



# Deep Learning Winter School for Computer Vision

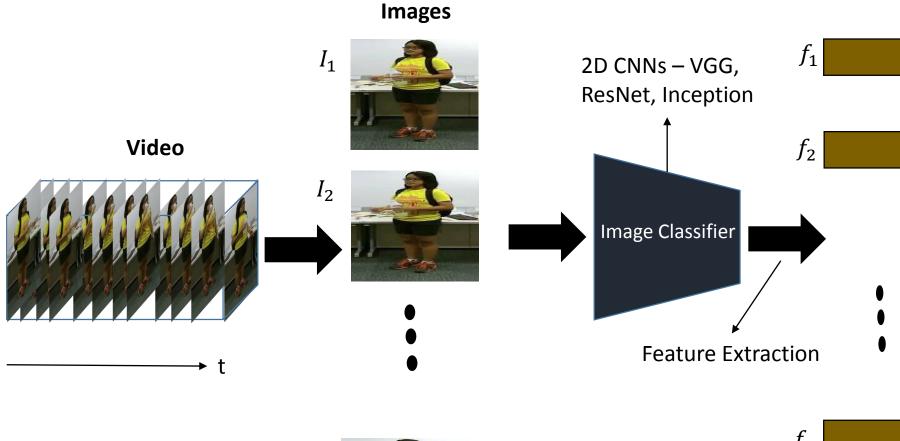
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**INRIA Sophia Antipolis** 

### Recap...

#### Frame-level Features



Feature-Aggregation

**Video-level features (F)** 

Max Pooling  $F = \max(f_i)$ 

Min Pooling  $F = \min(f_i)$ 

Mean Pooling

$$F = \frac{\sum_{i=1}^{t} f_i}{t}$$

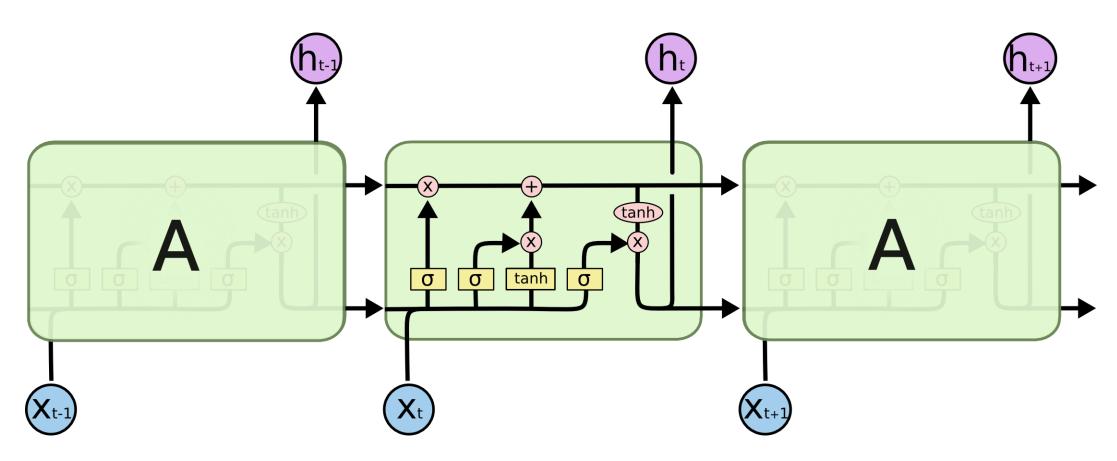
Max - Min Pooling  $F = \operatorname{concat}(\max(f_i)(\min(f_i))$ 

 $I_t$ 



1. Frame-level Aggregation

### Recap...



#### 2. LSTM

### Disadvantages (not discussed in last class)

 RNNs/LSTMs can only capture strong temporal evolution of the image level features.

 Not much efficient on small datasets (pre-training is not a good idea as they change the statistics learned by the gates).

