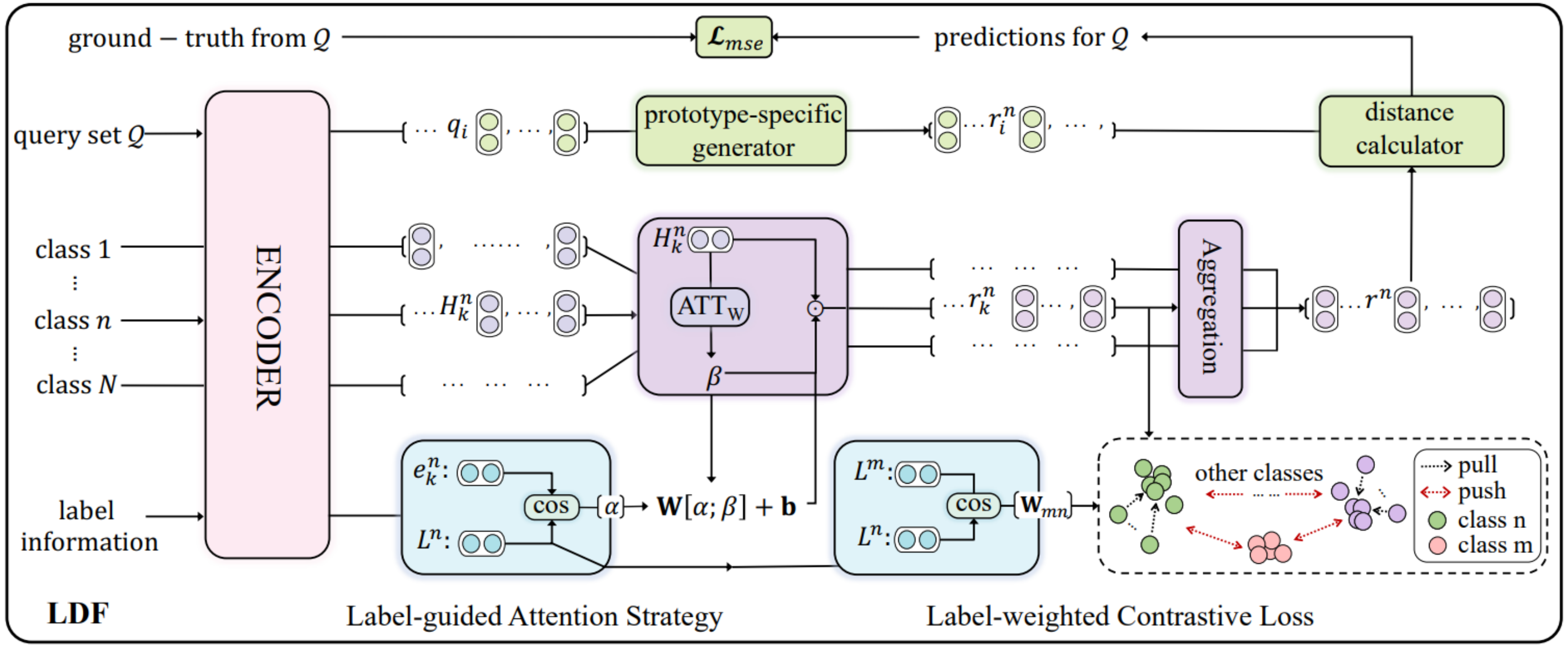
CNN $\qquad H_k^n$

$$\beta = \mathrm{ATT}_W(H_k^n), \quad (1)$$

$$r_k^n = \beta H_k^n, \quad (2)$$

where H_k^n is the k-th instance representation of the class n in the support set $\mathcal{S}$, $\mathrm{ATT}_W(\cdot)$ denotes an attention mechanism.

Method



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$$r^n = \text{Aggregation}(r_1^n, ..., r_K^n), \qquad (3)$$

where Aggregation$(\cdot)$ denotes the attention mechanism or average pooling operation.

