# Zhiyu Xue

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**Name**: Zhiyu Xue (Chris)

**College**: University of Electronic Science and Technology of China

**Major:** Data Science and Big Data Technology (School of Computer Science and Engineering)

**GPA**: 3.78/4.0

**TOEFL**: 86/100 (Taken at Sept. 2019)

**Supervisors:** Lixin Duan, Wen Li

**Research**: few-shot learning, interpretability, image captioning

# CONTENTS

# Research Experiences

# Relative Position and Map Networks in Few-shot Learning for Image Classification

Zhiyu Xue, Zhenshan Xie, Zheng Xing, Lixin Duan
UESTC

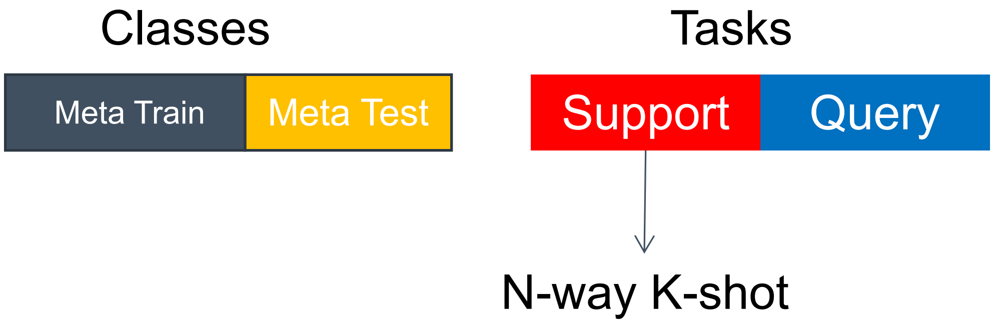
Accepted by CVPR 2020 VL3 Workshop

Codes: *https://github.com/chrisyxue/RMN-RPN-for-FSL.*

# Few-shot Learning

- Normal Training:


- Few-shot Training (Meta Training):



# Baseline

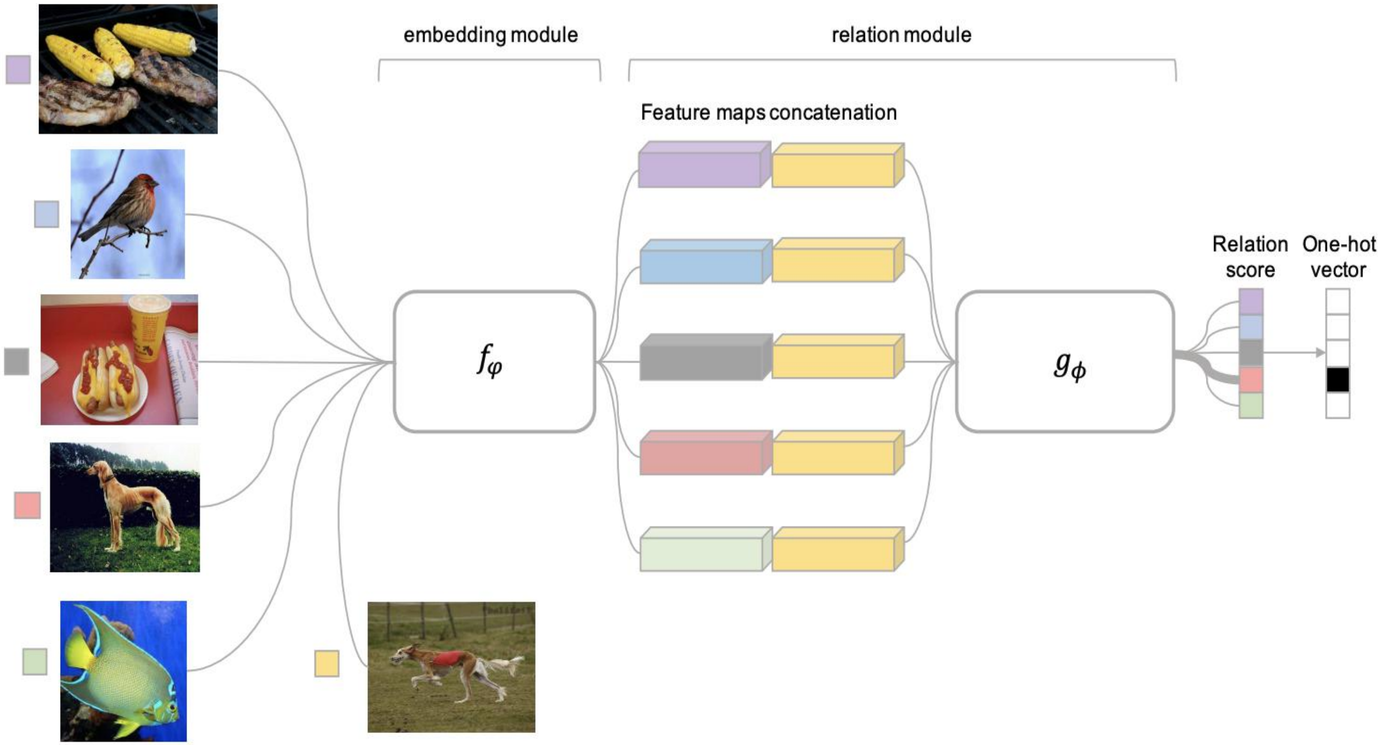
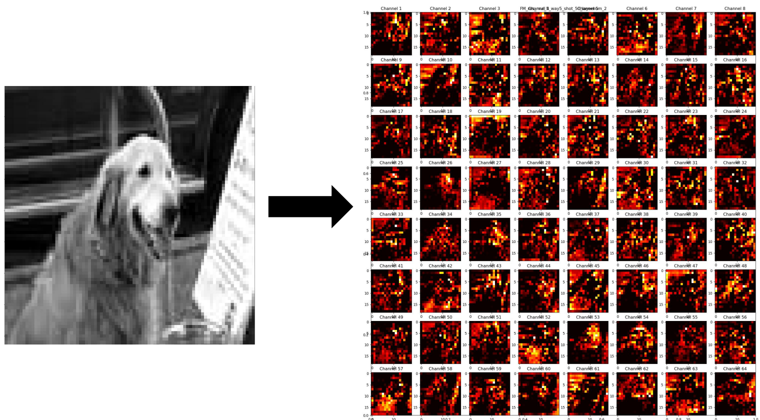



