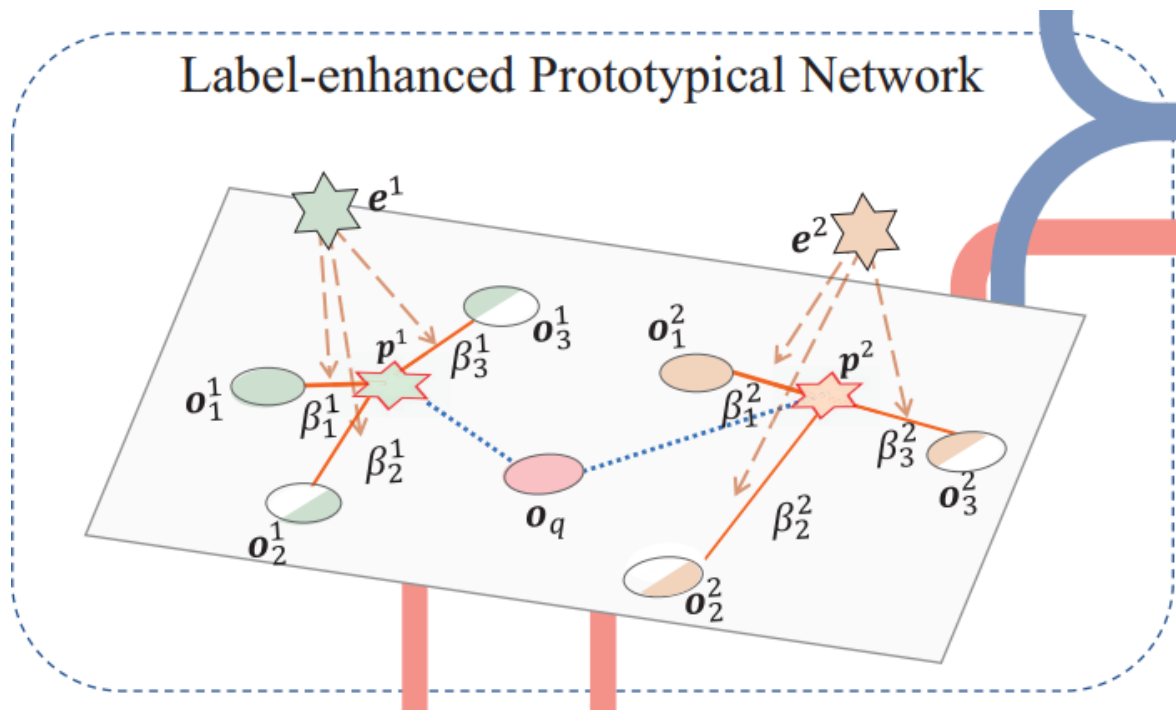


get is usually infeasible. Therefore, inspired by (Li et al., 2021), we perform k -means clustering on the hidden vectors of the training instances $\mathcal{H} = \{\mathbf{h}_i\}_{i=1}^{N_s}$ to generate k clusters as the prototypes $\mathcal{C} = \{\mathbf{c}_i\}_{i=1}^k$ with respect to the target-based representations of training set. Here, a prototype is defined as a representative embedding for a group of semantically similar instances (Li et al., 2021).

2022_ACL_JointCL: A Joint Contrastive Learning Framework for Zero-Shot Stance Detection

Code: <https://github.com/HITSZ-HLT/JointCL>



$$\alpha_j^i = \mathbf{o}_j^{iT} \mathbf{W} \mathbf{e}^i, \quad (4)$$

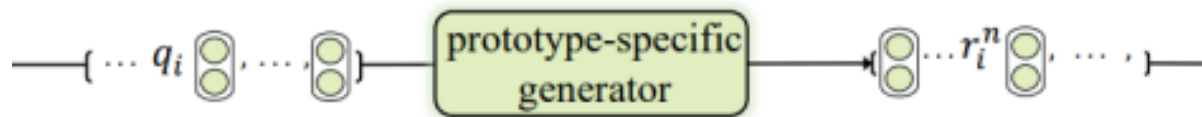
$$\alpha_j^i = \mathbf{o}_j^{iT} \mathbf{U} \mathbf{V}^T \mathbf{e}^i = \mathbf{1}^T (\mathbf{U}^T \mathbf{o}_j^i \circ \mathbf{V}^T \mathbf{e}^i), \quad (5)$$

$$\beta_j^i = \frac{\exp(\alpha_j^i)}{\sum_{j'=1}^K \exp(\alpha_{j'}^i)}. \quad (6)$$

$$\mathbf{p}^i = \sum_{j=1}^K \beta_j^i \mathbf{o}_j^i. \quad (7)$$

$$p(y = y^i | \mathbf{x}, \mathcal{S}) = \frac{\exp(-\|\mathbf{o} - \mathbf{p}^i\|_2^2)}{\sum_{j=1}^N \exp(-\|\mathbf{o} - \mathbf{p}^j\|_2^2)}, \quad (8)$$

$$\mathcal{L}_{lep_n} = \frac{1}{|Q|} \sum_{\mathbf{x} \in Q} \sum_{i=1}^N -y^i \log p(y = y^i | \mathbf{x}, \mathcal{S}), \quad (9)$$