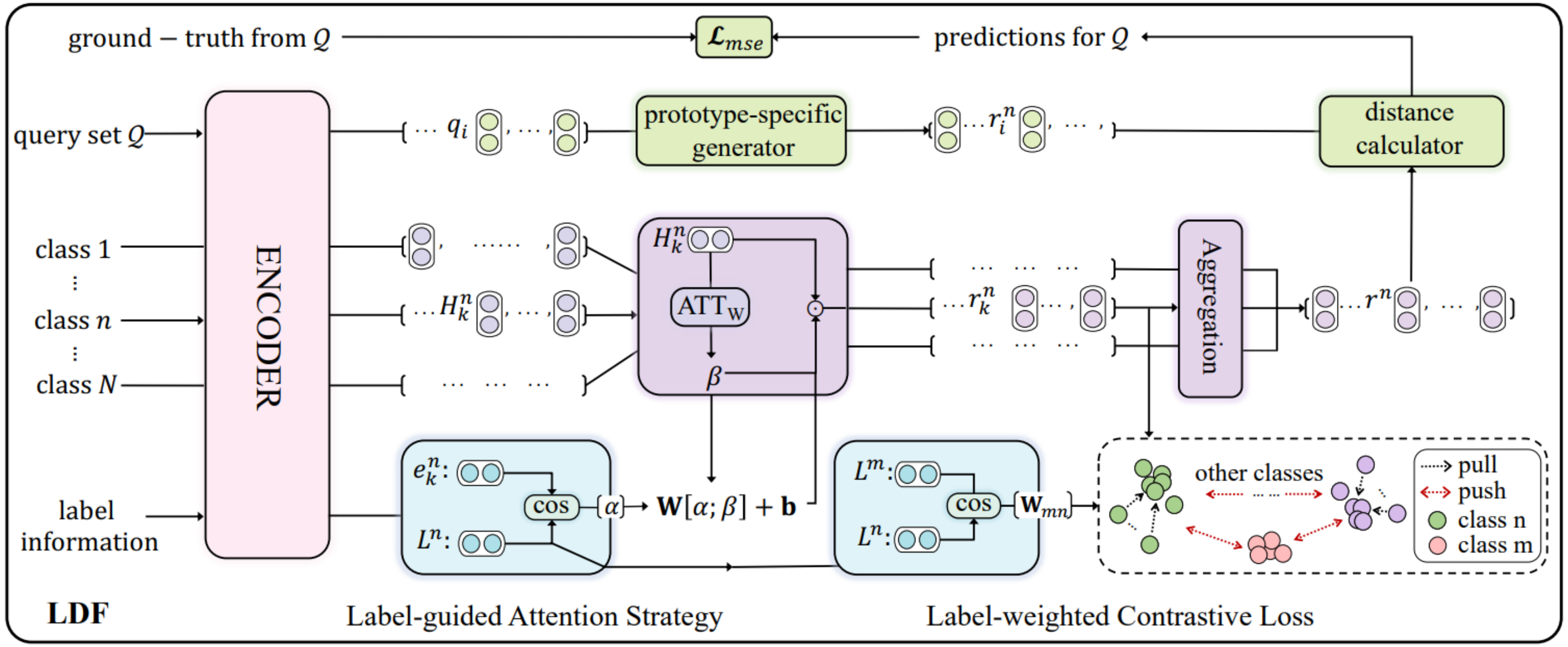
$$\{r^1, r^2, ..., r^n, ..., r^N\}$$

Similarly, for a query instance q_i, we first encode q_i to obtain its contextual representation, and then exploit an attention mechanism to produce N prototype-specific query representations r_i^n based on the N prototypes.

$$\hat{y}_i = \text{softmax}(-\text{ED}(r^n, r_i^n)), n \in [1, N] \qquad (4)$$

$$\mathcal{L}_{mse} = \sum_{i=1}^{M} (\hat{y}_i - y_i)^2 \qquad (5)$$

Method



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Label-guided Attention Strategy

