CMU-Informedia @ TRECVID 2014

Semantic Indexing

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Carnegie Mellon University

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People

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Outline

- Submission Review
- Going Beyond 60 concepts
  - Challenges
  - Theory
  - Implementations
- Summary
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Overview

• The training data is the same one used in 2013
  – IACC.1.tv10.training and IACC.1.A-C collections
• Our system includes:
  – Self-paced SVM pipeline (*discuss later in this talk*)
  – Deep Convolutional Neural Networks (DCNN)-based
Self-paced SVM Pipeline

- Individual feature performances on IACC.2.B.
  - Bow features: code book size 4,096, intersection kernel.
  - Fisher vector feature: dimension 109,056, linear kernel.
  - Intersection kernels

<table>
<thead>
<tr>
<th>Raw feature</th>
<th>Representation</th>
<th>infMAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIFT harris-laplace</td>
<td>Spatial Bow</td>
<td>0.0866</td>
</tr>
<tr>
<td>SIFT dense-sampling</td>
<td>Spatial Bow</td>
<td>0.1096</td>
</tr>
<tr>
<td>CSIFT harris-laplace [3]</td>
<td>Spatial Bow</td>
<td>0.0842</td>
</tr>
<tr>
<td>CSIFT dense-sampling [3]</td>
<td>Spatial Bow</td>
<td>0.0988</td>
</tr>
<tr>
<td>Improved Dense Trajectory [1]</td>
<td>Fisher Vector (non-spatial)[2]</td>
<td>0.1844</td>
</tr>
</tbody>
</table>

Self-paced SVM Pipeline

- Individual feature performances on IACC.2.B.
  - Bow features: code book size 4,096, intersection kernel.
  - Fisher vector feature: dimension 109,056, linear kernel.
  - Intersection kernel.

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</tr>
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- O1: Improved dense trajectory is the best single feature.
- O2: Dense-sampling seems to be better than harris-laplace.
Feature Fusion

• Feature fusion performances on IACC.2.B.
  – CMU_Run1: heuristic fusion + related concepts propagation + junk-frame removal.

<table>
<thead>
<tr>
<th>Raw feature</th>
<th>Comments</th>
<th>infMAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIFT</td>
<td>(harris + dense)</td>
<td>0.0963</td>
</tr>
<tr>
<td>CSIFT</td>
<td>(harris + dense)</td>
<td>0.0962</td>
</tr>
<tr>
<td>SIFT + CSIFT</td>
<td>Average fusion</td>
<td>0.1208</td>
</tr>
<tr>
<td>Improved Dense Trajectory</td>
<td>Fisher Vector (non-spatial)</td>
<td>0.1844</td>
</tr>
<tr>
<td>All Features Fusion</td>
<td>CMU_Run1</td>
<td>0.2265</td>
</tr>
</tbody>
</table>

• O3: SIFT and CSIFT offers complementary info to the motion features.
DCNN-based Pipeline

• Directly trained on keyframes.
  – Trained 347 concepts (346 + NULL)
  – Two strategies for unbalanced data:
    – Duplicate the positive training samples.
    – Not duplicate positive training samples.
    – Fusing the two result.

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<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>SIFT+CISFT</td>
<td>Self-paced SVM</td>
<td>0.121</td>
</tr>
<tr>
<td>DCNN-pipeline</td>
<td>DCNN-based</td>
<td>0.134</td>
</tr>
</tbody>
</table>

• **O4: DCNN-pipeline yields better performance than the static features fusion in SVM-pipeline [1], but not as good as improved dense trajectory (0.184).**

Main Submissions

Runs are under Type A condition (TRECVID data only)

- **CMU_Run1**: baseline run by Self-paced SVM pipeline.
- **CMU_Run2**: averages CMU_Run1 with DCNN-based pipeline on 15/60 concepts.
- **CMU_Run3**: CMU_Run2 + MMPRF [1] by visual and metadata feature.
- **CMU_Run4**: CMU_Run2 + weighted fusion (learned on the results on IACC.2.A)

<table>
<thead>
<tr>
<th>Run ID</th>
<th>infMAP</th>
<th>infNDCG</th>
<th>P@10</th>
<th>P@100</th>
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</thead>
<tbody>
<tr>
<td>CMU_Run1</td>
<td>0.2265</td>
<td>0.4660</td>
<td>0.6700</td>
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<td>CMU_Run2</td>
<td>0.2297</td>
<td>0.4710</td>
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<td>0.5683</td>
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<tr>
<td>CMU_Run3</td>
<td>0.2480</td>
<td>0.4975</td>
<td>0.7000</td>
<td>0.5900</td>
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<tr>
<td>CMU_Run4</td>
<td>0.2403</td>
<td>0.4844</td>
<td>0.6900</td>
<td>0.5730</td>
</tr>
</tbody>
</table>

- **O5**: MMPRF (MultiModal Pseudo Relevance Feedback) offers reasonable improvements (relative 8.0%, 1.8% absolute).
- **O6**: Weighted fusion yields reasonable improvements (relative 4.6%, absolute 1.1%).