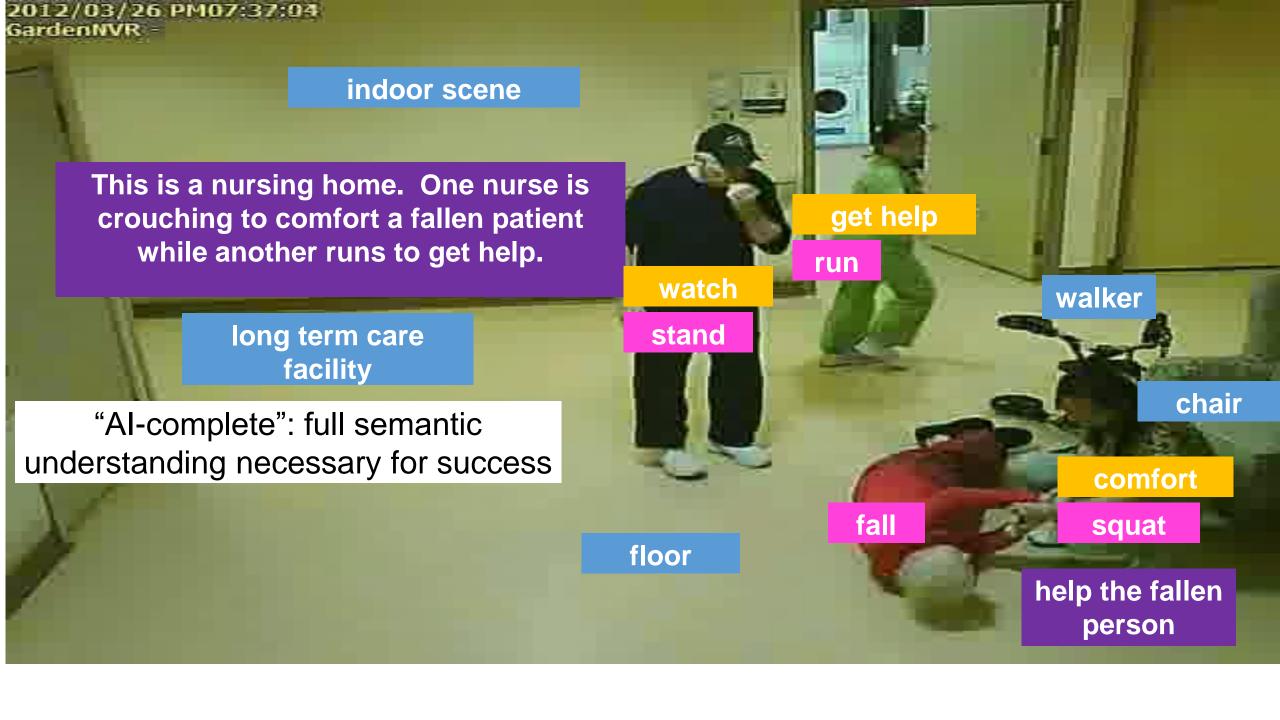
### Outline: Action Recognition

- Introduction to Action Recognition
- Different Features for Action classification
  - RGB
  - Optical Flow
  - Skeleton
- Action Recognition Framework
  - Two-streams
  - LRCN
  - 3D ConvNets



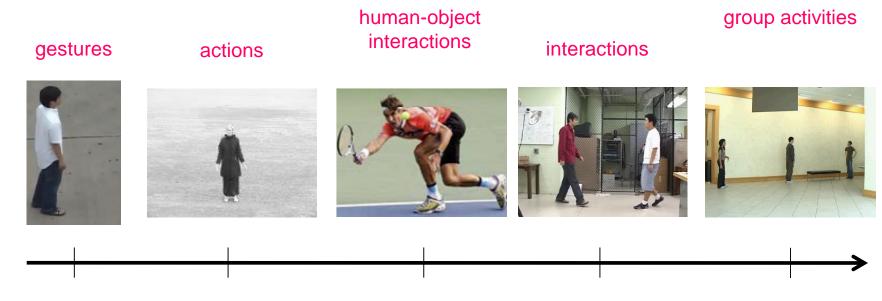






### Human Activity Recognition

- There are various types/levels of activities
  - The ultimate goal is to make computers recognize all of them reliably.



