PMAL: Open Set Recognition via Robust Prototype Mining

- Problems of learning prototypes in OSR
  - High quality sample
  - Low quality sample
  - Prototype

- Effect Visualization

(a) Quality

(b) Diversity

Undesired learned prototypes

Redundancy

Multifarious Appearance

TinyImageNet

Contact E-mail: lujing6@hikvision.com  Jing Lu
PMAL: Open Set Recognition via Robust Prototype Mining

Jing Lu\textsuperscript{1,*}, Yunlu Xu\textsuperscript{1,*}, Hao Li\textsuperscript{1}, Zhanzhan Cheng\textsuperscript{1,2†}, Yi Niu\textsuperscript{1}

\textsuperscript{1} Hikvision Research Institution, Hangzhou, China
\textsuperscript{2} Zhejiang University, Hangzhou, China
{lujing6, xuyunlu, lihao50, chengzhanzhan, niuyi}@hikvision.com
Problems

- **Implicit Learned Prototypes**

  - High quality sample
  - Low quality sample
  - Prototype

  - Undesired learned prototypes
  - Redundancy
  - Multifarious Appearance

(a) Quality

(b) Diversity
Motivation

- **Explicit Prototype Mining**: PMAL

(a) *Mine High-quality Candidates*

(b) *Filter with diversity*
Preliminary

- Open Set Recognition (OSR)

- **Ideal: Close Set Assumption**
  - Closed: Training and testing samples come from known classes
  - Multi-class Classification

- **Actually: Open Set Environment**
  - Open: Multiple known classes, many unknown classes

Scheirer, W. J., et al. 2013. Towards Open Set Recognition. TPAMI.
Preliminary

- Prototype-based OSR

  - Softmax-based close-set recognition

  - Prototype-based OSR

✓ Unable to tell UNKNOWN classes

✓ Learn compact intra-class embedding
✓ Reserve more space for UNKNOWN classes

Jaderberg, M, et al. 2015. Spatial Transformer Networks. NeurIPS.
Method

- Overview of PMAL
Method

• Mine \textit{high-quality} samples as prototype candidates

\begin{itemize}
  \item Data uncertainty modelling\textsuperscript{[1]}
    \begin{equation}
      z(x_i) = \phi(x_i) + n(x_i), \quad n(x_i) \sim \mathcal{N}(0, \sigma(x_i))
    \end{equation}
  \item Key properties of high-quality samples
    \begin{equation}
      d_M(\phi_i^1, \phi_j^1) \approx d_M(\phi_i^2, \phi_j^2)
    \end{equation}
    \textit{Mahalanobis distance}
  \item Embedding Topology
    \begin{equation}
      t(z_i) \triangleq (d_M(z_i, z_1), \ldots, d_M(z_i, z_N))
    \end{equation}
  \item Embedding Topology robustness
    \begin{equation}
      r(x_i) \triangleq \exp(-\|t(z_i^1) - t(z_i^2)\|_2)
    \end{equation}
\end{itemize}

High-quality samples satisfy\textsuperscript{[2]}:
\[ z_i \approx \phi_i \]

- For a high-quality samples \( x_i \)

\begin{itemize}
  \item Embedding space \( Z^1 \)
    \[ r(x_i) \rightarrow 1 \]
  \item Embedding space \( Z^2 \)
\end{itemize}
Method

• Mine *high-quality* samples as prototype candidates

✓ Data uncertainty modelling\(^1\)

Equa. 1: \( z(x_i) = \phi(x_i) + n(x_i), \ n(x_i) \sim \mathcal{N}(0, \sigma(x_i)) \)

✓ Key properties of high-quality samples

Equa. 2: \[ d_M(\phi^1_i, \phi^1_j) \approx d_M(\phi^2_i, \phi^2_j) \]

\( \text{Mahalanobis distance} \)

✓ Embedding Topology robustness

Equa. 3: \( t(z_i) \triangleq (d_M(z_i, z_1), \ldots, d_M(z_i, z_N)) \)

Equa. 4: \( r(x_i) \triangleq \exp(-\|t(z^1_i) - t(z^2_i)\|_2) \)

High-quality samples satisfy\(^2\):

\[ z_i \approx \phi_i \]

□ For a low-quality samples \( x_i \)

![Diagram](attachment:image.png)

(b)
Method

• Filter with diversity

- Local maximum robustness
- Large embedding distance

• Greedy filtering algorithm

\[
P_k = \bigcup_{i=1}^{T} \{ x_i | \max_{z_i \in C_k} \min_{x_j \in C_k} d_M(z_i, z_j) | r(x_j) > r(x_i) \}\]

- \( C_k \): candidate set of class \( k \)
- \( P_k \): final prototype set of class \( k \)
Method

