L1-regularized Logistic Regression Stacking and Transductive CRF Smoothing for Action Recognition in Video

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http://www.micc.unifi.it/vim/people
101 Classes, 5 types: Human-Object Interaction, Human-Human Interaction, Body-Motion Only, Playing Musical Instruments, Sports.

13320 videos (25 groups)

Pre-computed and pre-encoded (hard-assigned 4000 BoW) low-level features: STIP, Dense Trajectory Features (MBH, HOG, HOF, TR)

3 splits: 2/3 train, 1/3 test (disjoint groups in train/test)
Introduction

Our game plan and our goals

- **Priority**: establish a working BOW pipeline on given hard assigned coded features (MBH, HOG, HOF, STIP, TR) to establish our baseline
- **Limitations**:
  - Loss due of hard assignment
  - No contextual features
  - Lots and lots of classes and features, unclear how to fuse
- **Goal 1**: improve the features in our baseline
  - Use better encoding of provided features (after re-extraction)
  - Add static contextual features extracted from keyframes
- **Goal 2**: experiment with fusion schemes
  - Regularized stacking of experts
  - Transductive smoothing of expert outputs
- Note we did not use any external data or the provided attributes
Baseline with provided features (Run-1)

Run 1: a respectable baseline

- Late fusion (sum) of 1-vs-All SVM classifiers (Histogram Intersection Kernel) learned on $M = 5$ features

$$\text{class}(x) = \arg \max_c \sum_{f \in \mathcal{F}_{\text{org}}} E^f_c(x) \quad (1)$$

- Performance: 74.6% (Split1: 72.85%, Split2: 74.96%, Split3: 75.97%)
Better encoding of dense trajectories features

- Extraction of dense trajectories [Wang:2013]
  - On a modest cluster of 20 CPUs:
    - 5 nodes
    - Quad Core 2.7Ghz CPUs
    - 48GB Total RAM
  - Total time to extract: 25h
  - Disk usage: 660GB

- Extracted features:
  - Separate x- and y-components (MBHx and MBHy)
  - Standard concatenation of the two local descriptors (MBH).
  - Histogram of Gradients (HoG)

- Fisher encoding of all features independently:
  - 256 Gaussians with diagonal covariance
  - Gradients with respect to means and covariances
Is context relevant for action recognition?

- We extract the central frame of each video as keyframe
- Visualizing the mean keyframe each class is illuminating:
Is context relevant for action recognition?

- We extract the central frame of each video as keyframe
- Visualizing the mean keyframe each class is illuminating:
Additional contextual features

- Dense sampled Pyramidal-SIFT [Seidenari:2013] features (P-SIFT and P-OpponentSIFT) on keyframes
  - Pyramidal-SIFT: three pooling levels, corresponding to $2 \times 2$, $4 \times 4$, $6 \times 6$ pooling regions. Each level has its own dictionary: 1500, 2500 and 3000 words respectively.
  - Spatial pyramid configuration: 1x1, 2x2, 1x3
  - Locality-constrained Linear Coding and max pooling [Wang:2010]
Late fusion with all features (Run-2)

Run-2: more features, better encoding

- The Fisher encoded MBH, MBHx, MBHy, and the LLC encoded P-SIFT and P-OSIFT are fed to Linear 1-vs-all SVMs
- Combined with provided feature histograms: total of $M = 11$ features
- Performance: 82.46% (Split1: 81.47%, Split2: 83.01%, Split3: 82.88%) Run-1: 74.6%
Stacking

- Stacking: learn a classifier on top of the concatenation of expert decisions:
  \[
  S(x) = [E^j_i], \text{ for } j \in \{1, \ldots M\}, \ i \in \{1, \ldots N\} \tag{2}
  \]

- Having lots of class/feature experts makes THUMOS an excellent playground for this type of fusion approach.

- Our idea: use L1-regularized LR for class/feature expert selection.
Stacking

- Stacking: learn a classifier on top of the concatenation of expert decisions:

\[ S(x) = [E_i^j], \text{ for } j \in \{1, \ldots M\}, i \in \{1, \ldots N\} \]  

- Having lots of class/feature experts makes THUMOS an excellent playground for this type of fusion approach.
- Our idea: use L1-regularized LR for class/feature expert selection.
- **Doing it wrong:** decisions values on training samples from classifiers trained on those samples

![Train and Test](image)
Stacking

- Stacking: learn a classifier on top of the concatenation of expert decisions:
  \[ S(x) = [E_i^j], \text{ for } j \in \{1, \ldots M\}, i \in \{1, \ldots N\} \] (2)

- Having lots of class/feature experts makes THUMOS an excellent playground for this type of fusion approach.
- Our idea: use L1-regularized LR for class/feature expert selection.
- **Doing it right:** reconstruct the decisions on the training samples by running multiple held out training/test folds

(a) Train hold-out  
(b) Test
Logistic regression for stacking (Run-3)

**Run-3: L1 regularized logistic stacking**

- **Motivation:** smart weighted/selection scheme
- **Model** \((\beta_c, b_c)\) of class \(c\) obtained by minimizing the loss:

\[
(\beta_c, b_c) = \arg\min_{\beta, b} ||\beta||_1 + C \sum_{i=1}^{n} \ln(1 + e^{-y_i \beta^T S(x_i) + b})
\]  

(3)

- **Performance:** 84.44% (Split1: 83.70%, Split2: 85.56%, Split3: 84.07%) Run-2: 82.46%
Experts/Non-experts usage analysis

Analysis: easy/hard classes as mAP of their experts.
Experts/Non-experts usage analysis