Figure 1: Relation Network architecture for a 5-way 1-shot problem with one query example.

Sung, Flood, et al. "Learning to compare: Relation network for few-shot learning." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2018.

# Motivation

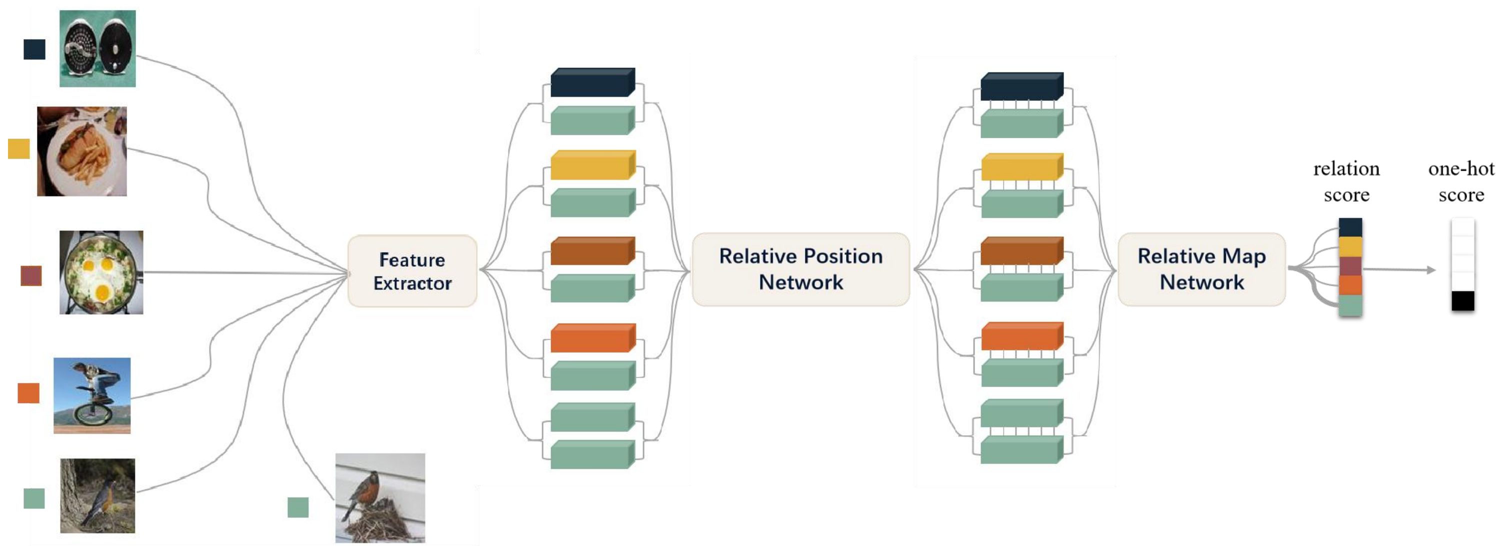


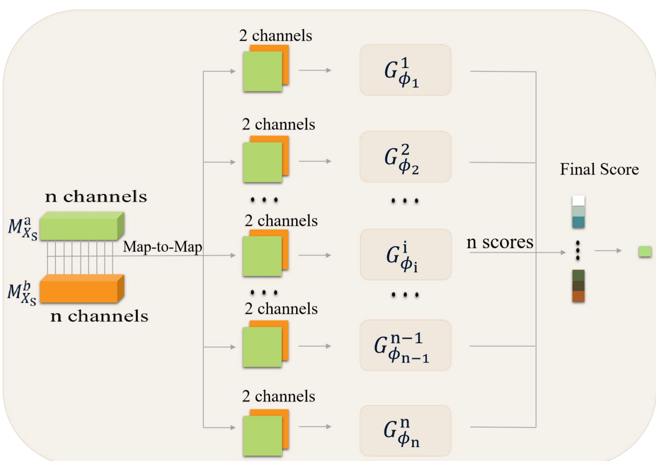
**RMN:different channels have different descriptions**