Levels of human activities

### Why is activity recognition important?

**User videos** 







~300 hours of videos per minute

 Video indexing and retrieval **Monitoring cameras** 



Streaming videos 24/7

- Surveillance
- Patient/elderly monitoring

Media





Content analysis, experience enrichment

- Recommendation systems
- Advertising
- Sports analytics

Wearables/robots



Streaming videos to be analyzed in real-time

- Lifelogging
- Robot operations and actions

### Categories of Action Recognition Data

#### **Sports 1M**



#### **Instruction videos**



First undo the nuts. Once that done, you can jack the car. Then withdraw the nuts completely so that you can remove the flat tire.

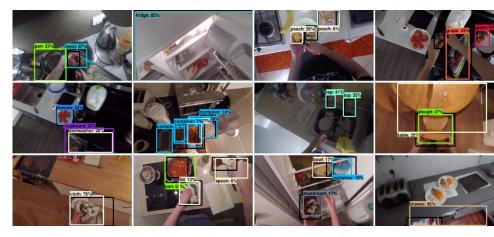
#### Cooking



#### Internet (Youtube8M)



#### **Ego-centric**



### Categories of Action Recognition Data

#### **Activities of Daily Living**



Cook (clean dishes)



Cook (clean up)



Cook (cut)



Cook (stir)



Cook (use stove)



