



2020 Study REPORT

Dynamic Memory Induction Network for Few-Shot Text Classification

本篇论文由北京阿里巴巴达摩院与加拿大皇后大学联合发表于2020ACL

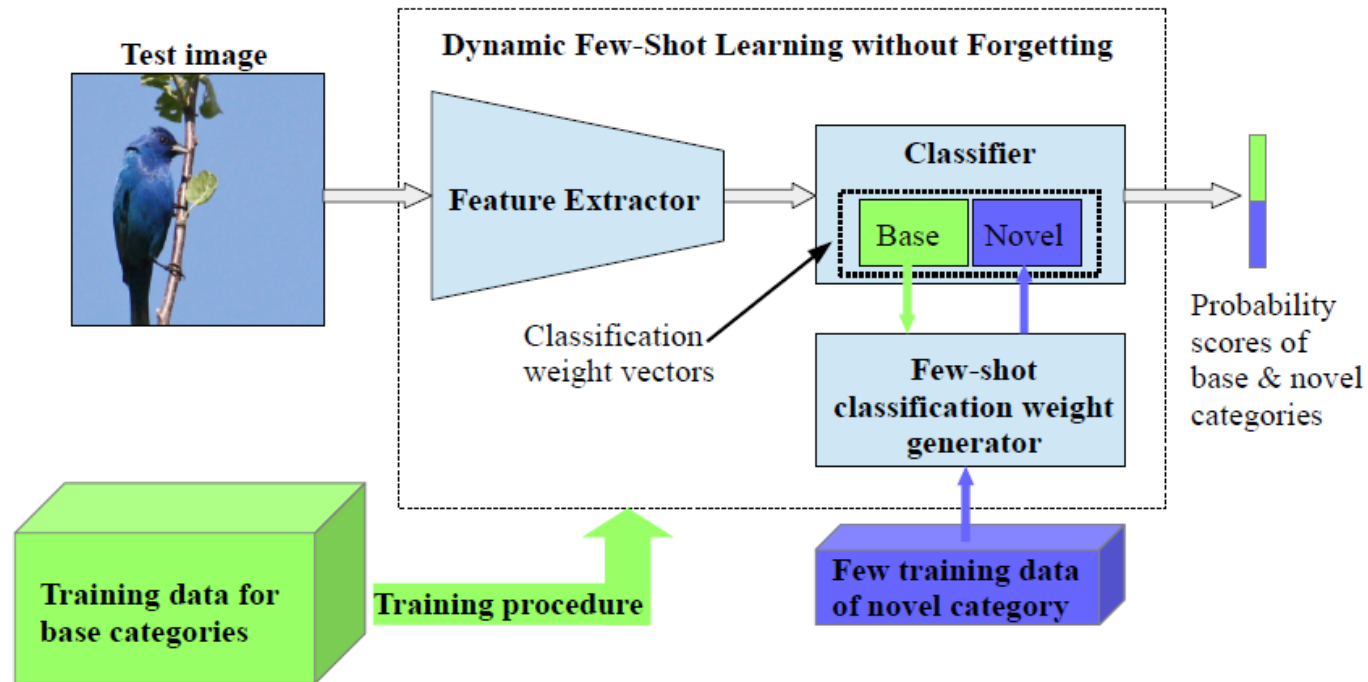


Content

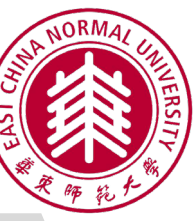
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1. Background



1. Few-shot classification-weight generator based on attention
2. Cosine-similarity based ConvNet recognition model.



1.1 Key Challenges

Problems

1. data sparseness
2. key information is lost to induce class-level representation
3. static memory
4. instance-level diversity