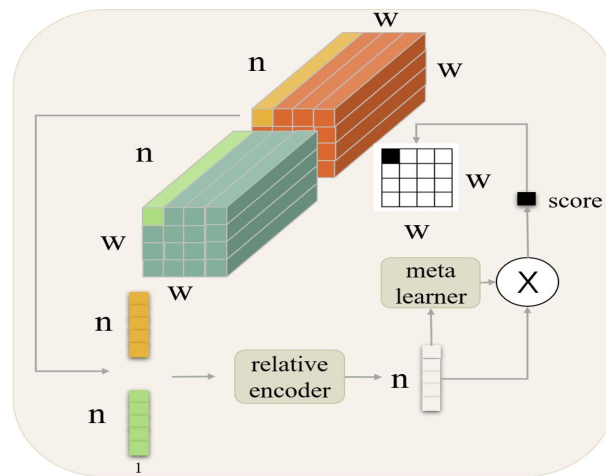
**RPN: the importance of each position is different**

# Architecture

CVPR SEATTLE JUNE 14-19 2020 WASHINGTON




$$P_{S,Q} = Sig(\sum_{i=1}^{n} w_i G^i_{\phi_i}(M^i_{x_S}, M^i_{x_Q}))$$

$$V^{s,q}_{i,j} = H([v^S_{i,j}, v^Q_{i,j}])$$

$$Att_{i,j} = w^T V^{s,q}_{i,j}$$

$$w = W_2 \cdot \sigma(W_1 \cdot V^{s,q}_{i,j})$$

$$M_{x^Q} := M_{x^Q} + Att \otimes M_{x^Q}$$

# Experiments

Table 1. Mean accuracies (%) of different methods on the MiniImageNet dataset. Results are obtained over 600 test episodes with 95% confidence intervals.

| Model | MiniImageNet (5-way) | |
|---|---|---|
| | 1-shot | 5-shot |
| MATCHING NETS [21] | 43.56±0.84 | 55.31±0.73 |
| META LSTM [15] | 43.44±0.77 | 60.60±0.71 |
| MAML [3] | 48.70±1.84 | 63.11±0.92 |
| PROTOTYPICAL NETS [19] | 49.42±0.78 | 68.20±0.66 |
| META SGD [12] | 50.47±1.87 | 64.03±0.94 |
| RN [20] | 50.44±0.82 | 65.32±0.70 |
| GNN [17] | 50.33±0.36 | 66.41±0.63 |
| PABN [6] | 51.87 | 65.37 |
| TPN [13] | 52.78±0.27 | 66.59±0.28 |
| EGNN(No Trans) [8] | - | 66.85 |
| R2-D2 [2] | 51.80±0.20 | 68.4±0.20 |
| Ours(Conv4) | 51.72±0.67 | 67.80±0.30 |
| **Ours(Our backbone)** | **53.35± 0.77** | **69.35± 0.61** |

Table 2. Mean accuracies (%) of different methods on the CIFAR-FS dataset. Results are obtained over 600 test episodes with 95% confidence intervals.

| Model | CIFAR-FS (5-way) | |
|---|---|---|
| | 1-shot | 5-shot |
| MAML [3] | 58.9±1.9 | 71.5±1.0 |
| PROTOTYPICAL NETS [19] | 55.5±0.7 | 72.0±0.6 |
| RN [20] | 55.0±1.0 | 69.3±0.8 |
| GNN [17] | 61.9 | 75.3 |
| R2-D2 [2] | 62.3±0.2 | 77.4±0.2 |
| **Ours** | **61.43** | **76.16** |

Table 3. Ablation study w.r.t. average accuracies (%) over 600 test episodes with 95% confidence intervals MiniImageNet in task 5-way K-shot about ablation study, where $K = 1, 3, 5, 7$ and 10.

| Ave Acc | 5-1 | 5-3 | 5-5 | 5-7 | 5-10 |
|---|---|---|---|---|---|
| RN [20] | 50.44 | 60.63 | 65.32 | 67.73 | 69.81 |
| RPN | 52.43 | 62.96 | 67.03 | 69.51 | 72.01 |
| RMN | 50.54 | 63.12 | 68.28 | 70.49 | 72.12 |
| **Ours** | **53.35** | **63.94** | **69.35** | **70.87** | **73.17** |

