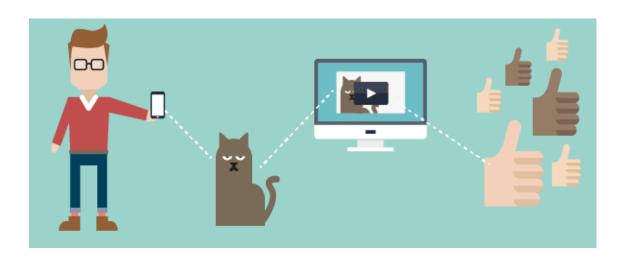
Action and Event Recognition

Zuxuan Wu

Massive Videos









AnwseringPhone FightingPerson GetingOutOfCar







Running



Birthday



Graduation



Parade



WeddingCeremony



CarAccidents



ChangingTire

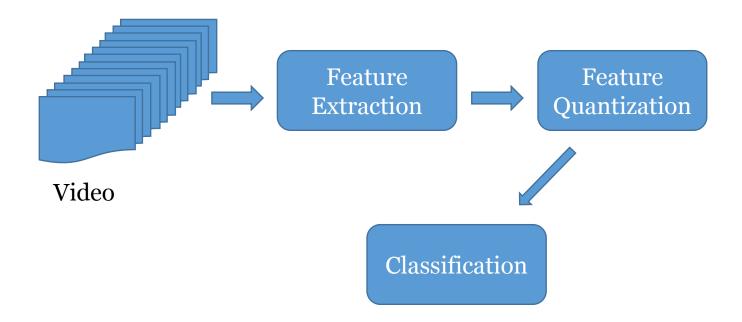


MakingPizza



PitchingTent

Visual Recognition Pipeline



Features

Videos are naturally *multimodal*

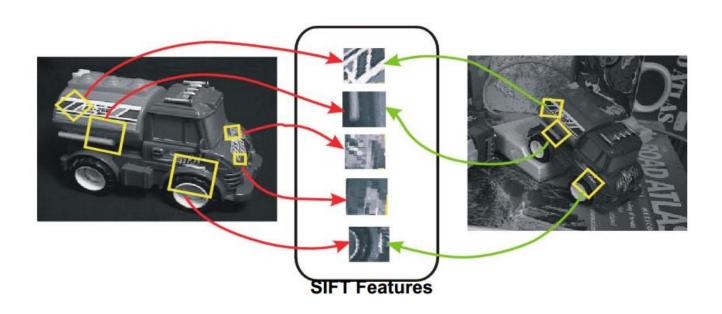
- Static Appearance Features
- Motion Features
- Acoustic Features
- High-level Features

Static Appearance Features

- Captures Static Appearance Information In *Each Frame*
 - > shape
 - > edge
 - > color
 - > even high-level appearance information
- Frame-level Features are averaged to generate Video-level representation

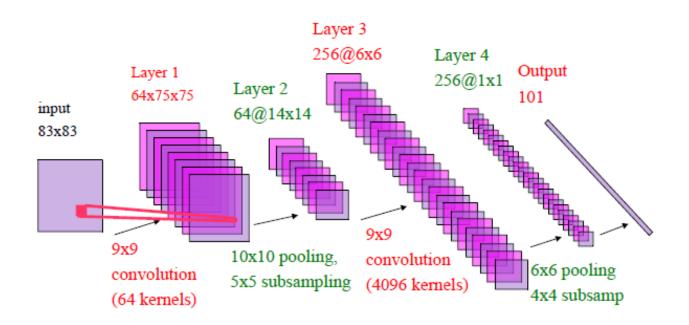
Static Appearance Features: SIFT

IDEA: Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters



Convolutional Neural Network Recap

CNN is a model of Deep Learning; Unlike hand-crafted features, CNN learn features from raw images



Convolutional Neural Network Recap

CNN is a model of Deep Learning; Unlike hand-crafted features, CNN learn features from raw images