Main Submissions

SIN14 submissions (Type A)

- CMU_RUN3
- CMU_RUN4
- CMU_RUN2
- CMU_RUN1

infM@P
No Annotation Submissions

- SVM models trained on web images retrieved by Bing.
- Maximum 1000 images for a concept.
- SIFT Feature + SVM RBF kernel.

<table>
<thead>
<tr>
<th>Run ID</th>
<th>Pipeline</th>
<th>infMAP</th>
<th>infNDCG</th>
<th>P@10</th>
<th>P@100</th>
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<tr>
<td>CMU_Run5</td>
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<td>0.0118</td>
<td>0.1099</td>
<td>0.1100</td>
<td>0.0757</td>
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<tr>
<td>CMU_Run6</td>
<td>no-annotation</td>
<td>0.0085</td>
<td>0.0956</td>
<td>0.0967</td>
<td>0.0680</td>
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</tbody>
</table>

- O7: Domain difference between still images and video shots is huge!
Observations

• **01:** Improved dense trajectory is the best single feature.
• **02:** Dense-sampling seems to be better than harris-laplace.
• **03:** SIFT&CSIFT offers complementary info to the motion features.
• **04:** DCNN-pipeline yields better performance than the static features fusion in SVM-pipeline, but not as good as improved dense trajectory.
• **05:** MMPRF offers reasonable improvements.
• **06:** Weighted fusion yields reasonable improvements.
• **07:** Domain difference between still images and videos is huge!
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Motivation and Challenges

• SIN 14 task: 60 concepts on 200k shots.
• SIN Full: 346 concepts on 500k shots.
• What if we go beyond: 1,000 concepts on 1 million shots.

• Many larger shot-based datasets are out there:
  – Yahoo YFCC100M (0.8 million videos) with tags & descriptions.
  – Google Sports (1.1 million videos) with automatically generated labels.
  – Data are noisy and no clean ground-truth labels are available in both datasets.

• Everybody knows that more concepts are better.
  – Recognize more objects/scenes/actions in videos.
  – Usually lead to improvement on search and retrieval.

Motivation and Challenges

• Large-scale concept training is challenging:
  – How to train robust models on millions of shots efficiently?
  – How to handle the noisy big data (no clean labels)?

• Existing approaches:
  – Augmented CascadeSVM – CMU Informedia [1]
  – Cascade SVMs – MediaCCNY [2]
  – Negative Bootstrapping – MediaMill [3,4]
  – Unit Models – IBM [5]

Tackling the highly imbalanced data

- Augmented Cascade SVM.
- Select negative samples in a sequential manner based on the learned model.
Cons:
• Most are **heuristic** approaches (random sampling).
• **Ad-hoc strategies** for selecting samples.
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Self-paced Learning

- Curriculum Learning (Bengio et al. 2009) or self-paced learning (Kumar et al. 2010) is a recently proposed learning paradigm that is inspired by the learning process of humans and animals.
- The samples are not learned randomly but organized in a meaningful order which illustrates from easy to gradually more complex ones.

Self-paced Learning

- Easy samples to complex samples.
  - Easy sample $\rightarrow$ smaller loss to the already learned model.
  - Complex sample $\rightarrow$ bigger loss to the already learned model.

$$\int_0^T \frac{1}{g - kv} \, dv = 1$$
$$\int_0^T \frac{1}{g - kv} \, dt = \int_0^T dt$$
$$\int_{v_0}^{v(T)} \frac{1}{g - kv} \, dv = T$$
$$-\frac{1}{k} \ln |g - kv| \bigg|_{v_0}^{v(T)} = T$$
$$\ln \left| \frac{g - kv(T)}{g - kv_0} \right| = -kT$$
$$\frac{g - kv(T)}{g - kv_0} = e^{-kT}$$
Self-paced Learning

- Easy samples to complex samples.
  - Easy sample $\rightarrow$ smaller loss to the already learned model.
  - Complex sample $\rightarrow$ bigger loss to the already learned model.
Easy and Complex samples in Pascal VOC dataset

Easy training samples of “Chair” in Pascal VOC dataset

Complex training samples of “Chair” in Pascal VOC dataset

Similar observations are also found by the others (Lapedriza et al. 2013)

Easy and Complex samples in Google Image Search

Easy training samples of “Dog” returned by Google Image

Difficult training samples of “Dog” returned by Google Image
Self-paced Learning

- In self-paced learning, we optimize the following function:

\[
\arg \min_{w, v} \sum_{i=1}^{n} v_i L_i + f(v, \lambda)
\]

\(L_i\) : the loss for the \(i^{th}\) sample. Can be any loss in off-the-shelf model, e.g. SVMs neural networks.

