Efficient Diverse Ensemble for Discriminative Co-Tracking

Kourosh Meshgi, Shigeyuki Oba, Shin Ishii
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Abstract

Addressed challenges of ensemble discriminative tracking:

- Creation: Random subsets of negative samples
- Diversity: Generating effective artificial samples
- Stability-Plasticity: Dual memory + query optimization
- Model Drift: Online bagging + artificial samples

Promoting Diversity

<table>
<thead>
<tr>
<th>Ensemble</th>
<th>Empirical Sample Distribution</th>
<th>$N(x, \sigma^2_x)$</th>
<th>$x_0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta(1)$</td>
<td>Artificial Sample Generator</td>
<td>$\theta(1</td>
<td>x, y_1)$</td>
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<tr>
<td>$\theta(2)$</td>
<td>Diversifying Label Generator</td>
<td>$\theta(2</td>
<td>x_0, y_1, y_2)$</td>
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<td>$\theta(i)$</td>
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COLLABORATIVE CLASSIFICATION

Using active learning to select which samples to query from long-memory auxiliary classifier, based on the uncertainty metric

- Gaining generalization and speed-up by querying only the most informative samples from the long-memory complex classifier
- Balances between long and short term memory automatically
- Reduce label classification uncertainty
- Breaks learning loop

BENEFITS OF ACTIVE CO-TRAINING

- Accurate (Comparable with state-of-the-art)
- Reliable (Graceful degradation)
- Real-time Processing (~22 fps)
- Robust (High performance under various challenges)
- Compatible with Embedded Systems

TRACKER PROPERTIES

- Compatible with Embedded Systems
- Reliable (Graceful degradation)
- Real-time Processing (~22 fps)
- Robust (High performance under various challenges)
- Adaptive (Robustness)

Results

- The effect of different update schemes: bagging, artificial diversity data, both.
- The effect of the `testness` parameter, balancing variability-plasticity equilibrium.

References:


Tracker Concept

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<th>COLLABORATIVE CLASSIFICATION</th>
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Benefits of Active Co-Training

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