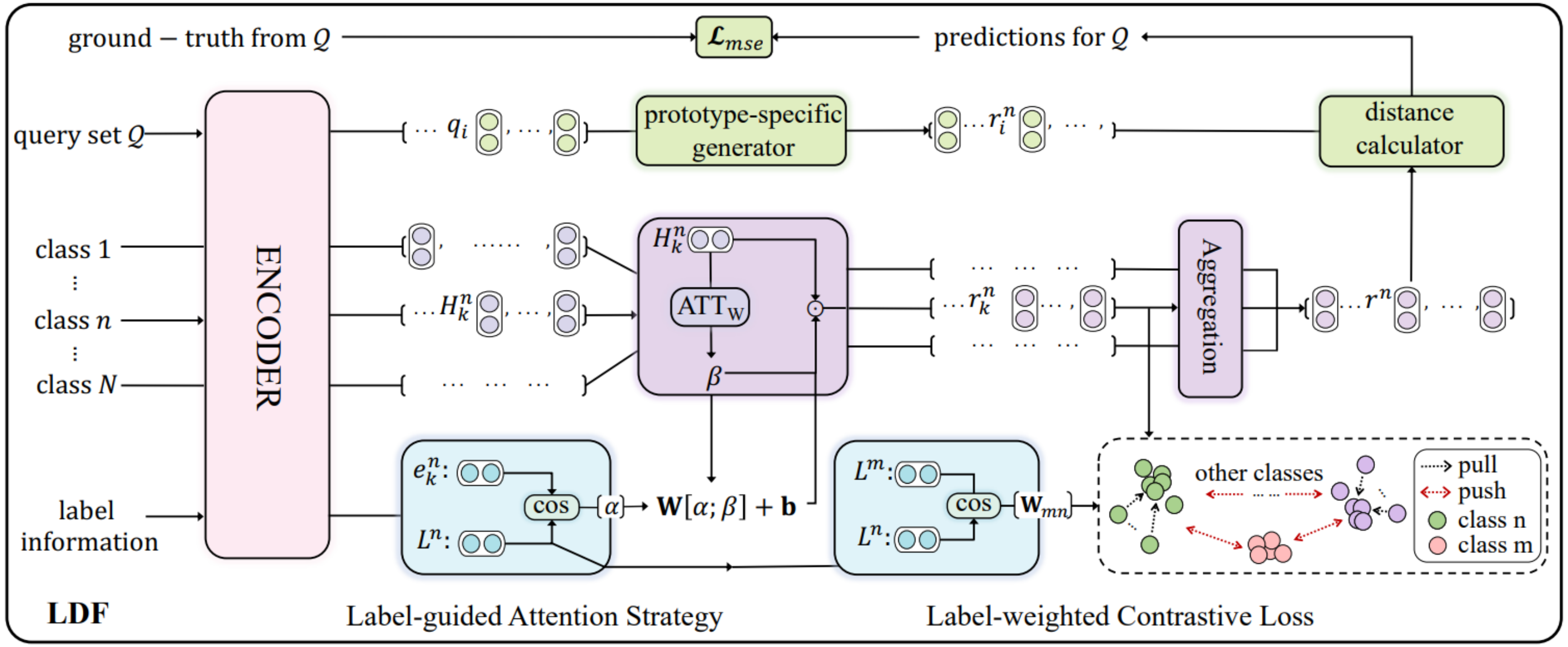
$$\alpha = \cos(L^n, e_k^n), \tag{6}$$

where W_g and b_g are weight matrices and bias, $[\cdot\,;\cdot]$ denotes the concatenation operation.

$$\theta = W_g[\alpha; \beta] + b_g \tag{7}$$

$$\widetilde{\theta} = \mathrm{softmax}(\theta)$$

Method



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Label-weighted Contrastive Loss

For example, "*food_food_meat_burger*" is semantically closer to "*food_mealtype_lunch*" than "*room_bed*". Thus, "*food_food_meat_burger*" should be farther from "*food_mealtype_lunch*" than "*room_bed*" in the negative set.

$$\mathcal{L}_{lcl} = \sum_{(n,k)\in(N,K)} \frac{-1}{|P(n,k)|} \sum_{r_p^n \in P(n,k)} \log \frac{\exp(r_k^n \cdot r_p^n/\tau)}{\sum_{r_k^m \in (N,K)\setminus(n,k)} w_{mn} \cdot \exp(r_k^n \cdot r_k^m/\tau)} \tag{10}$$

where $P(n,k)$ is the positive set of r_k^n in Equation 2, which contains all the other samples (e.g., r_p^n) of the same class with r_k^n in the support set.

$$w_{mn} = \cos(L^m, L^n), \tag{11}$$

where L^m and L^n are the label embedding of the class m and n.

$$\mathcal{L} = \mathcal{L}_{mse} + \lambda \mathcal{L}_{lcl} \tag{12}$$

Method

Dataset	**#cls.**	**#inst./cls.**	**#inst.**
FewAsp(single)	100	200	20000
FewAsp(multi)	100	400	40000
FewAsp	100	630	63000

Table 2: Statistics of three datasets. **#cls.** is the number of classes. **#inst.** is the total number of instances. **#inst./cls.** is the number of instances per class.