Convolutional Neural Network Recap

ImageNet Challenge 2012

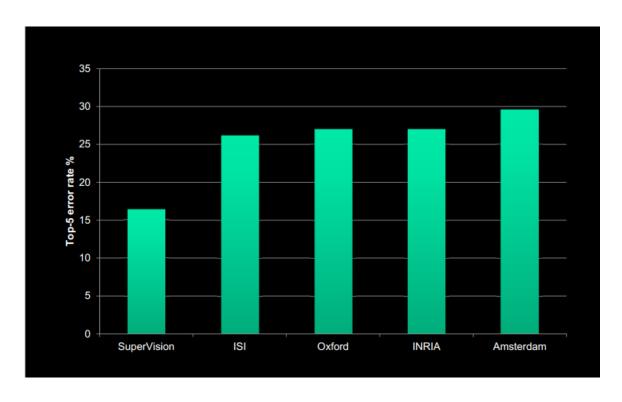


[Deng et al. CVPR 2009]

- ~14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon Turk
- Challenge: 1.2 million training images, 1000 classes

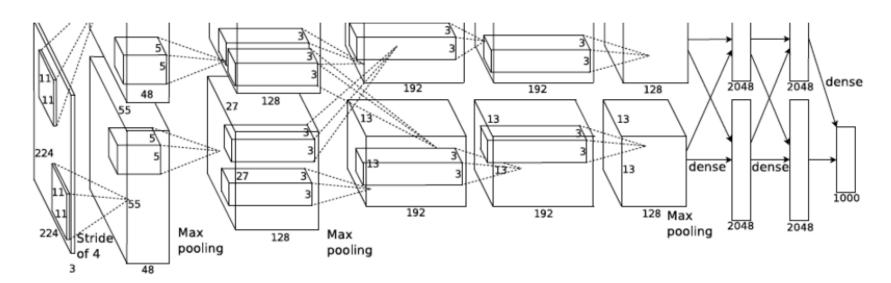
Convolutional Neural Network outperforms significantly

- Krizhevsky et al. -- 16.4% error (top-5)
- Next best (non-convnet) 26.2% error



Convolutional Neural Network outperforms significantly

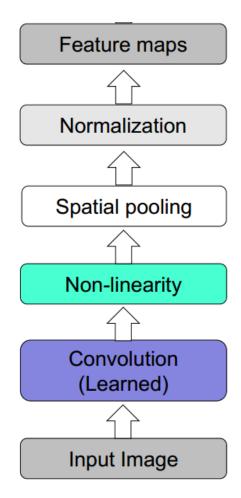
- Krizhevsky et al. -- 16.4% error (top-5)
- Next best (non-convnet) 26.2% error



Pre-trained On ImageNet
The Last 3 layers can be viewed as *features*

Convolutional Neural Network feature extraction

- Feed-forward feature extraction:
- 1. Convolve input with learned filters
- 2. Non-linearity
- 3. Spatial pooling
- 4. Normalization



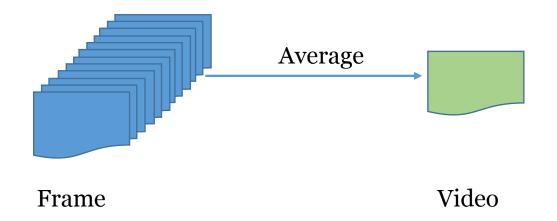
Convolutional Neural Network achieved a great success

Astounding Baseline with CNN features

Comparing Best State of the Art Methods with Deep Represenations																			
VOC07c VOC12c VOC12a MIT67 SUN397 VOC07d VOC10d VOC11s 200Birds 102Flowers H3Datt UIUCatt LFW YTF Paris6k Oxford5k Sculp6k Holidays															UKB				
best non- CNN results	70.5	82.2	69.6	64.0	47.2	34.3	40.4	47.6	56.8	80.7	69.9	~90.0	96.3	89.4	78.2	81.7	45.4	82.2	89.3
off-the- shelf ImageNet Model	80.1[13] 80.1[10] 77.2[1]	82.7[10] 79.0[6]	-	69.0[1]	40.9[4]	46.2[2] 46.1[11] 44.9[13]		-	61.8[1] 58.8[4]	86.8[1]	73.0[1]	91.5[1]	-	-	79.5[1]	68.0[1]	42.3[1]	84.3[1]	91.1[1]
off-the- shelf ImageNet Model + rep learning	-	-	-	68.9[3]	52.0[3]	-	-	-	65.0[4]	-	-	-	-	-	-	-	-	80.2[3]	•
fine- tuned ImageNet Model	82.42[10] 77.7[5]		70.2[5]	-	-	60.9[13] 58.5[2]	53.7[2]	47.9[2]	75.7[12]	-	-	-	-	-	-	-	-	-	-
Other Deep Learning Models	-	-	-	-	-	-	-	-	-	-	79.0[7]	-	97.35[8]	91.4[8]	-	-	-	-	-