- Embedding optimization

✓ Point to Set distance

\[ z_i \quad \text{query} \quad z(P_k) = (z(p_{k,1}), \ldots, z(p_{k,T})) \in \mathbb{R}^{D \times T} \]

Equa.1: \[ z_i^{\text{att}}(P_k) = \text{SoftMax}(\frac{z_i^T z(P_k)}{\sqrt{d}}) z(P_k) \]

Equa.2: \[ d(z_i, z(P_k)) = 1 - \frac{z_i^T z_i^{\text{att}}(P_k)}{|z_i^T| |z_i^{\text{att}}(P_k)|} \]
Method

• Embedding optimization

**PMAL:**  
*Explicitly* updated by model forward pass

**Existed methods:**  
*Implicitly* learned

Equation 1:
\[
\mathcal{L}_p = \frac{1}{N} \sum_{i=1}^{N} [d(z_i, \pi(P_m)) - d(z_i, \pi(P_u)) + \delta]^+ 
\]

Equation 2:
\[
P_u = \arg \min_{P_k \in P \setminus P_m} (d(z_i, \pi(P_k))) 
\]
Ablation

• Each component

| Components     | (a) | (b) | (c) | (d) | (e) | (f) |
|----------------|-----|-----|-----|-----|-----|-----|
| PM High-Quality | ✓   | ✓   | ✓   | ✓   | ✓   | ✓   |
| PM Diversity   | ✓   | ✓   | ✓   | ✓   | ✓   | ✓   |
| EO Point-to-Set |     | ✓   | ✓   | ✓   |     | ✓   |
| AUROC          | 80.3 | 78.1 | 81.6 | 80.2 | 81.9 | 83.1 |

• Both high quality and diversity matters for prototypes.
• Point-to-set distance helps learning better embedding space.
Ablation

• Each component

| Components     | (a) | (b) | (c) | (d) | (e) | (f) |
|----------------|-----|-----|-----|-----|-----|-----|
| PM High-Quality | ✓   | ✓   | ✓   | ✓   | ✓   | ✓   |
| Diversity      | ✓   | ✓   | ✓   | ✓   | ✓   | ✓   |
| EO Point-to-Set | ✓   | ✓   | ✓   | ✓   | ✓   | ✓   |
| AUROC          | 80.3| 78.1| 81.6| 80.2| 81.9| **83.1** |

• Both high quality and diversity matters for prototypes.
• Point-to-set distance helps learning better embedding space.
Ablation

- Replace components in PM with existed strategies

Table 4: Comparisons with other methods on the quality and diversity property.

| Method              | ACC  | AUROC |
|---------------------|------|-------|
| Probability         | 81.9 | 79.3  |
| (b)Deep Ensembles   | 82.3 | 80.5  |
| (c)MC-dropout       | 81.6 | 78.8  |
| (a)Randomization    | 81.5 | 79.1  |
| (b)Clustering       | 81.8 | 79.6  |
| Ours                | **84.7** | **83.1** |
Visualization

- High quality
Visualization

- Diversity

✓ Multifarious prototypes
Visualization

- Embedding space

Each color denotes different classes and ‘gray’ denotes unknowns.

- On simple MNIST, all prototype-based methods performs satisfying.
- On more complex TinyImageNet, PMAL performs much better.
## Performance

- Mainstream small-scale benchmarks

### Table 1: Close set ACC and Open set AUROC on small datasets. ‘*’ denotes implemented results and ‘C’ is short for ‘CIFAR’.

| Methods                        | Close set ACC |                   | Open set AUROC |       |       |       |       |       |       |       |       |       |       |       |
|--------------------------------|---------------|------------------|----------------|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|                               | MNIST         | SVHN             | C10            | C+10 | C+50  | TINY  | MNIST | SVHN             | C10            | C+10 | C+50  | TINY  |
| SoftMax                       | 99.5          | 94.7             | 80.1           | -    | -     | -     | 97.8  | 88.6             | 67.7           | 81.6  | 80.5   | 57.7  |
| CPN (Yang et al.)             | 99.7          | 96.7             | 92.9           | 94.8* | 95.0* | 81.4* | 99.0  | 92.6             | 82.8           | 88.1  | 87.9   | 63.9  |
| PROSER (Zhou, Ye, and Zhan)   | -             | 96.5             | 92.8           | -    | -     | 52.1  | 94.3  | -                | 89.1           | 96.0  | 95.3   | 69.3  |
| CGDL (Sun et al.)             | 99.6          | 94.2             | 91.2           | -    | -     | -     | 99.4  | 93.5             | 90.3           | 95.9  | 95.0   | 76.2  |
| OpenHybrid (Zhang et al.)     | 94.7          | 92.9             | 86.8           | -    | -     | -     | 99.5  | 94.7             | 95.0           | 96.2  | 95.5   | 79.3  |
| RPL-OSRCI (Chen et al.)       | 99.5*         | 95.3*            | 94.3*          | 94.6* | 94.7* | 81.3* | 99.3  | 95.1             | 86.1           | 85.6  | 85.0   | 70.2  |
| ARPL (Chen et al.)            | 99.5          | 94.3             | 87.9           | 94.7  | 92.9  | 65.9  | 99.7  | 96.7             | 91.0           | 97.1  | 95.1   | 78.2  |
| RPL-WRN (Chen et al.)         | 99.6*         | 95.8*            | 95.1*          | 95.5* | 95.9* | 81.7* | 99.6  | 96.8             | 90.1           | 97.6  | 96.8   | 80.9  |
| PMAL-OSRCI                    | 99.6          | 96.5             | 96.3           | 96.4  | 96.9  | 84.4  | 99.5  | 96.3             | 94.6           | 96.0  | 94.3   | 81.8  |
| PMAL-WRN                      | **99.8**      | **97.1**         | **97.5**       | **97.8** | **98.1** | **84.7** | **99.7** | **97.0**         | **95.1**       | **97.8** | **96.9** | **83.1** |
Performance