Experiments

Models	5-way 5-shot F1	5-way 5-shot AUC	5-way 10-shot F1	5-way 10-shot AUC	10-way 5-shot F1	10-way 5-shot AUC	10-way 10-shot F1	10-way 10-shot AUC
FewAsp								
Proto-HATT	70.26	91.54	75.24	93.43	57.26	90.63	61.51	92.86
LDF-HATT	**73.56**†±0.47	**92.60**†±0.23	**78.81**†±0.93	**94.75**†±0.43	**60.68**†±0.92	**91.22**±0.53	**67.13**†±0.94	**94.12**†±0.29
Δ	+3.30	+1.06	+3.57	+1.32	+3.42	+0.59	+5.62	+1.26
Proto-AWATT	75.37	93.35	80.16	95.28	65.65	92.06	69.70	93.42
LDF-AWATT	**78.27**†±0.89	**94.65**†±0.41	**81.87**†±0.48	**95.71**±0.26	**67.13**†±0.41	**92.74**±0.12	**71.97**†±0.49	**94.29**±0.25
Δ	+2.90	+1.30	+1.71	+0.43	+1.48	+0.68	+2.27	+0.87
FewAsp(single)								
Proto-HATT	83.33	96.45	86.71	97.62	73.42	95.71	77.65	97.00
LDF-HATT	**84.41**†±0.46	**97.06**±0.16	**88.15**†±1.00	**98.12**±0.31	**76.27**†±1.08	**96.38**±0.37	**80.54**†±0.97	**97.45**±0.14
Δ	+1.08	+0.61	+1.44	+0.50	+2.85	+0.67	+2.89	+0.45
Proto-AWATT	86.71	97.56	88.54	97.96	80.28	97.01	82.97	97.55
LDF-AWATT	**88.16**†±0.62	**98.29**±0.32	**89.32**±0.92	**98.38**±0.13	**81.73**†±0.96	**97.51**±0.33	**84.20**†±0.21	**97.96**±0.30
Δ	+1.45	+0.73	+0.78	+0.42	+1.45	+0.50	+1.23	+0.41
FewAsp(multi)								
Proto-HATT	69.15	91.10	73.91	93.03	55.34	90.44	60.21	92.38
LDF-HATT	**72.13**†±0.79	**92.19**†±0.33	**76.52**†±0.74	**93.68**±0.36	**59.10**†±1.04	**91.00**±0.51	**65.31**†±0.57	**92.99**±0.24
Δ	+2.98	+1.09	+2.61	+0.65	+3.76	+0.56	+5.10	+0.61
Proto-AWATT	71.72	91.45	77.19	93.89	58.89	89.80	66.76	92.34
LDF-AWATT	**73.38**†±0.73	**92.62**†±0.32	**78.81**†±0.19	**94.34**±0.15	**62.06**†±0.54	**90.87**†±0.48	**68.23**†±0.98	**92.93**±0.44
Δ	+1.66	+1.17	+1.62	+0.44	+3.17	+1.07	+1.47	+0.59

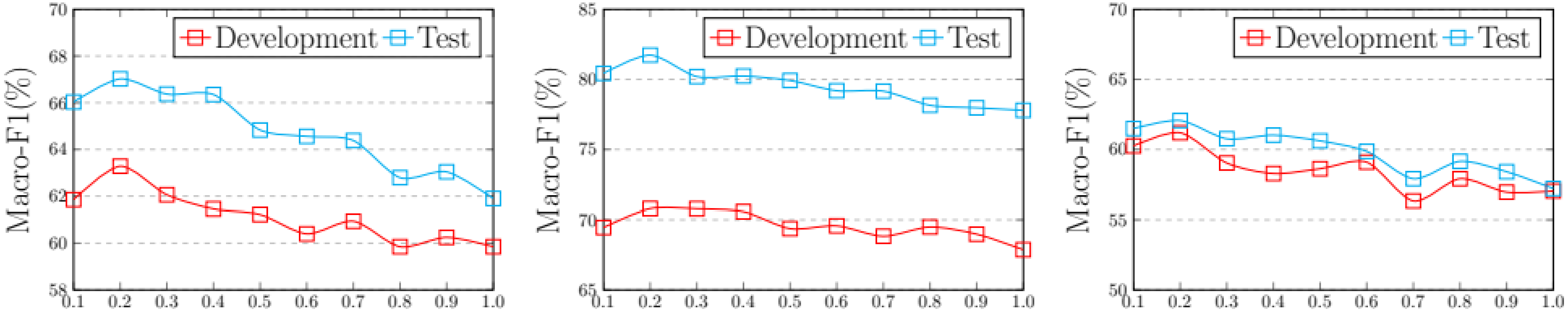
Table 3: Test Macro-F1 and AUC score on the FewAsp, FewAsp(single), and FewAsp(multi) datasets (%). The results of Proto-HATT and Proto-AWATT are retrieved from (Hu et al., 2021). We report the average performance and standard deviation over 5 runs, the thresholds in the 5-way setting and 10-way setting are set to {0.3, 0.2}. Best results are in bold. The marker † refers to significant test p-value < 0.05 when comparing with Proto-HATT and Proto-AWATT. Δ denotes the difference between the performance of Proto-HATT and LDF-HATT, as well as Proto-AWATT and LDF-AWATT. Due to space constraints, we report other baseline results in **Appendix** A.2.