Static Appearance Features

Frame-level Features are averaged to generate Video-level representation



Motion Features

Plays the most important role for video classification

We introduce

• Dense Trajectories today: state-of-the-art features nowadays (CVPR 11, citation 455 now), still beats DL till now.

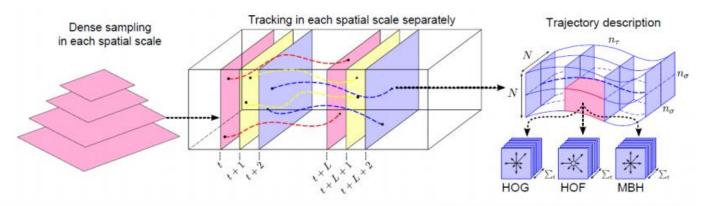
Motion Features

Plays the most important role for video classification

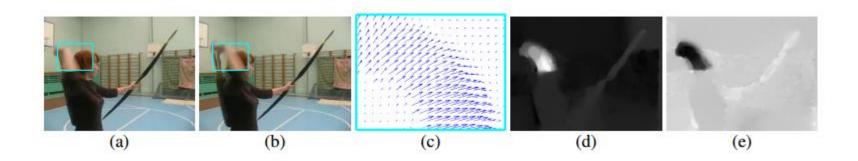
We introduce

• Dense Trajectories today: state-of-the-art features nowadays (CVPR 11, citation 455 now), still beats DL till now.

Motion Features: Dense Trajectories



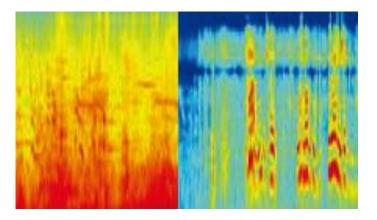
Wang et al, CVPR 2011, IJCV 2012



Acoustic Features: MFCC

• MFCC (Mel-frequency Cepstral Coefficients)