- Mainstream small-scale benchmarks

Table 1: Close set ACC and Open set AUROC on small datasets. ‘*’ denotes implemented results and ‘C’ is short for ‘CIFAR’.

| Methods | MNIST | SVHN | C10 | C+10 | C+50 | TINY | MNIST | SVHN | C10 | C+10 | C+50 | TINY |
|---------|-------|------|-----|------|------|------|-------|------|-----|------|------|------|-------|
| SoftMax | 99.5  | 94.7 | 80.1| -    | -    | -    | 97.8  | 88.6 | 67.7| 81.6 | 80.5 | 57.7 |
| CPN (Yang et al.) | 99.7 | 96.7 | 92.9| 94.8*| 95.0*| 81.4*| 99.0  | 92.6 | 82.8| 88.1 | 87.9 | 63.9 |
| PROSER (Zhou, Ye, and Zhan) | -    | 96.5 | 92.8| -    | -    | 52.1 | 94.3  | -    | 89.1| 96.0 | 95.3 | 69.3 |
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| OpenHybrid (Zhang et al.) | 94.7  | 92.9 | 86.8| -    | -    | -    | 99.5  | 94.7 | 95.0| 96.2 | 95.5 | 79.3 |
| RPL-OSCR (Chen et al.) | 99.5* | 95.3*| 94.3*| 94.6*| 94.7*| 81.3*| 99.3  | 95.1 | 86.1| 85.6 | 85.0 | 70.2 |
| ARPL (Chen et al.) | 99.5  | 94.3 | 87.9| 94.7 | 92.9 | 65.9 | 99.7  | 96.7 | 91.0| 97.1 | 95.1 | 78.2 |
| RPL-WRN (Chen et al.) | 99.6* | 95.8*| 95.1*| 95.5*| 95.9*| 81.7*| 99.6  | 96.8 | 90.1| 97.6 | 96.8 | 80.9 |
| PMAL-OSCR | 99.6  | 96.5 | 96.3| 96.4 | 96.9 | 84.4 | 99.5  | 96.3 | 94.6| 96.0 | 94.3 | 81.8 |
| PMAL-WRN | **99.8** | **97.1** | **97.5** | **97.8** | **98.1** | **84.7** | **99.7** | **97.0** | **95.1** | **97.8** | **96.9** | **83.1** |
Performance

- More large-scale benchmarks

Table 2: Comparisons on 3 large-scale datasets. We denote ‘ImageNet’ as ‘IN’ for simplicity.

| Method | Close Set ACC | | | Open Set AUROC | | | Additional Params |
|--------|---------------|---|---|---------------|---|---|
|        | IN-LT | IN-100 | IN-200 | IN-LT | IN-100 | IN-200 | IN-LT | IN-100 | IN-200 |
| Softmax | 37.8 | 81.7 | 79.7 | 53.3 | 79.7 | 78.4 | 0 | 0 | 0 |
| CPN     | 37.1 | 86.1 | 82.1 | 54.5 | 82.3 | 79.5 | 2M | 0.2M | 0.4M |
| RPL     | 39.0 | 81.8* | 80.7* | 55.1 | 81.2* | 80.2* | 2M | 0.2M | 0.4M |
| RPL++   | 39.7 | - | - | 55.2 | - | - | 4M | - | - |
| PMAL    | **42.9** | **86.2** | **84.1** | **71.7** | **94.9** | **93.9** | 0 | 0 | 0 |

✓ More obvious advantages on complicated scenarios
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Contact E-mail: lujing6@hikvision.com  Jing Lu

Our Team Homepage: https://davar-lab.github.io/