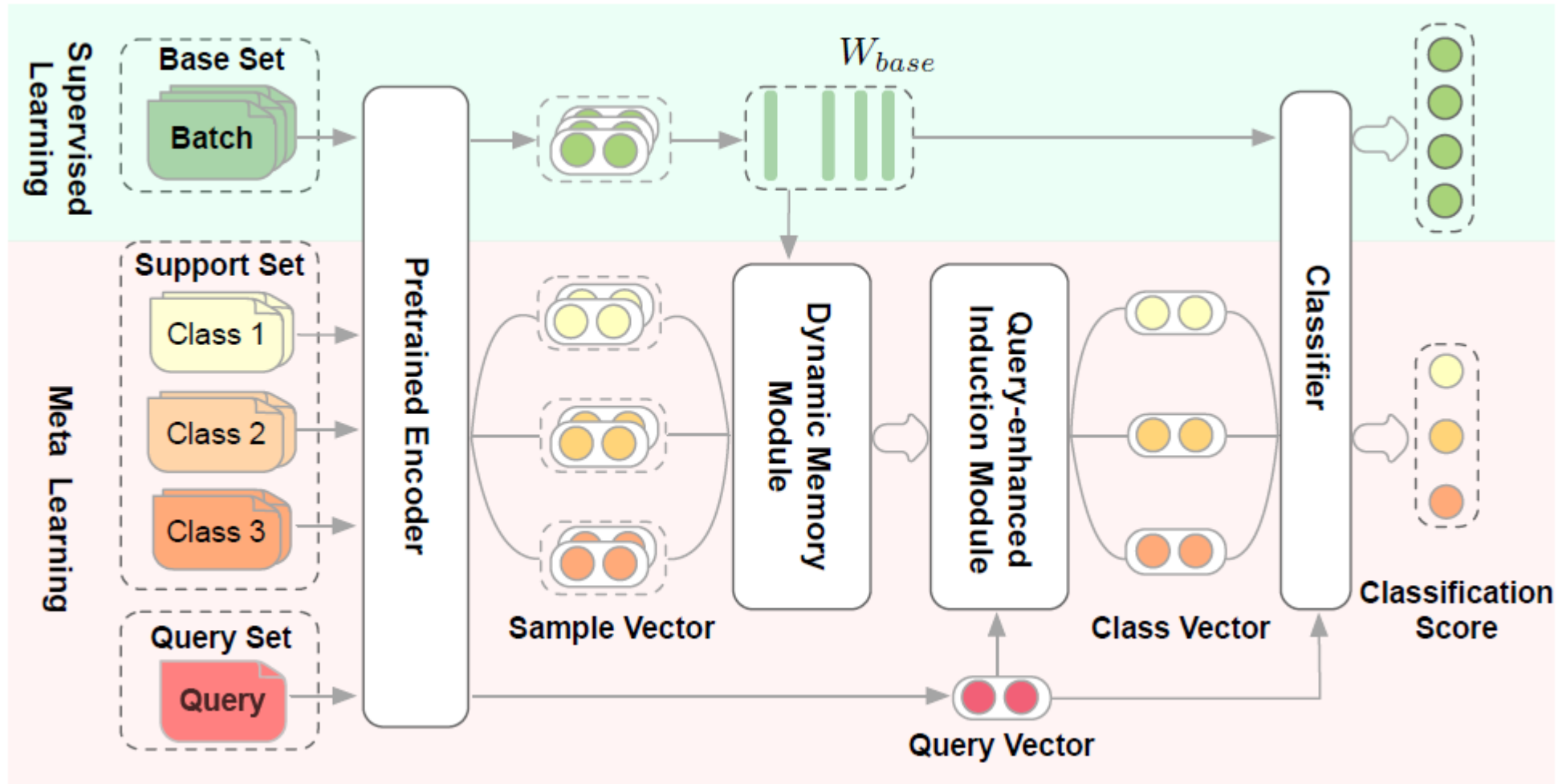
Solutions

1. data augmentation
2. extract transferable knowledge by meta-learning
3. memory component
4. query-aware methods

1. J. Salamon and J. P. Bello, Deep Convolutional Neural Networks and Data Augmentation for Environmental Sound Classification, in *IEEE Signal Processing Letters*
2. Tianyu Gao, Xu Han, Zhiyuan Liu, and Maosong Sun. Hybrid attention-based prototypical networks for noisy few-shot relation classification. In *AAAI-19*