• Spectrogram SIFT



High-level Features

- ASR (Automatic Speech Recognition)
- OCR



(a) Video frame

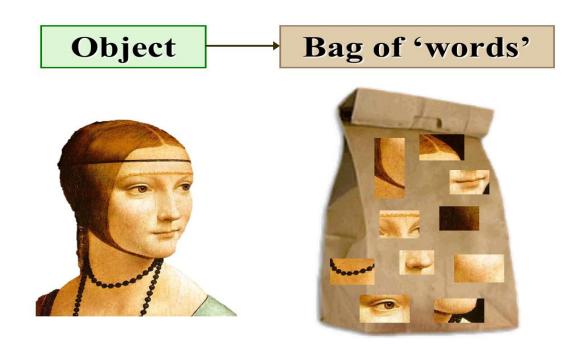




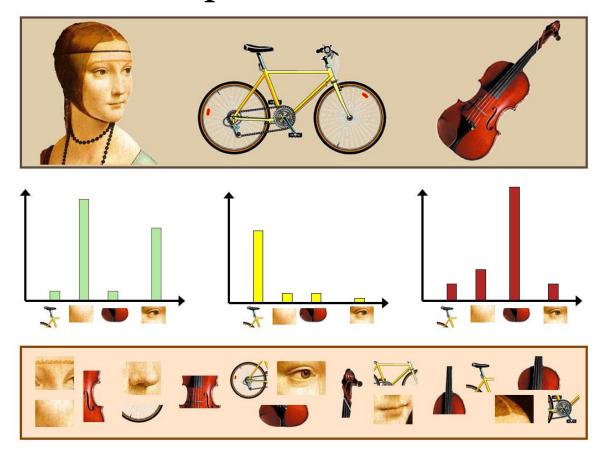
(b) Extracted MSERs

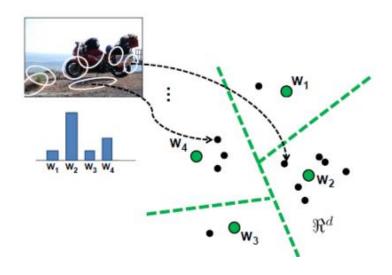
```
Exter-
150 grains or
1/5 of a 250g
block
```

Bag-of-words Representation



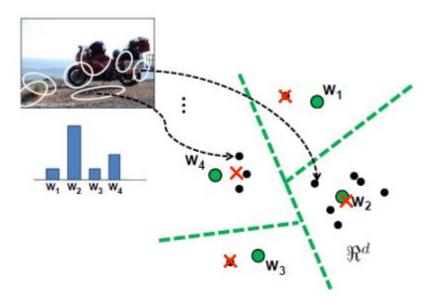
Bag-of-words Representation



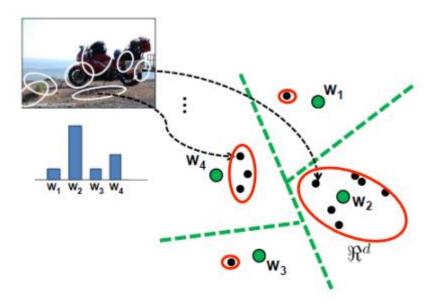


- BoW is only about counting the number of local descriptors assigned to each region
- Why not including other statistics?

- Fisher Vector Representation
- Including other statistics
- > mean of local descriptors



- Fisher Vector Representation
- Including other statistics
- > mean of local descriptors
- ➤ variance of local descriptors



Classification

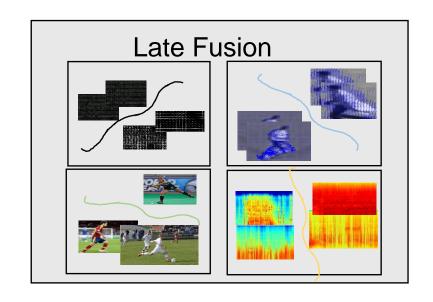
• For histogram-based features, non-linear \chi^2-kernel SVMs

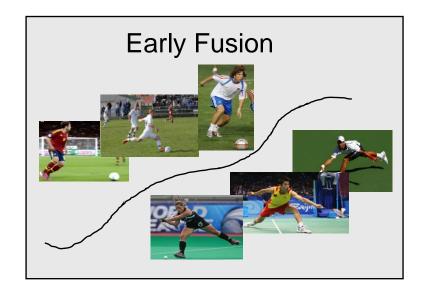
• For Fisher Vector based features, linear SVMs is good enough.

Fusion

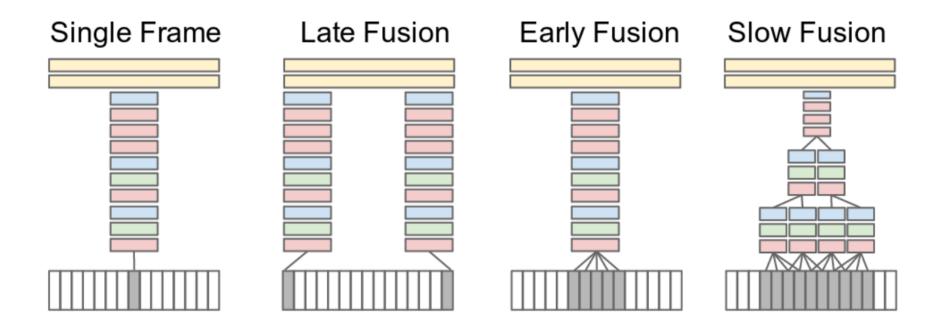
Late Fusion (Classifier)