# Region Comparison Network for Interpretable Few-shot Image Classification

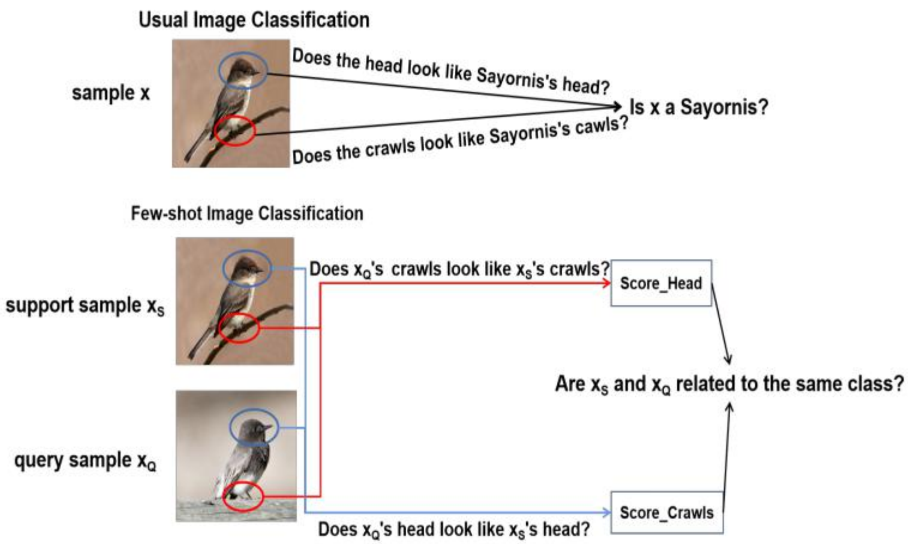
Zhiyu Xue, Wen Li, Lixin Duan, Lin Chen, Jiebo Luo
UESTC, Futurewei, UR

Finished in May 2020

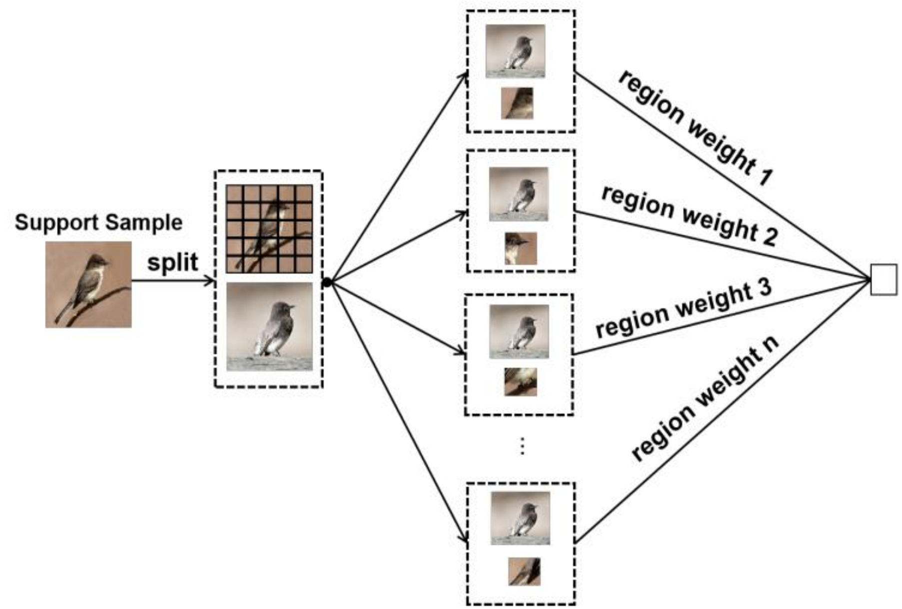
**Meta Review from ACM MM 2020:** The paper itself does not bring enough insights to the multimedia community. It uses single modality is thus more suitable for vision community.

We plan to submit this paper to AAAI 2020 or TIP, and the codes will be released if the paper is accepted by these conference or journal

# Motivation




(a)




(b)