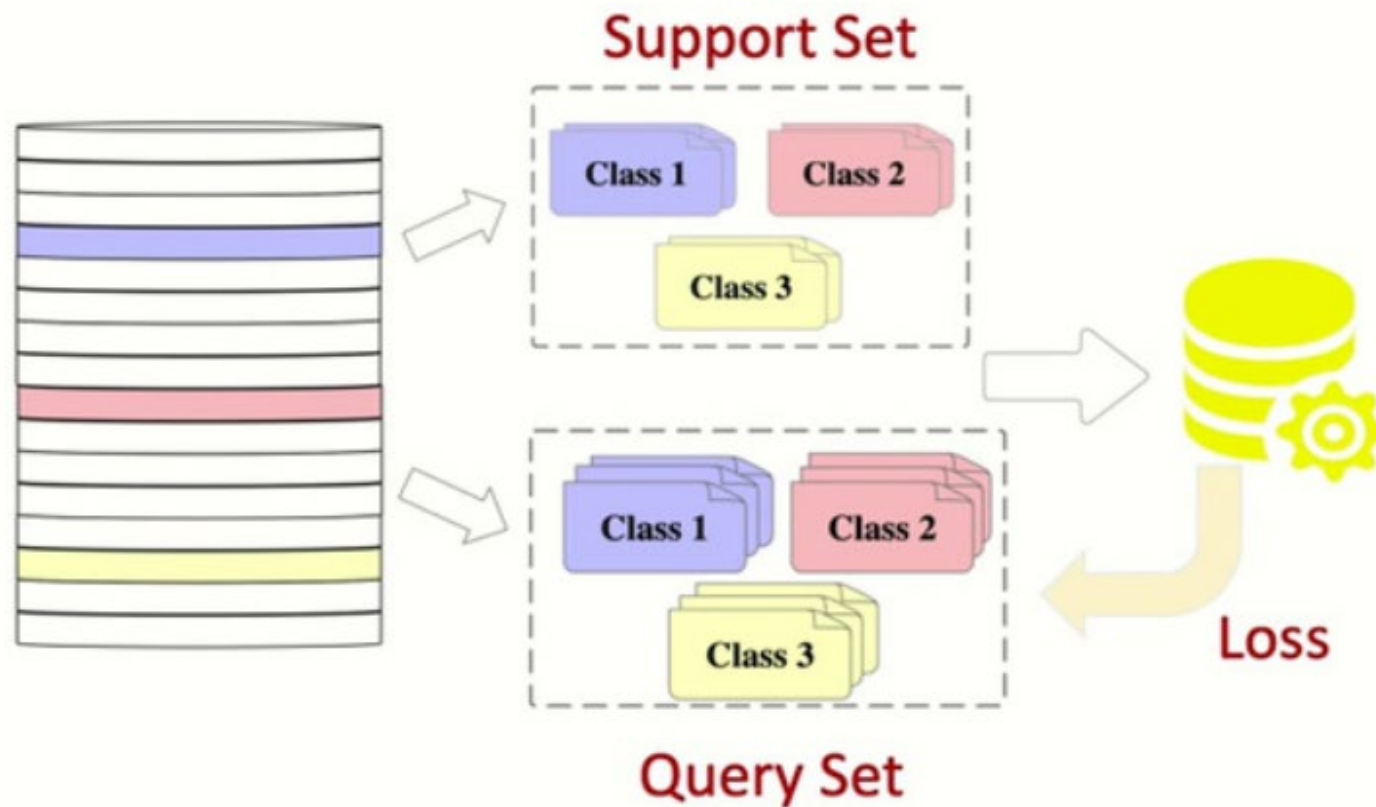
2. Dynamic Memory Induction Networks

DMIN



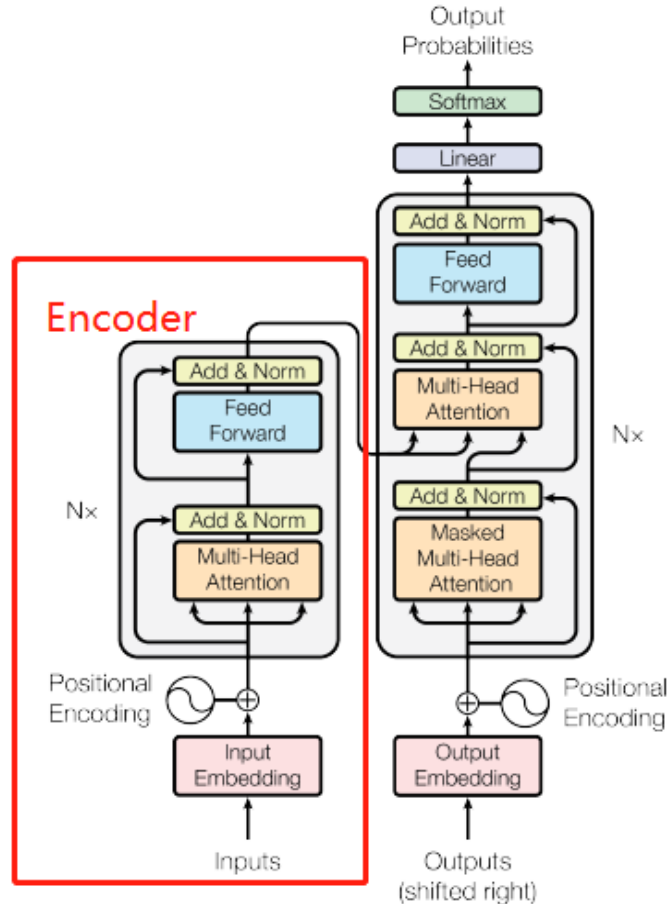
2.1 Meta-Training Episode

Episode Meta-Training



- Select C classes
- C -way K -Shot **Support Set**
- C -way **Query set**

2.2 Pre-trained Encoder



BERT: a multi-layer bidirectional Transformer encoder based on the original Transformer model