• Early Fusion (Feature)





Deep Learning Approach



Deep Learning Approach

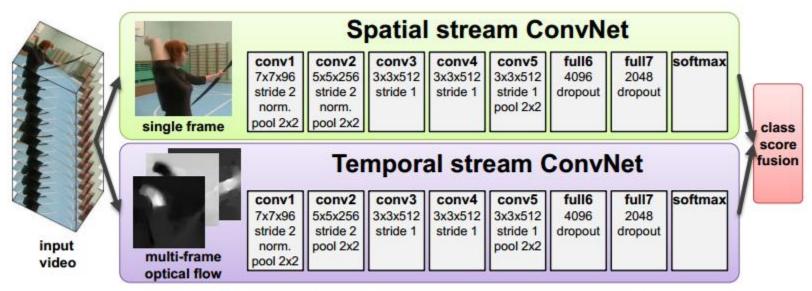


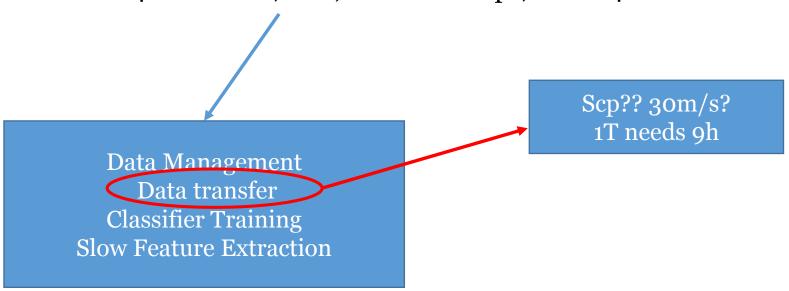
Figure 1: Two-stream architecture for video classification.

DATA extremely LARGE!

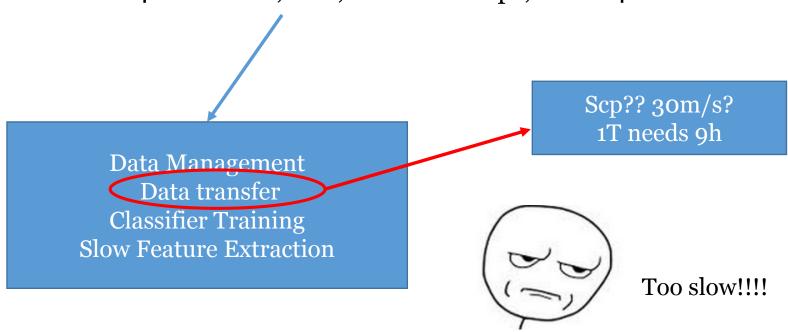
DATA extremely LARGE!



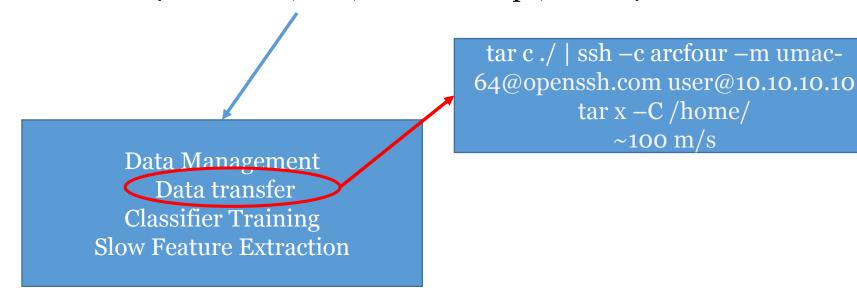
DATA extremely LARGE!



DATA extremely LARGE!



DATA extremely LARGE!



DATA extremely LARGE!

MED 14: TEST set, 200,000 video clips, about 4T

Data Management
Data transfer
Classifier Training
Slow Feature Extraction

tar c ./ | ssh -c arcfour -m umac-64@openssh.com user@10.10.10.10 tar x -C /home/ ~100 m/s



DATA extremely LARGE!

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LibLinear , LibSVM, WILL all collapse

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