Large-scale Video Classification with Convolutional Neural Networks

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Presenter: Esha Uboweja
Problem
Classification of videos in sports datasets
Standard approach to video classification

Bag of Words (BoW) approach:

1. Extraction of local visual features (dense/sparse)
2. Visual word encoding of features
3. Training a classifier (e.g. SVM)

Convolutional Neural Networks (CNNs) emulate all these stages in a single neural network
Motivations for using CNNs for video classification

1. CNNs outperform other approaches in image classification tasks (e.g. ImageNet challenge)

2. Features learned in CNNs transfer well to other datasets (e.g. fine-tuning top layers of a network trained using ImageNet for food recognition)
Current video datasets lack variety and number of videos to train a CNN:

UCF 101 dataset : 13,320 videos, 101 classes

KTH (human action) : 2391 videos, 6 classes

Sports-1M dataset : 1.1 million videos, 487 classes (new!)
Models
Baseline CNN

Krizhevsky et al. ’12
Baseline CNN

Goal: Extend 2D convolutional layers to 3D to learn spatio-temporal filters

Call this **Single-frame baseline**
Temporal Fusion in CNNs

Modify 1st convolutional layer to be of size $11 \times 11 \times 3 \times T$ pixels

$T = \# \text{ frames (authors use 10)}$
Temporal Fusion in CNNs

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2 single-frame networks 15 frames apart merge in 1st fully connected layer

The fully connected layer can compute global motion characteristics
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The fully connected layer can compute global motion characteristics

Spatial + temporal convolutions, and higher layers get more global information
Multiresolution CNNs

To improve runtime performance:
Input = 178 x 178 frame video clip

Low-Res Context stream gets down sampled 89 x 89 (entire frame)
High-Res Fovea stream gets cropped center 89 x 89 patch
Both streams merge in 1st fully connected layer
Multiresolution CNNs

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Input = 178 x 178 frame video clip

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Both streams merge in 1st fully connected layer
Train Procedure

1. Randomly sample a video

2. Sample a 15 frame (~0.5 secs) clip from (1)

3. Randomly crop, flip frames in clip, subtract mean of all pixels in images (data augmentation + preprocessing)

Test Procedure is similar
Experiments
Feature Histogram Baseline

1. Extraction of local visual features:
   HoG, Texton, Cuboids, Hue-Saturation, Color moments, #Faces detected

2. Visual word encoding of features:
   Spatial pyramid encoding in histograms after k-means: Finally obtain a 25,000 D feature vector for the entire video

3. Training a classifier:
   Use a 2-hidden layer neural net (worked better than any linear classifier)
Testing Procedure

1. Randomly sample 20 clips for a given test video

2. Present each clip individually to the network (with different crops and flips)

3. Individual clip class predictions are averaged to get a class result for the entire video
Results on Sports-1M dataset
Video Results

https://www.youtube.com/watch?v=qrzQ_AB1DZk

Cycling

Basketball
Quantitative Results

- Baseline: 55.3
- Single Frame: 59.3
- Single Frame + Multires: 60.0
- Time-fusion: 60.9
- CNN Average: 63.9
Qualitative Results

1. The confusion matrix shows that the network doesn’t do well on fine-grained classification.

2. Slow-fusion networks are sensitive to small motions, hence “motion-aware”, but don’t work well with presence of camera translation and zoom.
Transfer Learning
UCF-101 dataset

5 main categories of data

1. Human Object Interaction
2. Body-Motion only
3. Human-Human interaction
4. Playing Musical Instruments
5. Sports

Soomro et al. ’12
Transfer learning to Sports data in UCF 101 Results

- Soomro et al: 43.9
- Baseline: 59
- Fine-tune top layer: 64.1
- Fine-tune top 3 layers: 65.4
- Fine-tune all layers: 62.2
- Train CNN from scratch: 64.1
Discussion