# Architecture

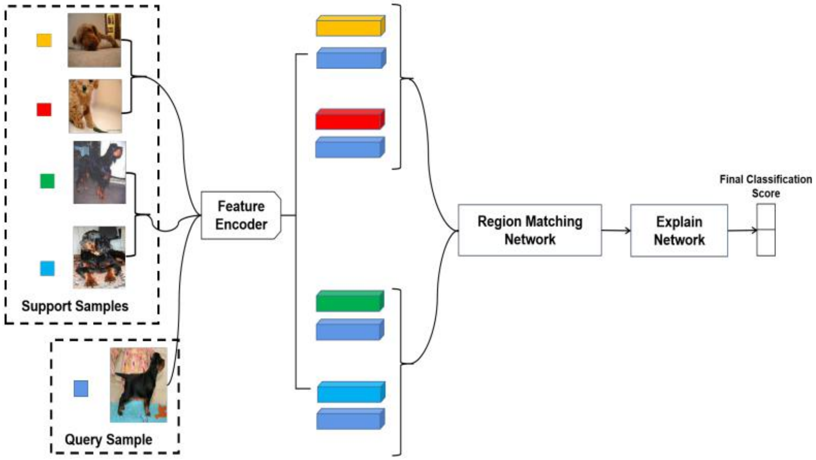



Figure 2: The architecture of 2-way 2-shot

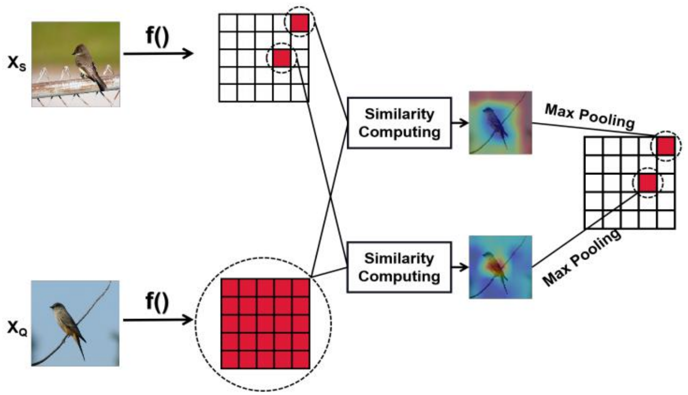



Figure 3: The structure of region matching network for $w = h = 5$, where $X_S$ and $X_Q$ denote support sample and query sample respectively.

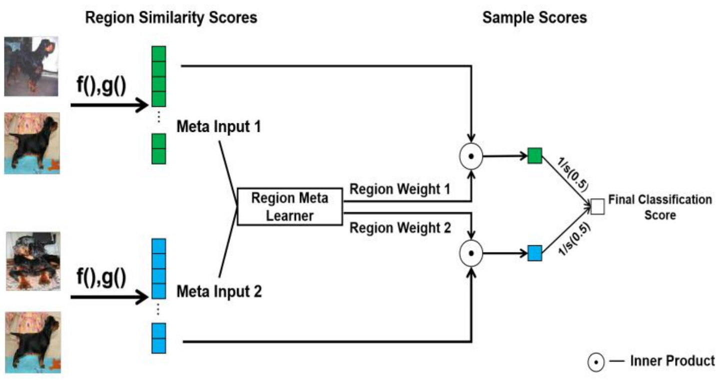



Figure 4: The structure of explain network for 2-shot task(images are from Mini-ImageNet)

# Performance

Table 1: Mean accuracies (%) of different methods on the MiniImageNet and CIFAR-FS dataset. Results are obtained over 600 test episodes with 95% confidence intervals. Note that Conv4-n denotes 4-layer convolution network outputting feature maps with n channels. *: [47] uses feature extractor as 6-layer convolution networ with deformable convolution kernel [5]

| Model | Backbone | Type | Mini-ImageNet (5-way) | | CIFAR-FS (5-way) | |
|---|---|---|---|---|---|---|
| | | | 1-shot | 5-shot | 1-shot | 5-shot |
| META LSTM [34] | Conv4-32 | Meta | 43.44±0.77 | 60.60±0.71 | - | - |
| MAML [7] | Conv4-32 | Meta | 48.70±1.84 | 63.11±0.92 | 58.9±1.9 | 71.5±1.0 |
| Dynamic-Net [11] | Conv4-64 | Meta | 56.20±0.86 | 72.81±0.62 | - | - |
| Dynamic-Net [11] | Res12 | Meta | 55.45±0.89 | 70.13±0.68 | - | - |
| SNAIL [30] | Res12 | Meta | 55.71±0.99 | 68.88±0.92 | | |
| AdaResNet [24] | Res12 | Meta | 56.88±0.62 | 71.94±0.57 | - | - |
| MATCHING NETS [43] | Conv4-64 | Metric | 43.56±0.84 | 55.31±0.73 | - | - |
| PROTOTYPICAL NETS [40] | Conv4-64 | Metric | 49.42±0.78 | 68.20±0.66 | 55.5±0.7 | 72.0±0.6 |
| RELATION NETS [41] | Conv4-64 | Metric | 50.44±0.82 | 65.32±0.70 | 55.0±1.0 | 69.3±0.8 |
| GNN [9] | Conv4-64 | Metric | 50.33±0.36 | 66.41±0.63 | 61.9 | 75.3 |
| PABN [17] | Conv4-64 | Metric | 51.87±0.45 | 65.37±0.68 | - | - |
| TPN [28] | Conv4-64 | Metric | 52.78±0.27 | 66.59±0.28 | - | - |
| DN4 [26] | Conv4-64 | Metric | 51.24±0.74 | 71.02±0.64 | - | - |
| R2-D2 [2] | Conv4-512 | Metric | 51.80±0.20 | 68.4±0.20 | 65.3±0.2 | 79.4±0.1 |
| GCR [25] | Conv4-512 | Metric | 53.21±0.40 | 72.32±0.32 | - | - |
| PARN [47] | * | Metric | 55.22±0.82 | 71.55±0.66 | - | - |
| RCN | Conv4-64 | Metric | 53.47±0.84 | 71.63±0.70 | 61.61±0.96 | 77.63±0.75 |
| RCN | Res12 | Metric | **57.40±0.86** | **75.19±0.64** | **69.02±0.92** | **82.96±0.67** |

