Out-of-Distribution Detection Using Union of 1-Dimensional Subspaces

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https://github.com/zaeemzadeh/OOD
https://github.com/mmlab-cv/OOD_video
Out-of-distribution Detection

The goal of *out-of-distribution (OOD)* detection is to handle novel situations.

*How can we make the in-distribution samples more distinguishable from OOD samples with unknown distribution?*
OOD Detection Using Union of 1D Subspaces

- Distribution-agnostic minimization of error
- No need for OOD samples to tune hyperparameters
- Does not rely on sample generation or reconstruction
- Easy to implement
- Modality-independent
Distribution-Agnostic Minimization of Error Probability

- Consider a binary classification problem:
- If one of the classes is degenerate, the detection can be performed with zero error probability.
Distribution-Agnostic Minimization of Error Probability

\( p_i \): The probability that the sample belongs to \( \mathcal{N}(\mu_i, \Sigma_i) \)

\( p_o \): The probability that the sample belongs to \( \mathcal{N}(\mu_o, \Sigma_o) \)

\[ \Delta = \mu_i - \mu_o \]

\[ B = \frac{1}{8} \Delta^T \left( \frac{\Sigma_i + \Sigma_o}{2} \right)^{-1} \Delta + \frac{1}{2} \ln \left( \frac{\det \left( \frac{\Sigma_i + \Sigma_o}{2} \right)}{\sqrt{\det(\Sigma_i) \det(\Sigma_o)}} \right) \]

The classification error probability can be upper bounded by

\[ p_e \leq \sqrt{p_i p_o} e^{-B} \]

The probability of error can be decreased by making the distribution of the known classes as compact as possible (e.g. 1D subspace).
OOD Detection Using Union of 1-Dimensional Subspaces

Deep Feature Extractor

Feature vectors for class $l$

Union of 1-dimensional subspaces embedding

Spectral discrepancy

$p(\phi_n \leq \phi^* | \mathbf{i}_n)$

OOD Test

OOD sample or not

Monte Carlo Sampling

SVD

Orthogonality constraint

$\mathbf{w}_l^T \mathbf{w}_{l'} = 0, l \neq l'$

Cosine Similarity

$\mathbf{w}_l^T \mathbf{x}_n / \|\mathbf{w}_l\| / \|\mathbf{x}_n\|$

Softmax

Label $l$

Training Set

Testing Sample $\mathbf{i}_n$

Training

Testing
Experiments

3-dimensional visualization of the features extracted from CIFAR10

- Training Set
  - w/o Cosine similarity
  - w/ Cosine similarity
  - w/ Cosine similarity (normalized)

- Test Set
  - In-distribution
  - Out-of-distribution
Experiments: Image Classification

The proposed spectral discrepancy measure can effectively distinguish between the ID (CIFAR10) and OOD samples.

AUROC: Area under receiver operating characteristic curve
AUPR: Area under precision recall curve
FPR/TPR: False/True Positive Rate

OOD detection can be improved by making the known classes as compact as possible.
### Experiments: Video Classification

Our method can generalise for multiple modalities (images, videos)

New baseline for OOD detection on action recognition in videos on UCF 50 and UCF 101 datasets

<table>
<thead>
<tr>
<th>Training dataset</th>
<th>OOD dataset</th>
<th>FPR at 95% TPR</th>
<th>Detection Error</th>
<th>AUROC</th>
<th>AUPR In</th>
<th>AUPR Out</th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Down</td>
<td>Up</td>
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<td>UCF51</td>
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<td>36.8/36.1/30.0</td>
<td>66.0/68.3/75.7</td>
<td>89.8/90.1/74.3</td>
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<td>HMDB26</td>
<td>82.0/85.2/84.5</td>
<td>41.8/44.5/40.8</td>
<td>59.7/56.4/61.9</td>
<td>88.9/87.6/65.4</td>
<td>20.4/19.7/56.6</td>
</tr>
</tbody>
</table>
Conclusions

- We can improve the OOD detection performance by engineering the distribution of in-distribution samples.
- Our approach does not have hyperparameters, does not need extra information, and can be easily applied to existing methods with minimal change.
- Our approach is modality-independent and can be applied to different input types.
Thank You!

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