University of Amsterdam's Deep Net for Video Event Detection

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Summary



Top performance for example-based event detection tasks.

This talk



This talk



Starting point

Google's Inception Network [Szegedy et al. CVPR 2015].

- Very deep network with inception modules.
- Trained with standard ImageNet setup.
- 1.2 million images from 1,000 classes.



Observation

Not all 1,000 classes are equally relevant for event detection.

Only 8% of complete ImageNet hierarchy is used.

- Full ImageNet hierarchy contains 14 million images from 21,841 classes.

We leverage the complete ImageNet hierarchy for training.

Problems with the complete hierarchy

Imbalance in image distribution.

- 'Yorkshire terrier' has 3047 examples.
- 296 classes have 1 example.



Yorkshire terrier

Over-specific classes for event detection.

- *'siderocyte'* and *'gametophyte'* not likely to be relevant for event detection.





Siderocyte





Proposal 1: <u>Roll up</u> all classes with only 1 child.



Proposal 2: <u>Bind</u> all subtrees with less than 3000 examples.



Proposal 3: <u>Promote</u> all classes with less than 200 examples.





Sauce

Proposal 4: <u>Sample</u> for classes with more than 2000 examples.

Advantages of our proposal

1. All images in the ImageNet hierarchy are used.

2. Over-specific and small classes are merged with their parents.

3. Compact semantic frame representations (12,988 classes).

This talk



Pooling: Main idea

An event video is an interplay of sub-events.

Birthday Party



We aim to pool over individual sub-events, not average over all.

Algorithm overview

Find the most discriminative fragments from training videos.

Encode a video using a score for each discriminative fragment.

Step 1: Propose

Training video



Step 2: Select

Step 3: Encode

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Experiments



Experiment 1: AlexNet vs. GoogleNet



GoogleNet outperforms AlexNet.

Experiment 2: 1,000 vs. all ImageNet classes



GoogleNet outperforms AlexNet.

Using all ImageNet classes helps.

Experiment 3: Our ImageNet reorganization



GoogleNet outperforms AlexNet.

Using all ImageNet classes helps.

We do better than directly using all classes.

Our feature vector is twice as small.

Experiment 4: 100 Example results



GoogleNet outperforms AlexNet.

Using all ImageNet classes helps.

We do better than directly using all classes.

Our feature vector is twice as small.

Idem for 100 Examples.

Experiment 5: Average pooling vs. Bag-of-Fragments

MED 2014 100 Examples:

Method	AlexNet [ICMR results]	GoogleNet [new results]
Averaging	0.232	0.351
Bag-of-Fragments	0.276	0.317
Combination	0.373	0.381

Bag-of-Fragments is both competitive and complementary to average pooling.

TRECVID 2015: 10 Examples



Fusion:

- Deep Net with averaging.
- Motion (MBH with Fisher Vectors).
- Audio (MFCC with Fisher Vectors).

Results:

- Our fusion yields top result.
- 'Deep Net only' already near top.

TRECVID 2015: 100 Examples



Fusion:

- Deep Net with averaging.
- Deep Net with Bag-of-Fragments.
- Motion (MBH with Fisher Vectors).
- Audio (MFCC with Fisher Vectors).

Results:

- Our fusion yields top result.
- 'Deep Net only' second place.

Conclusions

Training on organized ImageNet hierarchy helps event detection.

Bag-of-Fragments yields complementary video representations.

Contact information

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