Take pills



Eat at table



Cut bread



Drink from bottle



Drink from can



Drink from cup



Drink from glass



Get up



Lay down



Sit down



Walk



Enter



Leave

### Web videos vs Activities of Daily Living (ADL)

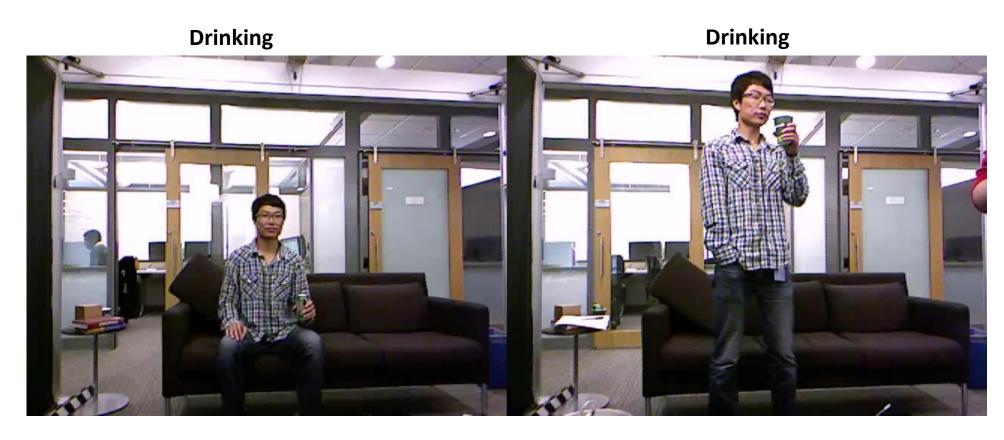
#### **Web Videos**



#### **ADL**



### Challenges in ADL



Same background

High intra-class variation

### Challenges in ADL

**Typing a keyboard** 

Reading



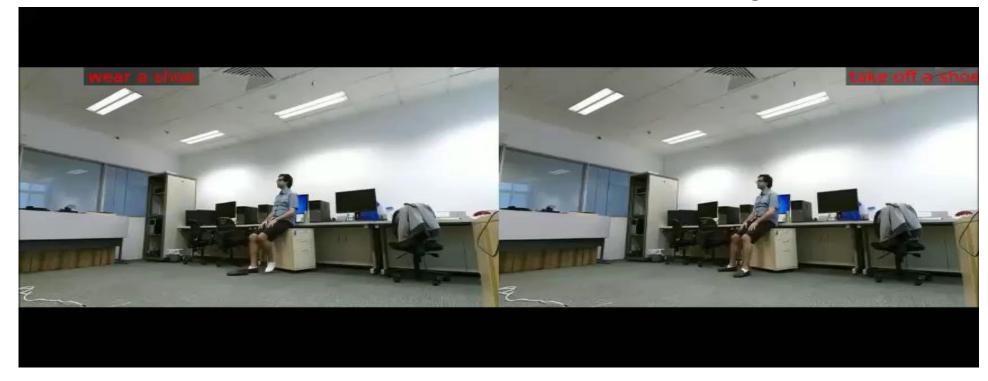
Same background

• Actions with subtle motion

### Challenges in ADL

Wear a shoe

Taking off a shoe

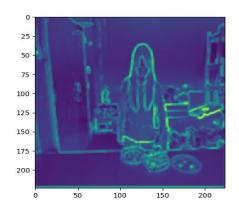


Same background

• Actions with similar appearance

### Different features for modeling Actions

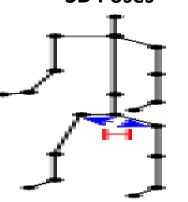
#### **Appearance (RGB)**

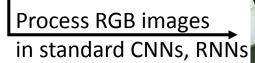


#### **Optical Flow**



**3D Poses** 

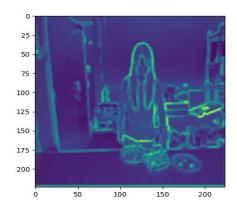




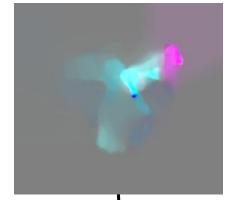


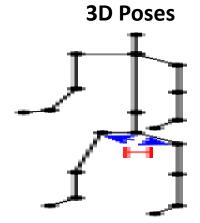
### Different features for modeling Actions

#### **Appearance (RGB)**



#### **Optical Flow**



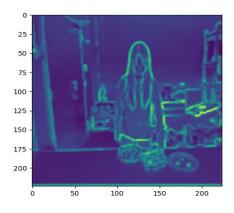


Process color coded optical flow images in standard CNNs.



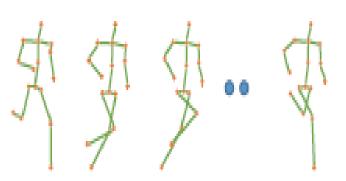
### Different features for modeling Actions

#### **Appearance (RGB)**

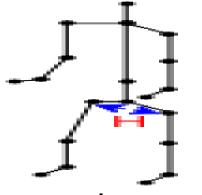


#### **Optical Flow**







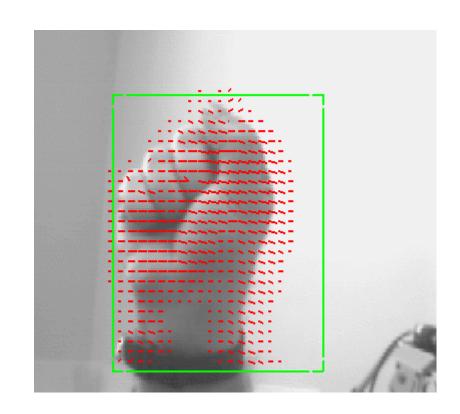


3D poses are highly informative, robust to illumination and view changes.

They are processed by RNNs, CNNs (especially Graph CNNs)

 Computes the displacement of each pixel compared to the previous frame. (How much does the pixel move?)

 Represented by two displacement vectors (one along x, another along y).



It is 2D vector field where each vector is a displacement vector showing the movement of points from first frame to second.

