Divergence-Based One-Class Classification Using Gaussian Processes

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One-class classification (OCC)

- Given: a set of only positive training samples of a single class
- Goal: estimate a soft membership score for a test sample
- Why?: negative data is difficult to model or is hard to obtain

Aim of this work

- Shed light on one-class classification from a completely different theoretical perspective
- Measure how strongly a new test sample would influence the current model if it was used for training
- Estimation of model change by comparing reclassification results
- Probabilistic framework based on information theory

Gaussian process regression [RW06]

- Continuous outputs $y_*$ are assumed to be generated according to:
  $$y_*(x) = f(x) + \epsilon$$
  \(f\) ... latent function, \(\epsilon\) ... noise term
- Output values of unknown samples $x^*$ are predicted in a probabilistic fashion by marginalising over latent functions $f$

Assumptions:

1. Latent functions $f$ are drawn from a Gaussian process prior with mean function being zero and covariance function $k_f(\cdot, \cdot)$
2. The noise term is normally distributed: $\epsilon \sim \mathcal{N}(0, \sigma_n^2)$

⇒ Predictive output value $y_*$ for a new sample $x^*$ given the data $D^*$ is normally distributed as well:
$$y^*_\epsilon = k_f^T(K + \sigma_n^2 I)^{-1}k + \sigma_n^2$$

⇒ Label regression for OCC [KRD10]: GP-Mean, GP-Var, GP-Pred

Divergence-based one-class classification

- Assumed label of test sample: $y^* \in \{-1, 1\}$
- Reclassification result of test sample: $Y^* \in \{-1, 1\}$
- Influence of test sample on current model via conditional mutual information:
$$I(Y^*, y^* \mid D^*) = H(Y^* \mid D^*) - H(Y^* \mid y^*, D^*)$$

Continuous outputs $y_*$

Conditional mutual information turns out to be equal to the Jensen-Shannon (JS) divergence:
$$I(Y^*, y^* \mid D^*) = \frac{1}{2} D_{KL}(p_* \mid \mid p_{\pi})$$

Experimental Results

- UCI datasets (best three results of each task are underlined)
<table>
<thead>
<tr>
<th>OCC method</th>
<th>Iris-Versicolor, Iris-Virginica</th>
<th>Sonar-Rocks</th>
<th>Sonar-Mines</th>
</tr>
</thead>
<tbody>
<tr>
<td>GP-Prob</td>
<td>0.783</td>
<td>0.969</td>
<td>0.765</td>
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<tr>
<td>bal. JS div.</td>
<td>0.993</td>
<td>0.967</td>
<td>0.942</td>
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<td>imbal. JS div.</td>
<td>0.984</td>
<td>0.968</td>
<td>0.773</td>
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<tr>
<td>Parzen [Bis06]</td>
<td>0.973</td>
<td>0.960</td>
<td>0.602</td>
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<td>SVDD [TD04]</td>
<td>0.986</td>
<td>0.922</td>
<td>0.609</td>
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<tr>
<td>GP-Mean [KRD10]</td>
<td>0.983</td>
<td>0.972</td>
<td>0.761</td>
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<tr>
<td>GP-Var [KRD10]</td>
<td>0.979</td>
<td>0.964</td>
<td>0.608</td>
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<tr>
<td>GP-Pred [KRD10]</td>
<td>0.980</td>
<td>0.968</td>
<td>0.624</td>
</tr>
</tbody>
</table>

ImageNet (Visual Object Recognition)

- One-class classification framework based on information theory
- Gaussian process probabilities are suitable for this framework
- Results comparable to state-of-the-art

Conclusions

- New one-class classification framework based on information theory
- Gaussian process probabilities are suitable for this framework
- Results comparable to state-of-the-art

References