Table 4: Mean accuracies (%) of different methods on the Mini-ImageNet and CUB-200(using split criterion as [26]). Results are obtained over 600 test episodes with 95% confidence intervals. Note that the items in region weight of fixed layer are all equal to $\frac{1}{h \times w}$

| Version | Mini-ImageNet | | CUB-200 | |
|---|---|---|---|---|
| | 1-shot | 5-shot | 1-shot | 5-shot |
| Fixed (5×5) | 49.30±0.89 | 55.51±0.71 | 62.61±1.63 | 67.26±0.83 |
| Linear (5×5) | 55.97±0.86 | 72.80±0.63 | 73.23±0.90 | 88.12±0.56 |
| Meta Learner (5×5) | **57.40±0.86** | **75.19±0.64** | **78.64±0.88** | **90.10±0.50** |
| Fixed (4×4) | 51.79±0.90 | 57.40±0.70 | 65.18±1.08 | 71.65±0.83 |
| Linear (4×4) | 55.18±0.84 | **73.25±0.64** | 75.12±0.89 | 87.63±0.54 |
| Meta Learner (4×4) | **55.73±0.83** | 72.78±0.62 | **76.48±0.86** | **87.89±0.57** |
| Fixed (3×3) | 51.51±0.90 | 56.02±0.70 | 65.97±1.03 | 74.59±0.89 |
| Linear (3×3) | **56.50±0.87** | **73.48±0.62** | **76.15±0.87** | **88.10±0.51** |
| Meta Learner (3×3) | 55.41±0.85 | 72.16±0.68 | 75.63±0.88 | 86.96±0.57 |
| Fixed (2×2) | 51.58±0.91 | 57.59±0.70 | 68.95±1.05 | 77.64±0.81 |
| Linear (2×2) | **56.03±0.85** | 72.23±0.64 | 73.79±0.85 | **87.42±0.57** |
| Meta Learner (2×2) | 55.65±0.83 | **72.36±0.64** | **75.79±0.87** | 86.64±0.55 |
| Fixed (1×1) | 52.22±1.03 | 57.34±0.75 | 70.70±0.78 | 78.43±0.43 |
| Linear (1×1) | 54.80±0.86 | 71.80±0.69 | **75.83±0.85** | **86.97±0.53** |
| Meta Learner (1×1) | **55.40±0.89** | **72.78±0.62** | 73.83±0.98 | 84.77±0.54 |

Table 2: Mean accuracies (%) of different methods on the CUB-200. Results are obtained over 600 test episodes with 95% confidence intervals. †: Split CUB as [26]. ‡: Split CUB as [4]

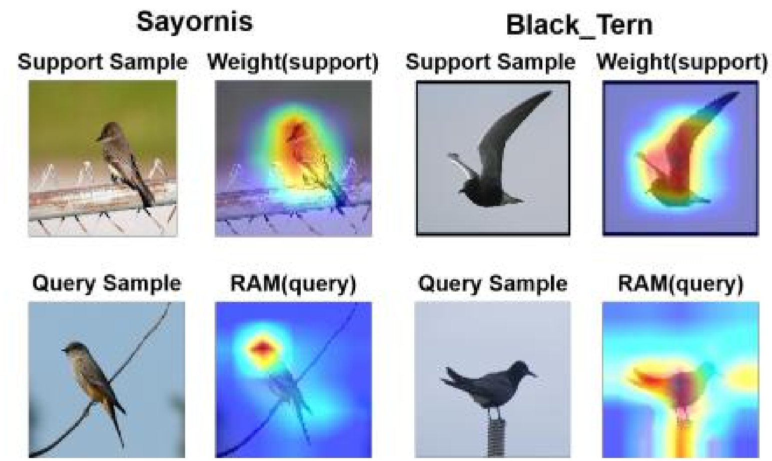
| Model | Backbone | Type | CUB-200 (5-way) | |
|---|---|---|---|---|
| | | | 1-shot | 5-shot |
| PCM† [45] | Conv4-64 | Metric | 42.10±1.96 | 62.48±1.21 |
| MATCHING NETS† [43] | Conv4-64 | Metric | 45.30±1.03 | 59.50±1.01 |
| PROTOTYPICAL NETS† [40] | Conv4-64 | Metric | 37.36±1.00 | 45.28±1.03 |
| GNN† [9] | Conv4-64 | Metric | 51.83±0.98 | 63.69±0.94 |
| DN4† [26] | Conv4-64 | Metric | 53.15±0.84 | 81.90±0.60 |
| RCN† | Conv4-64 | Metric | 66.48±0.90 | 82.04±0.58 |
| RCN† | Res12 | Metric | **78.64±0.88** | **90.10±0.50** |
| Baseline++‡ [4] | Res10 | Metric | 69.55±0.89 | 85.17±0.50 |
| MAML++(High-End)+SCA‡ [1] | - | Meta | 70.46±1.18 | 85.63±0.66 |
| GPShot(CosSim)‡ [31] | Res10 | Meta | 70.81±0.52 | 83.26±0.50 |
| GPShot(BNCosSim)‡ [31] | Res10 | Meta | 72.27±0.30 | 85.64±0.29 |
| RCN‡ | Conv4-64 | Metric | 67.06±0.93 | 82.36±0.61 |
| RCN‡ | Res12 | Metric | **74.65±0.86** | **88.81±0.57** |

Table 3: Mean accuracies (%) of different methods on the Stanford Dogs. Results are obtained over 600 test episodes with 95% confidence intervals.