Brightness constancy assumption

$$f(x, y, t) = f(x + dx, y + dy, t + dt)$$



#### Taylor Series

$$f(x, y, t) = f(x, y, t) + \frac{\partial}{\partial x} dx + \frac{\partial}{\partial y} dy + \frac{\partial}{\partial t} dt$$

$$f_x dx + f_y dy + f_t dt = 0$$

$$f_x u + f_y v + f_t = 0$$
 Optical Flow equation

We cannot solve this one equation with two unknown variables. So several methods are provided to solve this problem and one of them is Lucas-Kanade.

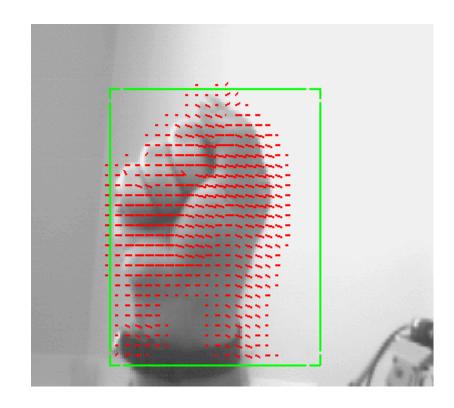
Color Coded Optical Flow -> We call them flow images.



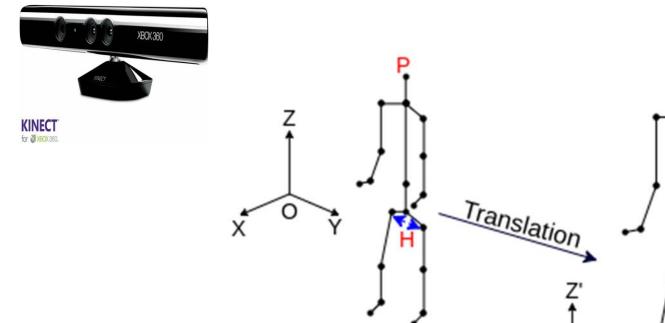
These flow images can be used in 2D CNNs for feature extraction.

• Is informative for instantaneous motion.

• Thus used in Action classification tasks.



### 3D Poses (Skeletons)

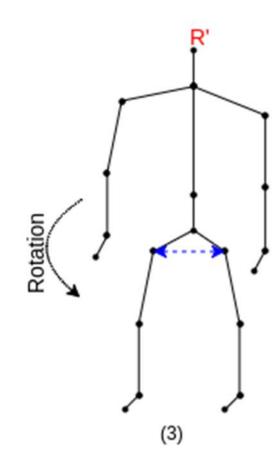


(1)

Camera-body translation

Rotation of bones wrt a line parallel to the hip

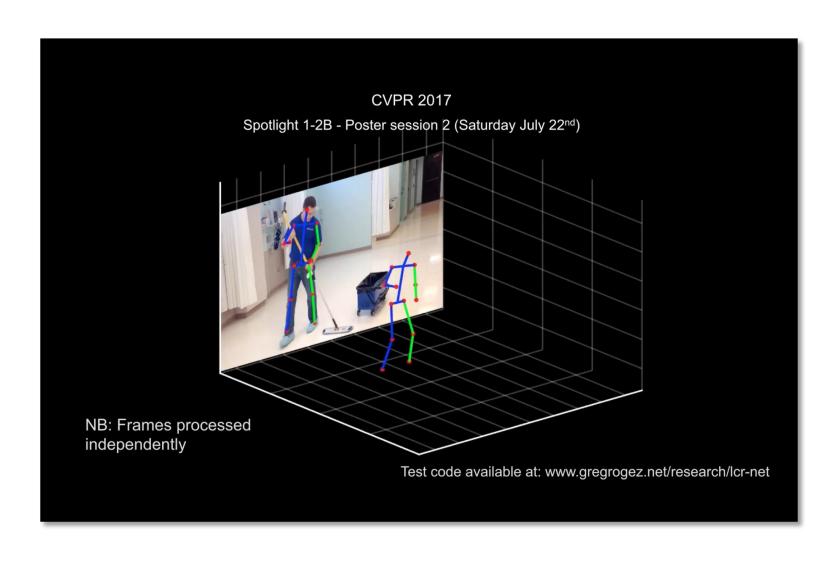
Normalizing the bones



(2)

Temporal evolution of 3D poses can provide inferences about pose related actions.

