

Learning TRECVID'08 High-level Features from YouTube

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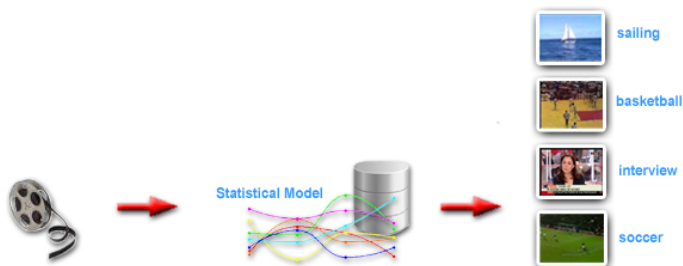
Motivation

Online Video Concept Detection

TRECVID'08 Experiments

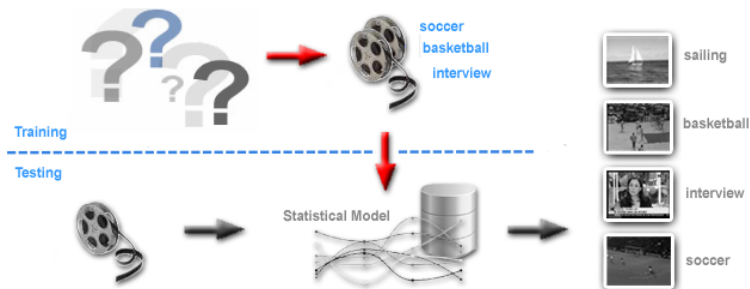
More Experiments

Discussion



Detection of generic semantic concepts in video

- ▶ objects ("US flag"), locations ("desert"), events ("interview")
- ▶ main application: video search



Key issue - training data acquisition

- ▶ training sets must be large-scale and annotated

- ▶ high-quality manual annotations
- ▶ TRECVID [Smeaton06], Mediamill [Snoek06], LSCOM [naphade06], ...
- ▶ detectors exist for 100s of concepts

- ▶ high-quality manual annotations
- ▶ TRECVID [Smeaton06], Mediamill [Snoek06], LSCOM [naphade06], ...
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Limitations

- ▶ need to scale up further
(1,000s of concepts [Hauptmann07])
- ▶ annotations are bound to a dataset
- ▶ annotations are static

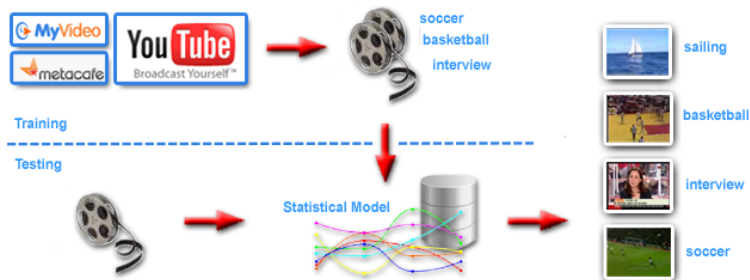
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Idea: use **online video** as training data

- ▶ tags provided by users are used as annotations
- ▶ video taggers can learn autonomously

Benefits

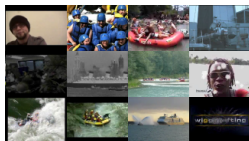
- ▶ scalability: can scale up to 1,000s of concepts
- ▶ flexibility: web community keeps content up-to-date

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Problems

- ▶ web video is a mixture of domains with varying **production style** (TV news, home video, music clips, ...)
- ▶ annotations are **coarse** and **weak**
- ▶ (*for benchmarking*) potential **mismatch** between TRECVID and YouTube concepts.



YouTube



YouTube (filtered)



TRECVID

How Well Do Concept Detectors Trained on YouTube Work?

Key Idea

- ▶ use a standard concept detection approach (visual words + SVM)
- ▶ train it on YouTube and on a standard dataset (TRECVID-devel)
- ▶ benchmark both detectors

Experiments

1. participation in TRECVID'08
2. further experiments: TV05, TV07, YouTube

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- ▶ Keyframe Extraction
 - ▶ adaptive clustering [Borth08]
- ▶ Features: Bag-of-visual-words
 - ▶ dense sampling over several scales (ca. 3,600 features / frame)
 - ▶ SIFT descriptors
 - ▶ 2,000-means clustering to codebook
- ▶ Classifier: SVMs
 - ▶ χ^2 kernel
 - ▶ cross-validation for γ and C maximizing avg. prec.
 - ▶ roughly balanced training sets (downsample negative class)
- ▶ Fusion over keyframes
 - ▶ simple averaging

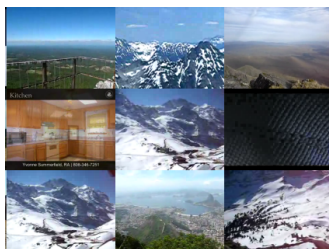
- ▶ Test
 - ▶ standard TV'08 test data

- ▶ Training 1: TV'08
 - ▶ standard TV'08 training data
- ▶ Training 2: YouTube
 - ▶ downloaded using the YouTube API
 - ▶ 100 videos per concept of up to 3 min. length
 - ▶ two refinements:
 1. **by category**: mountain →
 mountain[travel&places]
 2. **manually**: mountain[travel&places] →
 mountain+panorama[travel&places]