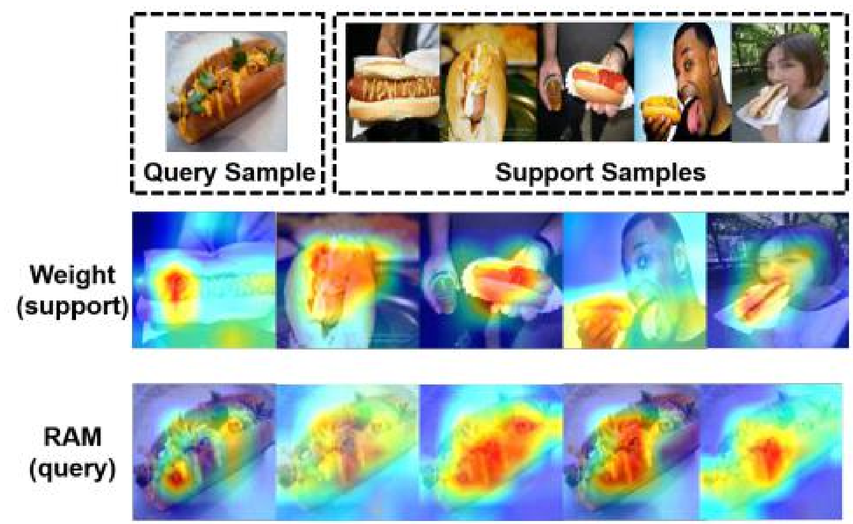
| Model | Backbone | Type | CUB-200 (5-way) | |
|---|---|---|---|---|
| | | | 1-shot | 5-shot |
| PCM [45] | Conv4-64 | Metric | 28.78±2.33 | 46.92±2.00 |
| MATCHING NETS [43] | Conv4-64 | Metric | 45.30±1.03 | 59.50±1.01 |
| PROTOTYPICAL NETS [40] | Conv4-64 | Metric | 37.59±1.00 | 48.19±1.03 |
| GNN [9] | Conv4-64 | Metric | 46.98±0.98 | 62.27±0.95 |
| DN4 [26] | Conv4-64 | Metric | 45.73±0.76 | 66.33±0.66 |
| RCN | Conv4-64 | Metric | 54.29±0.96 | 72.65±0.72 |
| RCN | Res12 | Metric | **66.24±0.96** | **81.50±0.58** |

# VISUALIZATION OF MODEI INTERPRETABILITY

$$RAM = \sum_{i=1}^{h \times w} W_p[i] \cdot k(S_{S,Q}^{i})$$




(a)



# GENERALIZATION AND QUANTIFICATION OF MODEL INTERPRETABILITY

$$f(x, W_{:,j}) = \frac{1}{\sigma_j \sqrt{2\pi}} \exp\left(-\frac{(x-\mu_j)^2}{2\sigma_j^2}\right) \quad (6)$$

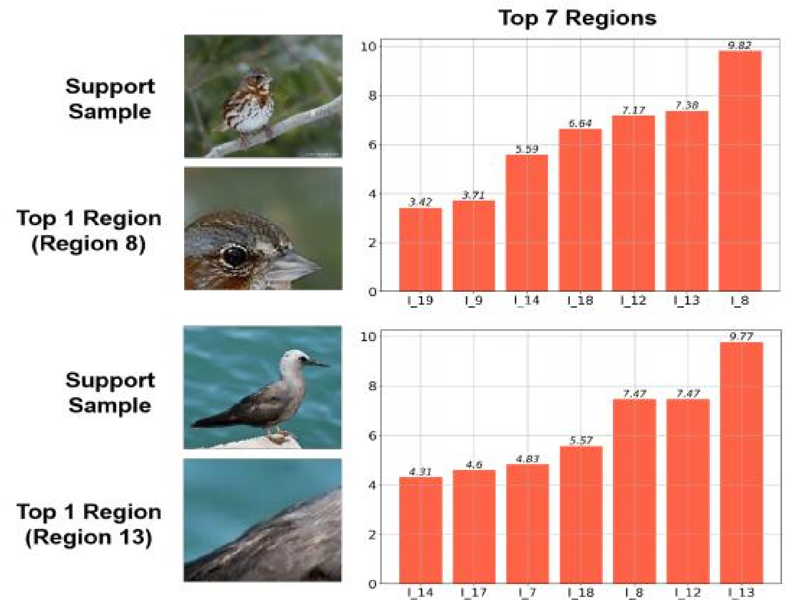
$$I_j = \int_{\mu_j - 2a}^{\mu_j + 2a} f(x, W_{:,j}) x \mathrm{d}x$$