### 3D Poses (from RGB)



### 3D Poses

• The temporal evolution of these highly informative 3D poses are often exploited for Action classification (especially in indoor settings).

 The 3D poses can provide strong clue of where (both space and time) an action is happening.

### Popular Action Recognition Frameworks

• Input: a fixed number of frames, Output: a class

Action

ConvNet

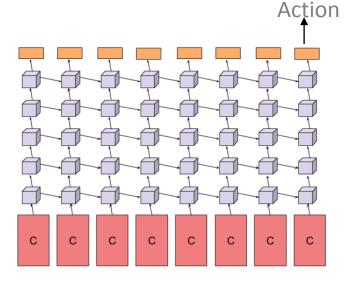
ConvNet

Optical
Flow 1 to N



 1 frame RGB + 10 frames of optical flow

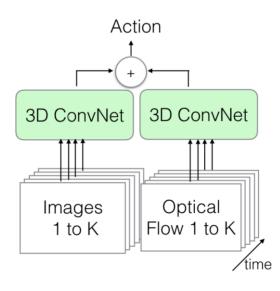
[Carreira and Zisserman, 2017]



#### **Sequential models RNNs**

 model 'sequences' of per-frame CNN representations (RGB/3D Poses)

[J. Ng et al., 2015]

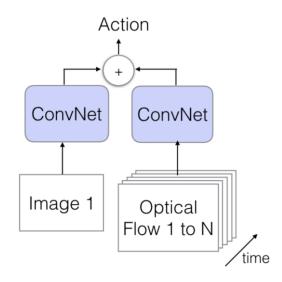


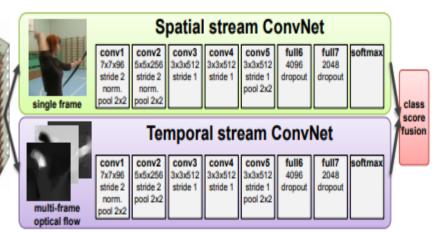
#### **3-D XYT CNNs**

- 15~99 frames (RGB + Flow)
- Facebook C3D, Google I3D

#### Introduction to optical flow ConvNets

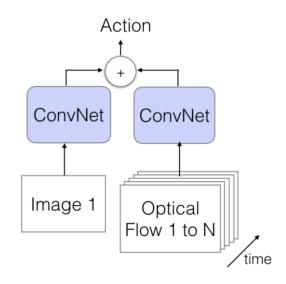
- the input to this model is formed by stacking optical flow displacement fields between several consecutive frames.
- stack the flow channels  $d_t^{x,y}$  of L consecutive frames to form a total of 2L input channels
- sample a 224 × 224 × 2L subvolume from a video and pass it to the net as input

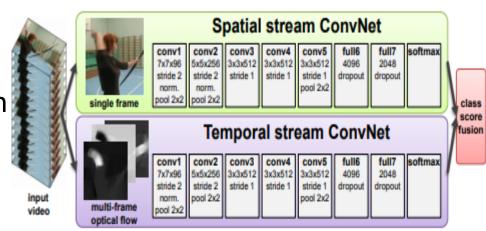




#### Multitask Learning

- Input to the Spatial stream ConvNet
  - One image randomly sampled from the video. (encodes object/appearance information)
- Input to the Temporal stream
   ConvNet 2L optical flow images
   from a video. (encodes short-term
   motion)
- Both the networks learning together.