Using Google BERT-Base model as text encoder, fine-tune the model in training procedure

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding <https://arxiv.org/abs/1810.04805>

Attention Is All You Need <https://arxiv.org/abs/1706.03762>

2.3 Dynamic Memory Routing Process

DMR

Algorithm 1 Dynamic Memory Routing Process

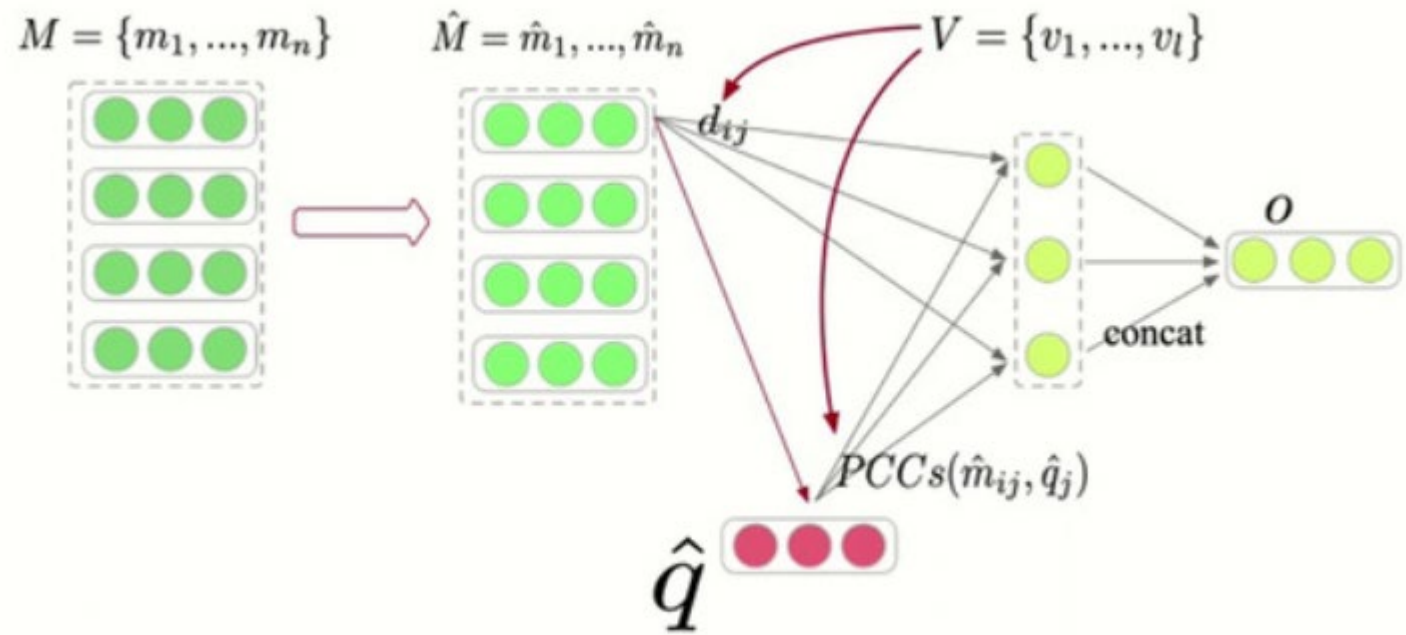
Require: r , q and memory $M = \{m_1, m_2, \dots, m_n\}$