\(v_i \in [0, 1]\) : the weight for the \(i^{th}\) sample.

The loss is discounted by a sample weight.
Self-paced Learning

- In self-paced learning, we optimize the following function:

\[
\arg \min_{w,v} \sum_{i=1}^{n} v_i L_i + f(v, \lambda) \quad v = [v_1, \ldots v_n]
\]

- The self-paced function determines a learning scheme on how models learn new samples.

- **Physically it corresponds to learning schemes that human use to learn different tasks.**
More Self-paced Functions

- **Binary:**
  \[ f(v; \lambda) = -\lambda \|v\|_1 \]

  \[ f(v; \lambda) = \lambda \left( \frac{1}{2} \|v\|_2^2 - \sum_{i=1}^n v_i \right) \]

- **Linear:**
  \[ f(v; \lambda) = \sum_{i=1}^n \zeta v_i - \frac{\zeta v_i}{\log \zeta} \]

  \( \zeta = 1 - \lambda, (0 < \lambda < 1) \)

- **Logarithmic:**
  \[ f(v; \lambda) = -\zeta \sum_{i=1}^n \log(v_i + \frac{\zeta}{\lambda}) \]

  \( \zeta = \frac{\gamma \lambda}{\lambda - \gamma}, (\lambda > \gamma > 0) \)

- **Mixture:**
  \[ f(v; \lambda, \gamma) = -\lambda \|v\|_1 - \gamma \|v\|_{2,1} \]


*Function is non-convex but still can find optimal.
Learning with Diversity
Learning with Diversity

• Learning easy samples:

\[ f(v; \lambda) = -\lambda \|v\|_1 \]

Learning with Diversity

- Learning easy and diverse samples[1]:
  \[ f(\mathbf{v}; \lambda, \gamma) = -\lambda\|\mathbf{v}\|_1 - \gamma\|\mathbf{v}\|_{2,1} \]

Learning with Diversity

• Learning easy and diverse samples[1]:

\[ f(v; \lambda, \gamma) = -\lambda \|v\|_1 - \gamma \|v\|_{2,1} \]

The self-paced function determines a learning scheme on how models learn new samples.

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Practical lessons

• Training a quadratic programming problem with linear kernel
  – Primal (to obtain the parameters in the original space)
  – Dual (to obtain the support vectors)
• For nonlinear kernels, apply explicit feature mapping[1].

## Practical lessons

<table>
<thead>
<tr>
<th>Primal</th>
<th>Dual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficient in testing</td>
<td>Efficient in training with pre-computed kernel (preferred in shared memory)</td>
</tr>
<tr>
<td>Low memory usage</td>
<td>Minimum duplicate computation</td>
</tr>
<tr>
<td></td>
<td>Good for high-dimensional dense vector</td>
</tr>
</tbody>
</table>

- It used to take 60 days on 1000 cores to extract SIN features for 100k videos using dual form. Now it takes **1 day on 32 cores using primal form**.

- Pre-compute kernel → Training (dual form) → Testing (primal)
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Conclusions

• We have built tools for shot-based concepts training on big data.
  – Suppose we have 500 concepts each of which has 1,000 positive videos (500,000 in total).
  – Using the improved dense trajectory feature (best single feature with 100k dimension).
  – We can finish the training within 48 hours on 512 CPU cores.
  – After getting the models, the prediction for a shot/video only takes 0.125s on a 16-core machine with 16GB memory.

• The feature extracted by this pipeline can be used for some other tasks e.g. multimedia event detection (more tomorrow).
THANK YOU.

Q&A?
APPENDIX
Practical Discussions

- Practical lessons for applying self-paced learning in your problems:
  - Choose reasonable starting values using prior knowledge[1].
  - Pace positive/negative separately for unbalanced data.
  - Pace the age parameter so that it includes a certain number of samples for the next iteration.
  - Use reasonable validation sets to determine the optimal age of the final model (when to stop), which follows a similar distribution as the test set. Physically it corresponds to mock exams used to evaluate the learning progress.