Experiments

Models	5-way 5-shot		5-way 10-shot		10-way 5-shot		10-way 10-shot	
	F1	AUC	F1	AUC	F1	AUC	F1	AUC
Proto-AWATT	75.37	93.35	80.16	95.28	65.65	92.06	69.70	93.42
Proto-AWATT+LAS	77.31±1.96	94.42±0.67	81.19±0.84	95.49±0.36	66.48±3.02	92.54±0.70	71.12±1.14	94.26±0.40
Proto-AWATT+LCL	77.06±0.71	94.20±0.26	80.78±0.39	95.44±0.22	66.20±1.26	92.38±0.45	70.83±0.66	94.07±0.33
Proto-AWATT+SCL	76.11±1.76	93.67±0.80	80.24±2.99	95.31±1.01	65.76±2.17	92.36±0.60	70.03±2.69	93.93±0.67
LDF-AWATT	**78.27**±0.89	**94.65**±0.41	**81.87**±0.48	**95.71**±0.26	**67.13**±0.41	**92.74**±0.12	**71.97**±0.49	**94.29**±0.25

Table 4: Ablation study over two main components on FewAsp dataset. The ablation results of FewAsp(single) and FewAsp(multi) datasets are included in **Appendix** A.3.

Experiments



(a) FewAsp (b) FewAsp(single) (c) FewAsp(multi)

Figure 3: Effect of λ in the 10-way 5-shot setting on three dataset.

Experiments

Models	GloVe + CNN		BERT	
	F1	AUC	F1	AUC
Proto-HATT♣	57.26	90.63	57.33	89.70
LDF-HATT	60.68±0.92	91.22±0.53	63.72±0.27	91.99±0.12
Proto-AWATT♣	65.65	92.06	70.09	94.59
LDF-AWATT	67.13±0.41	92.74±0.12	72.76±0.29	95.31±0.19

Table 5: The effect of different encoders in the 10-way 5-shot scenario on FewAsp dataset. The results with symbol ♣ are retrieved from (Hu et al., 2021).

Models	10-way 5-shot	
	F1	AUC
Proto-AWATT	65.65	92.06
Proto-AWATT (LSW)	57.84±0.49	90.85±0.22

Table 6: The effect of label similarity weight α in the 10-way 5-shot scenario on FewAsp dataset.