Ensure: $v = v_1, v_2, \dots, v_l, q'$

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1: for all  $m_i, v_j$  do
2:    $\hat{m}_{ij} = \text{squash}(W_j m_i + b_j)$ 
3:    $\hat{q}_j = \text{squash}(W_j q + b_j)$ 
4:    $\alpha_{ij} = 0$ 
5:    $p_{ij} = \tanh(\text{PCCs}(\hat{m}_{ij}, \hat{q}_j))$ 
6: end for
7: for  $r$  iterations do
8:    $d_i = \text{softmax}(\alpha_i)$ 
9:    $\hat{v}_j = \sum_{i=1}^n (d_{ij} + p_{ij}) \hat{m}_{ij}$ 
10:   $v_j = \text{squash}(\hat{v}_j)$ 
11:  for all  $i, j$ :  $\alpha_{ij} = \alpha_{i,j} + p_{ij} \hat{m}_{ij} v_j$ 
12:  for all  $j$ :  $\hat{q}_j = \frac{\hat{q}_j + v_j}{2}$ 
13:  for all  $i, j$ :  $p_{ij} = \tanh(\text{PCCs}(\hat{m}_{ij}, \hat{q}_j))$ 
14: end for
15:  $q' = \text{concat}[v]$ 
16: Return  $q'$ 

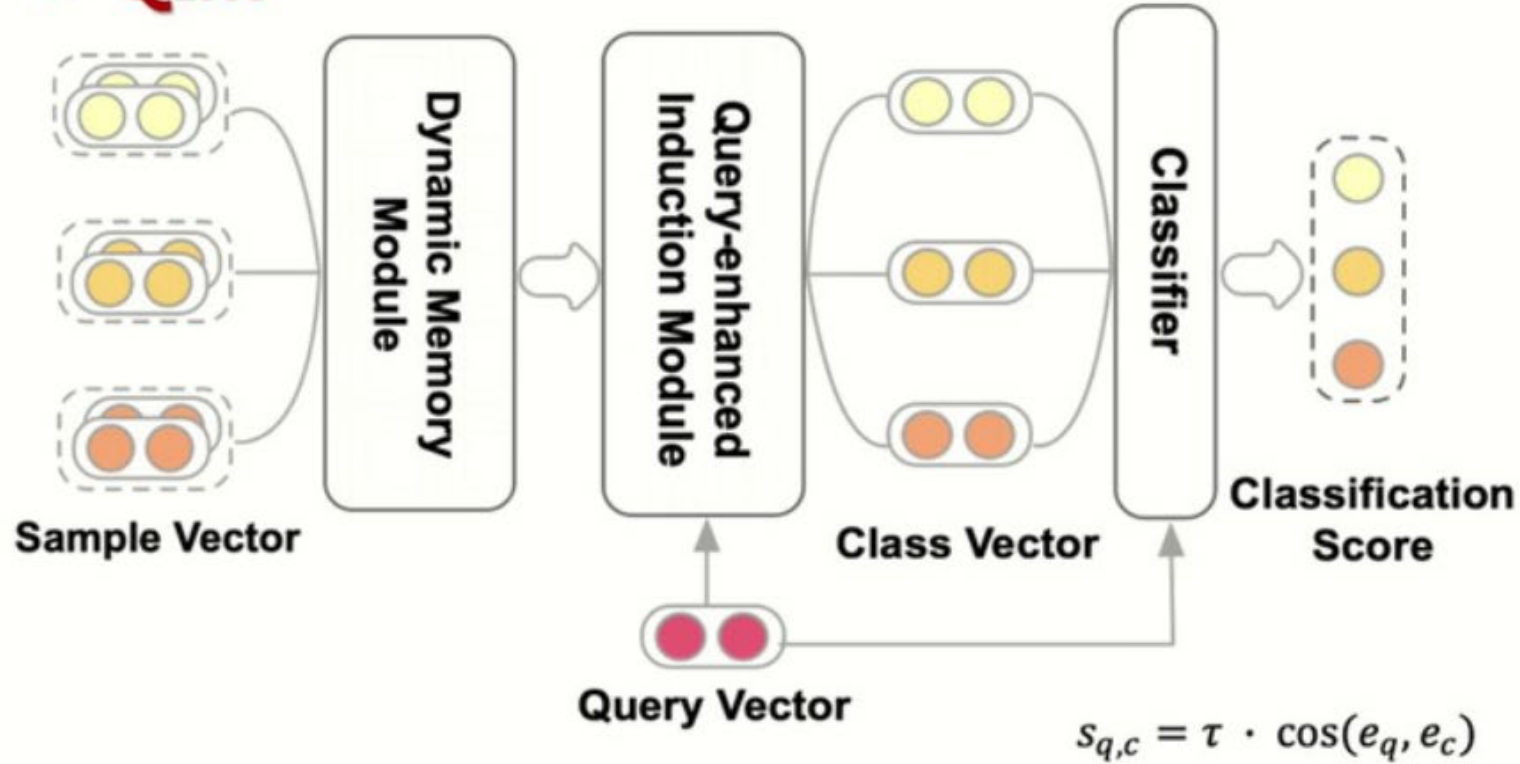
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$$e'_{c,s} = \text{DMR}(W_{base}, e_{c,s})$$