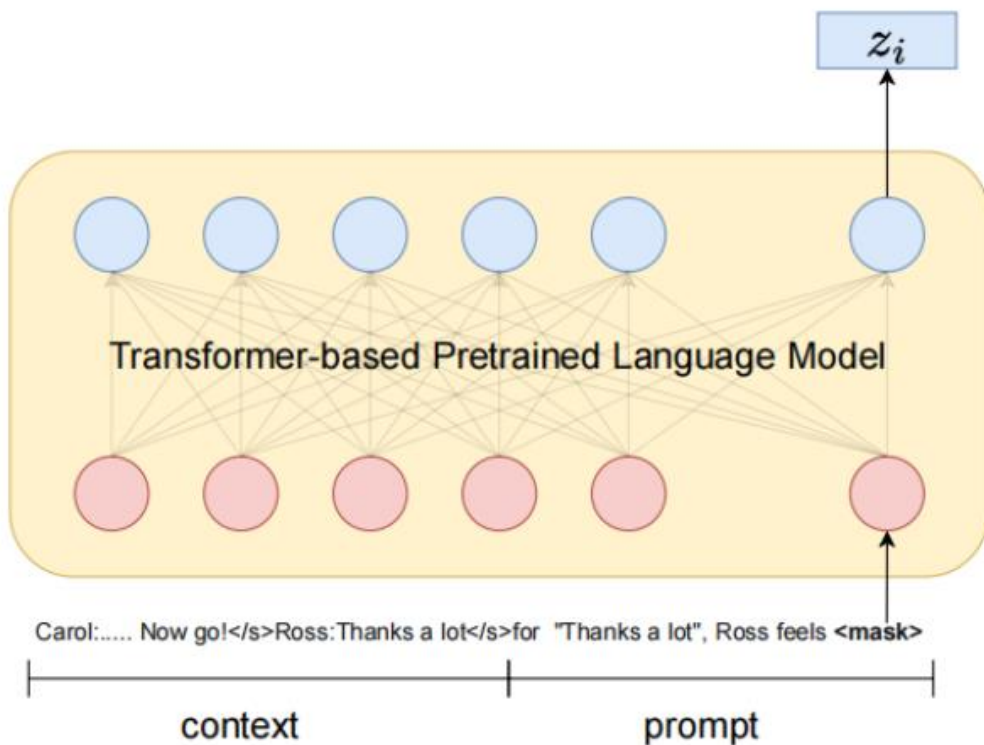
attention mechanism. After that, we aggregate all instance representations for the class n to produce the prototype:

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

where $\text{Aggregation}(\cdot)$ denotes the attention mechanism or average pooling operation. After processing all classes in the support set \mathcal{S} , we obtain N prototypes $\{r^1, r^2, \dots, r^n, \dots, r^N\}$.

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

<https://github.com/1429904852/LDF>



Prototypical Contrastive Learning

$$\bar{Q}_i = [z_1^i, z_2^i, \dots, z_M^i]$$

$$S_K = \text{RANDOMSELECT}(Q_i, K) \quad (8)$$

$$\mathbf{T}_i = \frac{1}{K} \sum_{z_j^i \in S_K, j \in [1 \dots K]} z_j^i \quad (9)$$

$$\mathcal{N}_{spcl}(i) = \mathcal{N}_{sup}(i) + \sum_{k \in \mathcal{E} \setminus y_i} \mathcal{F}(z_i, \mathbf{T}_k) \quad (10)$$

$$\mathcal{P}_{spcl}(i) = \mathcal{P}_{sup}(i) + \mathcal{F}(z_i, \mathbf{T}_{y_i}) \quad (11)$$

$$\mathcal{L}_i^{spcl} = -\log \left(\frac{1}{|P(i)| + 1} \cdot \frac{\mathcal{P}_{spcl}(i)}{\mathcal{N}_{spcl}(i)} \right) \quad (12)$$

$$\mathcal{L}^{spcl} = \sum_{i=1}^N \mathcal{L}_i^{spcl} \quad (13)$$

2022_EMNLP_Supervised Prototypical Contrastive Learning for Emotion Recognition in Conversation

<https://github.com/caskcsg/SPCL>