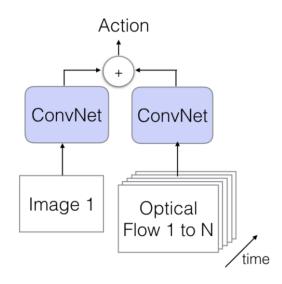


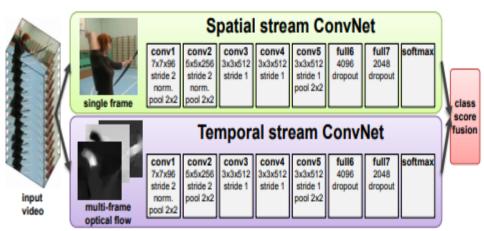


A still from 'Quo Vadis' (1951). Where is this going? Are these actors about to kiss each other, or have they just done so?

#### Disadvantages

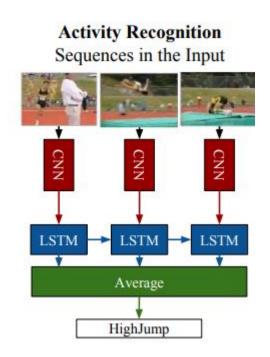
- Temporal information is not encoded.
- Long-term motion is ignored!





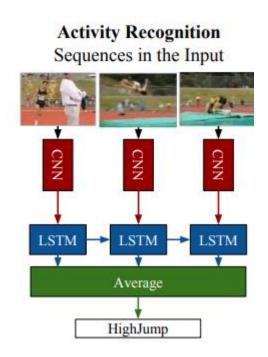
## Long-term Recurrent Convolutional Networks for Action Recognition

- Obvious solution is, using sequential networks to model time.
- Uniformly sample images from the video, extract their CNN features and feed to LSTM.
- The Loss is computed from the average error at each time step of the LSTM.



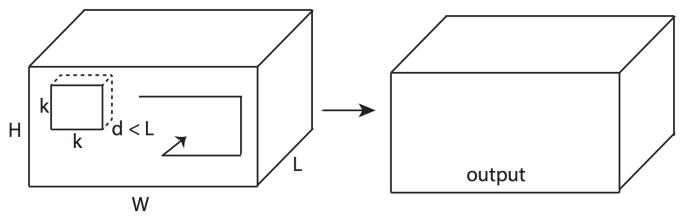
## Long-term Recurrent Convolutional Networks for Action Recognition

- Disadvantages
  - Doesn't work for actions with subtle changes in the scene.
  - Spatial and temporal operations are dissociated disabling the model to extract intrinsic spatio-temporal patterns.



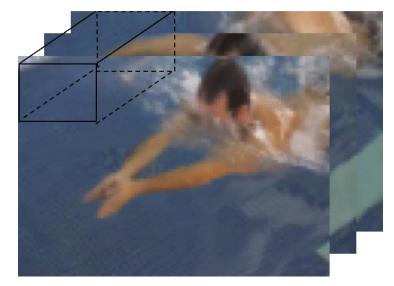
### 3D CNNs (XYT) for Action Recognition

- Facebook C3D [Tran et al., 2015]
  - Spatio-temporal filters for short video segments (e.g., 15 frames) –
     coupling space and time