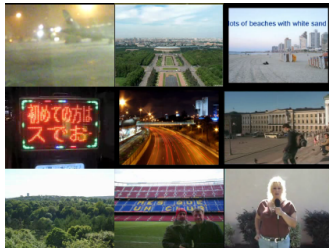
TRECVID



YouTube



mountain



cityscape

TRECVID



YouTube



singing



telephone

Top detections of YouTube-based detector

mountain



cityscape

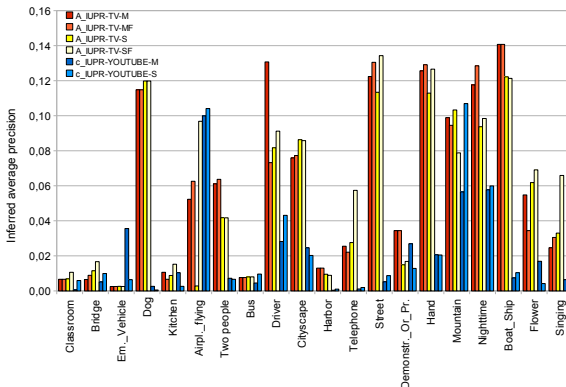


singing



telephone





- ▶ infMAP for TRECVID runs: 5.3-6.3 %
- ▶ infMAP for YouTube runs: 2.1-2.2 %
- ▶ *performance strongly depends on the concept*

Concept “Dog”:



TRECVID training “dogs”



detected TRECVID test “dogs”

- ▶ specialized detectors make use of **duplicates** in the dataset
- ▶ the YouTube-based tagger cannot do this

if annotations on the target domain are given, specialized detectors outperform YouTube-based ones in terms of MAP.
Influence of Duplicates?

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Goal: Compare YouTube-based detectors with standard ones on a third target domain where no annotations are given!

- ▶ Approach / Concepts: *see last experiments*
- ▶ Datasets:
 1. **TV05**: TRECVID'05 video data with LSCOM annotations
 2. **TV07**: TRECVID'07 video data with TRECVID'08 annotations
 3. **YouTube**: *see last experiment*

Setup

- ▶ split each dataset for training and testing
- ▶ train on all datasets → 3 detectors
- ▶ **test each detector on all 3 datasets**

MAP[%]			
training / testing	TV05	TV07	YOUTUBE
TV05	18.40	3.82	14.68
TV07	3.32	9.65	16.49
YOUTUBE	2.83	3.51	31.33

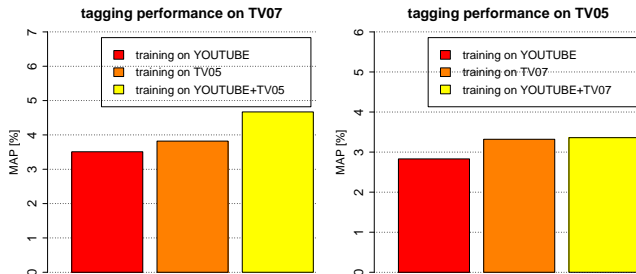
- ▶ specialized detectors always perform best! (*also for YouTube*)
- ▶ all detectors generalize poorly!
- ▶ in-depth analysis: duplicates in all datasets

MAP[%]			
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- ▶ the relative performance loss for the YouTube-based detector is moderate (11.4%)

Enhancing standard training sets with YouTube material

- ▶ join two datasets, test on third one



- ▶ **Combining training sets with YouTube material slightly increases generalization performance (11.7%)**

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YouTube helps on domains with **no training annotations** when...

- ▶ ... **replacing** standard datasets (11.4% performance loss, but autonomous training)
- ▶ ... **complementing** standard datasets (11.7% increase in generalization capabilities)
- ▶ more: [TRECVID Notebook Paper], [adrian.ulges@dfki.de]

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- ▶ more: [TRECVID Notebook Paper], [adrian.ulges@dfki.de]

Issues

- ▶ Scaling to 1000 tags?
- ▶ Adapting YouTube-based detectors to other target domains?

Thanks for Your Attention!

(thanks also to Marcel Worring and Alexander Hauptmann for helpful discussions!)

- ▶ [Smeaton06]: A. Smeaton, P. Over, W. Kraaij. *Evaluation Campaigns and TRECVID*. MIR 2006.
- ▶ [Snoek06]: C. Snoek, M. Worring, J. van Gemert, J. Geusebroek, A. Smeulders. *The Challenge Problem for Automated Detection of 101 Semantic Concepts in Multimedia*. Multimedia 2006.
- ▶ [Naphade06]: M. Naphade, J. Smith, J. Tesic, S. Chang, W. Hsu, L. Kennedy, A. Hauptmann, J. Curtis. *Large-Scale Concept Ontology for Multimedia*. IEEE Multimedia, 2006.
- ▶ [Hauptmann07]: A. Hauptmann, R. Yan, W. Lin. *How many High-Level Concepts will Fill the Semantic Gap in News Video Retrieval?*. CIVR, 2007.
- ▶ [Ulges08]: A. Ulges, C. Schulze, D. Keysers, T. Breuel. *A System that Learns to Tag Videos by Watching Youtube*. ICVS, Santorini, 2008.
- ▶ images taken from: [youtube,TRECVID datasets]