- Easy classes rely more on their own experts, lower total energy
Experts/Non-experts usage analysis

- L1LRS model of “easiest” class: “Billiards”
Experts/Non-experts usage analysis

- Hard classes rely more on other classes experts, higher total energy
Experts/Non-experts usage analysis

- L1LRS model of “hardest” class: “Handstand Walking”
Features/Experts usage analysis

- L1LRS is able to select the most relevant features...
Features/Experts usage analysis

Features/Experts usage analysis

- Classes relying most on MBHx features: 14 - “Hammer Throw”, 4 - “Pommel Horse”, 1 - “Breaststroke”, 22 - “Throw Discus”, 60 - “Rowing”
Features/Experts usage analysis

Features/Experts usage analysis

... and L1LRS can also discard the least relevant features
Transductive labelling

- Obtain more consistent labelling using unsupervised local constraints. Previously applied to re-identification [Karaman:2012], first try on another task
- CRF defined as a graph $G = (\mathcal{V}, \mathcal{E})$ where $\mathcal{V}$ nodes (all samples) and $\mathcal{E}$ edges of a kNN graph. Energy minimization formulation:

$$W(\hat{c}) = \sum_{i \in \mathcal{V}} \phi_i(\hat{c}_i) + \lambda \sum_{(v_i, v_j) \in \mathcal{E}} \psi_{ij}(\hat{c}_i, \hat{c}_j),$$

(4)

- Data cost uses L1LRS output: \(\phi_i(\hat{c}_i) = e^{- (\beta^T \hat{x}_i S(x_i) + b \hat{c}_i)}\)
- Smoothness cost: \(\psi_{ij}(\hat{c}_i, \hat{c}_j) = \psi_{ij}(\hat{c}_i, \hat{c}_j)\)
  - Similarities between stacked expert outputs to create and weight the edges of k-NN graph: \(\psi_{ij} = \exp \left(- \frac{||S(x_i) - S(x_j)||_2}{\sigma_i \sigma_j} \right)\)
  - Label cost inversely proportional to confusability between labels: \(\psi(\hat{c}_i, \hat{c}_j)\)
Transductive labelling (Run-4)

Run-4: the whole shebang

- Energy minimization solved by Graph-Cut [Boykov:2001]
- Performance: 85.71% (Split1: 85.32%, Split2: 86.64%, Split3: 85.16%) Run-3: 84.44%
- Improves labeling of ambiguous samples given similar scores by several classifiers [Karaman:PR]
- Similar training and test samples in stacked feature space enable this

<table>
<thead>
<tr>
<th></th>
<th>( \mathcal{F}_{\text{org}} )</th>
<th>( \mathcal{F}_{\text{ours}} )</th>
<th>L1LRS</th>
<th>CRF</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Run-1</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
<td>74.6%</td>
</tr>
<tr>
<td>Run-2</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td>82.4%</td>
</tr>
<tr>
<td>Run-3</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td>84.4%</td>
</tr>
<tr>
<td>Run-4</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>85.7%</td>
</tr>
</tbody>
</table>

Table 1: Summary of our four runs.
## Results

<table>
<thead>
<tr>
<th>#</th>
<th>Participant</th>
<th>Avg.</th>
<th>Split 1</th>
<th>Split 2</th>
<th>Split 3</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>ID39 INRIA</td>
<td>85.900</td>
<td>84.734</td>
<td>85.862</td>
<td><strong>87.105</strong></td>
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<tr>
<td>2</td>
<td>ID40 Florence</td>
<td>85.708</td>
<td><strong>85.319</strong></td>
<td>86.642</td>
<td>85.164</td>
</tr>
<tr>
<td>3</td>
<td>ID35 Canberra</td>
<td>85.437</td>
<td>84.761</td>
<td>86.367</td>
<td>85.183</td>
</tr>
<tr>
<td>4</td>
<td>ID38 CAS-SIAT</td>
<td>84.164</td>
<td>83.515</td>
<td>84.607</td>
<td>84.368</td>
</tr>
<tr>
<td>5</td>
<td>ID25 Nanjing</td>
<td>83.979</td>
<td>83.111</td>
<td>84.597</td>
<td>84.229</td>
</tr>
<tr>
<td>6</td>
<td>ID34 UCF-BoyrazTappen</td>
<td>82.829</td>
<td>82.640</td>
<td>83.352</td>
<td>82.496</td>
</tr>
<tr>
<td>7</td>
<td>ID36 UCSD-MSRA-SJTU</td>
<td>80.895</td>
<td>79.410</td>
<td>81.251</td>
<td>82.025</td>
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<tr>
<td>8</td>
<td>ID28 USC</td>
<td>77.360</td>
<td>76.154</td>
<td>77.704</td>
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<tr>
<td>9</td>
<td>ID31 NII</td>
<td>73.389</td>
<td>71.102</td>
<td>73.671</td>
<td>75.393</td>
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<td>10</td>
<td>ID44 UNITN</td>
<td>70.504</td>
<td>70.446</td>
<td>69.797</td>
<td>71.270</td>
</tr>
</tbody>
</table>

Table 2: Top 10 results of the challenge.
Discussion

Conclusion
- Better encoding makes a big difference
- Logistic regression for stacking is interesting to leverage the power of several class/features experts
  - automatically adjust sparsity for easy/hard classes
  - select relevant class/features experts
- CRF incorporates local similarity constraints to obtain a more reliable labelling

Future works
- Test logistic regression for stacking with many class/features experts
- Spatial/temporal pooling
References

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