2.4 Query-enhanced Induction Module / Similarity Classifier

DMM -> QIM



$$e'_{c,s} = DMR(W_{base}, e_{c,s})$$

$$e_c = DMR(\{e'_{c,s}\}_{s=1,\dots,K}, e_q)$$

3. Experiments and Analysis

Model	5-way Acc.		10-way Acc.	
	1-shot	5-shot	1-shot	5-shot
BERT	30.79 \pm 0.68	63.31 \pm 0.73	23.48 \pm 0.53	61.18 \pm 0.82
ATAML	54.05 \pm 0.14	72.79 \pm 0.27	39.48 \pm 0.23	61.74 \pm 0.36
Rel. Net	59.19 \pm 0.12	78.35 \pm 0.27	44.69 \pm 0.19	67.49 \pm 0.23
Ind. Net	60.97 \pm 0.16	80.91 \pm 0.19	46.15 \pm 0.26	69.42 \pm 0.34
HATT	60.40 \pm 0.17	79.46 \pm 0.32	47.09 \pm 0.28	68.58 \pm 0.37
LwoF	63.35 \pm 0.26	78.83 \pm 0.38	48.61 \pm 0.21	69.57 \pm 0.35
DMIN	65.72\pm0.28	82.39\pm0.24	49.54\pm0.31	72.52\pm0.25

Table 1: Comparison of accuracy (%) on miniRCV1 with standard deviations.

Model	Iteration	1 Shot	5 Shot
w/o DMM	3	81.79	90.19
w/o QIM	3	82.37	90.57
DMIN	1	82.70	90.92
DMIN	2	82.95	91.18
DMIN	3	83.46	91.75

Table 3: Ablation study of accuracy (%) on ODIC in a 5-way setup.

Model	5-way Acc.		10-way Acc.	
	1-shot	5-shot	1-shot	5-shot
BERT	38.06 \pm 0.27	64.24 \pm 0.36	29.24 \pm 0.19	64.53 \pm 0.35
ATAML	79.60 \pm 0.42	88.53 \pm 0.57	63.52 \pm 0.34	77.36 \pm 0.57
Rel. Net	79.41 \pm 0.42	87.93 \pm 0.31	64.36 \pm 0.58	78.62 \pm 0.54
Ind. Net	81.28 \pm 0.26	89.67 \pm 0.28	64.53 \pm 0.38	80.48 \pm 0.25
HATT	81.57 \pm 0.47	89.27 \pm 0.58	65.75 \pm 0.61	81.53 \pm 0.56
LwoF	79.52 \pm 0.29	87.34 \pm 0.34	65.04 \pm 0.43	80.69 \pm 0.37
DMIN	83.46\pm0.36	91.75\pm0.23	67.31\pm0.25	82.84\pm0.38

Table 2: Comparison of accuracy(%) on ODIC with standard deviations.

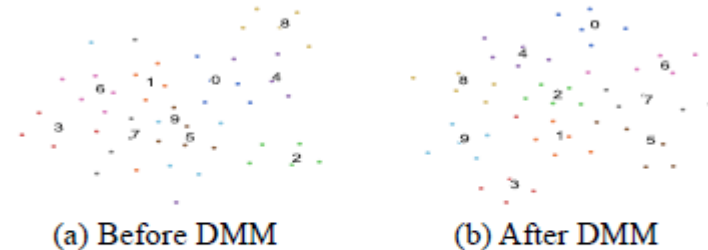


Figure 2: Effect of the Dynamic Memory Module in a 10-way 5-shot setup.

4. Personal Conclusions

- find a mistake in this paper
- the DMIN can also be used in VC
- the DMR of DMIN solves the problem of static memory by dynamic routing algorithm.
- QIM improves the problem of instance-level diversity



THANKS

Thanks.
And Your Slogan Here.

Speaker name and title

Date