$$a = \frac{1}{M} \sum \sigma_j \quad (7)$$

**Algorithm 1** Generalization Method

**Input:** $x_S, \{x_Q^i\}_{i=1}^{N-1}$
**Output:** $\{I_j\}_{j=1}^{M}$

```
W = [] is a two-dimensional matrix
M = 0
for x_Q^i ∈ {x_Q^i}_{i=0}^{N-1} do
    S_i = m(g(f(x_S), f(x_Q^i)))
    if S_i ≠ 0⃗ then
        W = [W; S_i]
        M+ = 1
    else
        continue
    end if
end for
for j ∈ [1, 2, ...M] do
    I_j = ∫_{μ_j−2a}^{μ_j+2a} f(x, W_{:,j}) x dx
end for
```



# Explain Class Imbalance Problem by Using Feature Transformation Complexity

Ongoing Project with Prof. Quanshi Zhang in SJTU

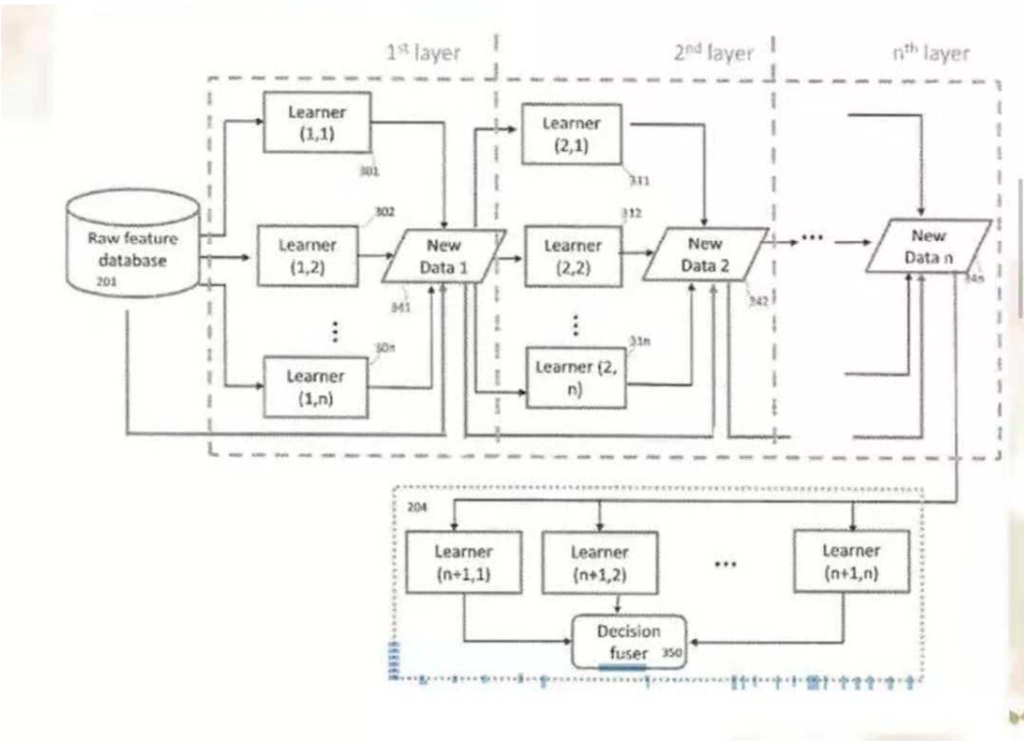
**Explain and Improve Few-shot Learning Models by Inversing the Network**

Ongoing Project with Prof. Jiebo Luo and Prof. Lixin Duan

The idea is presented by me

# Working Experiences

# Data Engineer in Fintell




Patent, IBM 2016, Dr. Changshen Li
Data: ronghui_v7

# Reviwer of CVPR VL3 Workshop


I'm on the organizer list of https://www.learning-with-limited-labels.com/organizers

# Spare-time Life

Voluntary Teaching, Sri Lanka


Summer School, UC Berkeley


Violist, Ochestra of UESTC

# Comments from My Mentors

Overall, Zhiyu is one of the most excellent and diligent students I have ever supervised. I believe his great potentials will continue his driving for excellence in the future, and I know for sure that your prestigious program will boost Zhiyu' s future of success.

-- Prof. Lixin Duan, UESTC, Leader of DIG Lab

During his internship, I found Zhiyu is a warm and friendly student who cooperated well with his teammates. He is always willing to share ideas and organize discussions to find solutions.

-- Dr. Jing Wang, CEO of Fintell Financial Service

# Self-summary

Strengths:

1. Self-motivated
2. Quite good at Python
3. Creative (but it sometimes causes blue sky thinking)

Weaknesses & Solutions：

1. Not have a strong mathematics background （Plan to read some papers and books, and I'm highly interested in researching ML problem in the aspect of math）
2. Not good at English （Plan to take GRE test）
3. Time schedule （Force myself to finish the work the day before the deadline）

# Thanks for Watching