Latent Space Autoregression for Novelty Detection

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1. Problem Statement

Novelty detection is defined as the discrimination of new samples that significantly differ from training data. In this work, we focus on the semi-supervised setting, where the novelties are the ones exhibiting significantly different traits w.r.t. an underlying model of regularity, built from a collection of normal samples.

2. Model

Our model leverages an auto-encoding architecture, composed by:
- an encoder \( f(x; \theta_f) : \mathbb{R}^m \rightarrow \mathbb{R}^d \);
- a decoder \( g(z; \theta_g) : \mathbb{R}^d \rightarrow \mathbb{R}^m \);
- an estimator \( h(z; \theta_h) : \mathbb{R}^d \rightarrow [0,1] \).

Objectives:
\[
\mathcal{L} = \mathcal{L}_{REC}(\theta_f, \theta_g) + \lambda \mathcal{L}_{LLK}(\theta_f, \theta_h)
\]

\[
= E_{p(x)} [||x - \hat{x}||^2 + \lambda \log(h(z; \theta_h))]
\]

reconstruction term

log-likelihood term

3. Autoregression

Autoregressive models factorize the joint density function on \(d\) variables through the chain rule of probability:
\[
p(x) = \prod_{i=1}^{d} p(z_i|x_{<i})
\]

We introduce the Masked Fully Connection (MFC) and Masked Stacked Convolution (MSC) layers enforcing an autoregressive procedure within the estimator \(h(z; \theta_h)\).

4. Entropy Regularization

The \(\mathcal{L}_{LLK}\) objective leads to the minimization of the differential entropy underlying the encoding distribution.

5. Video Anomaly Detection

Results on the UCSD Ped2 and ShanghaiTech datasets are reported as Area Under ROC Curve (AUROC).

<table>
<thead>
<tr>
<th>UCSD Ped2</th>
<th>ShanghaiTech</th>
</tr>
</thead>
<tbody>
<tr>
<td>ConvAE [1]</td>
<td>0.850 0.609</td>
</tr>
<tr>
<td>Hinami et. al [2]</td>
<td>0.922 -</td>
</tr>
<tr>
<td>TSC [4]</td>
<td>0.910 0.679</td>
</tr>
<tr>
<td>Stacked RNN [4]</td>
<td>0.922 0.680</td>
</tr>
<tr>
<td>FFP [3]</td>
<td>0.945 -</td>
</tr>
<tr>
<td>FFP+MC [3]</td>
<td>0.954 0.728</td>
</tr>
<tr>
<td>Ours</td>
<td>0.954 0.725</td>
</tr>
</tbody>
</table>

6. One-Class Novelty Detection

We test the model in one class settings, training it on each class of either MNIST or CIFAR-10 separately. We report the comparison in terms of average AUROC.

7. DR(eye)VE Outlier Detection

We measure the correlation about the novelty score and the attentional shifts labeled in the DR(eye)VE dataset.

8. Model Analysis

We compare MFC and MSC against recurrent layers.

<table>
<thead>
<tr>
<th>CIFAR-10</th>
<th>UCSD Ped2</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSTM[100]</td>
<td>0.623 0.849</td>
</tr>
<tr>
<td>LSTM[32,32,32,100]</td>
<td>0.622 0.845</td>
</tr>
<tr>
<td>MFC[100]</td>
<td>0.625 0.849</td>
</tr>
<tr>
<td>MFC[32,32,32,100]</td>
<td>0.641 0.954</td>
</tr>
</tbody>
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References