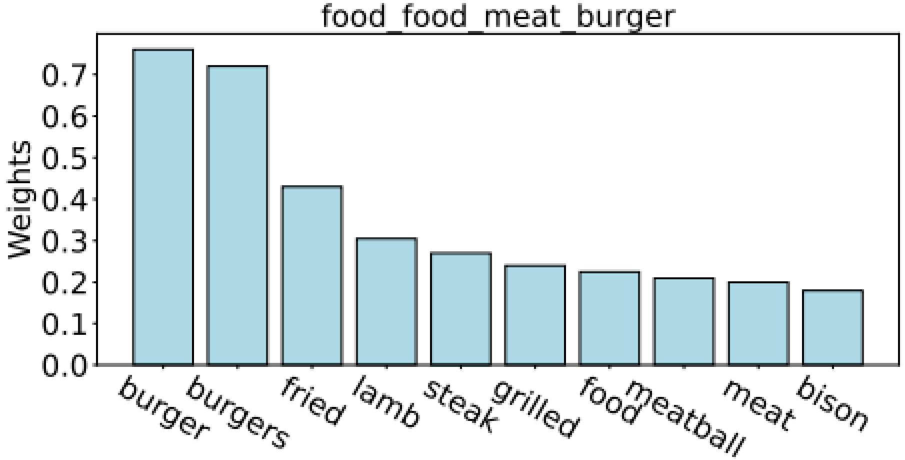
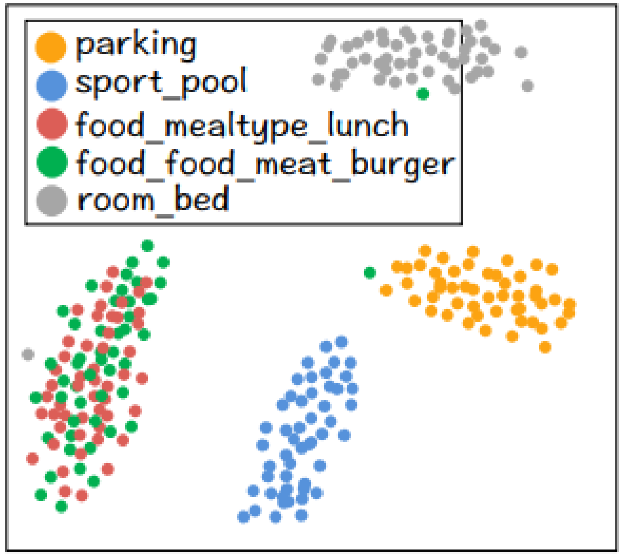
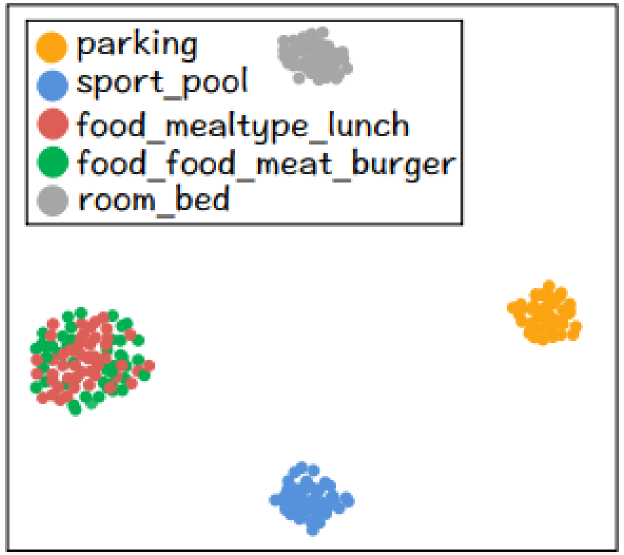


Figure 4: Visualize the top-10 words for the prototype of aspect category *food_food_meat_burger* based on the attention weights of *Proto-AWATT+LAS*.

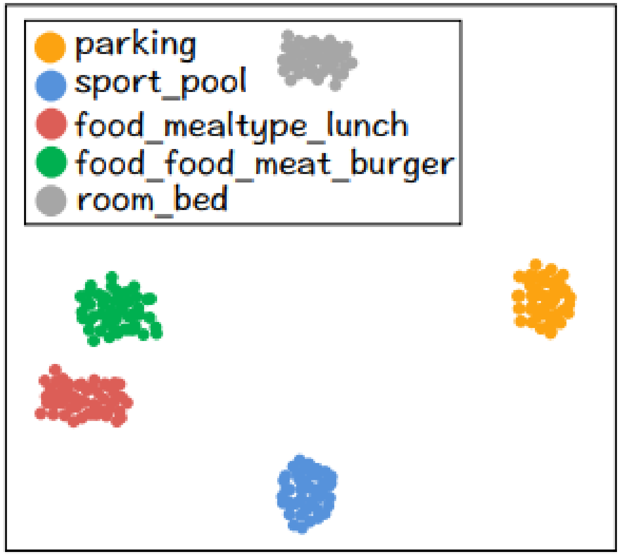
Experiments



(a) Proto-AWATT



(b) Proto-AWATT+LAS



(c) LDF-AWATT

Figure 5: Visualization of prototype representations for Proto-AWATT, Proto-AWATT+LAS and LDF-AWATT.

Thanks