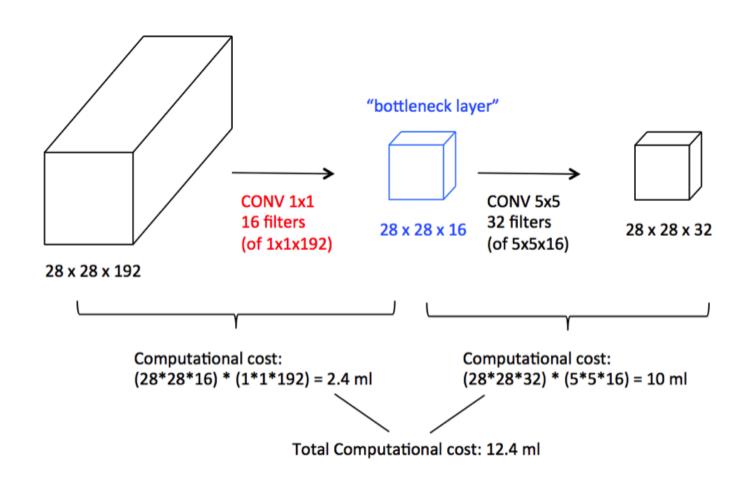




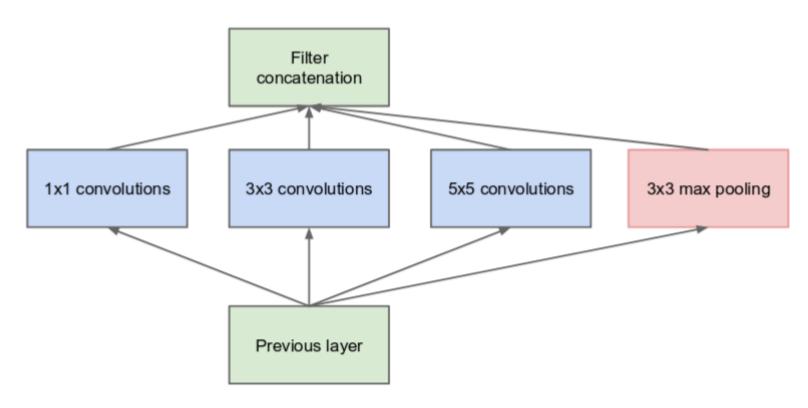
Extended by inflation from Spatial domain



### Recap: Network in Networks (Bottleneck)



### Recap: Inception

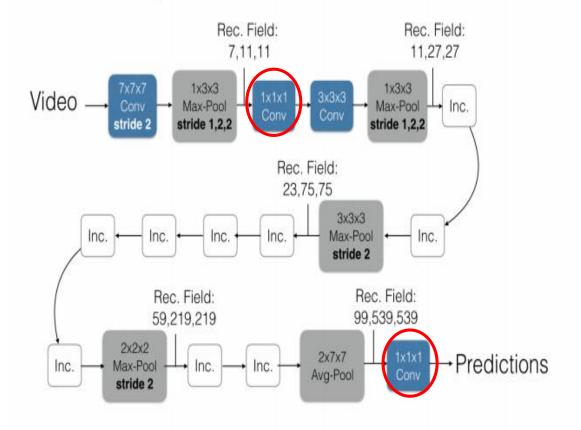


(a) Inception module, naïve version

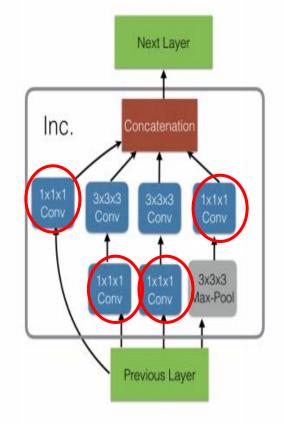
### 13D

- Inflation
- Bottleneck
- Concept of inception

#### Inflated Inception-V1



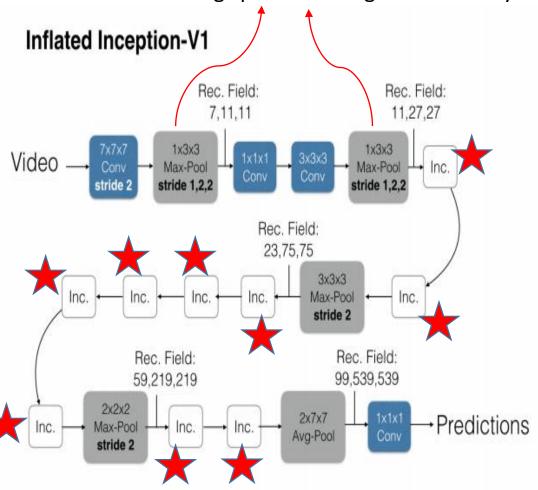
#### Inception Module (Inc.)



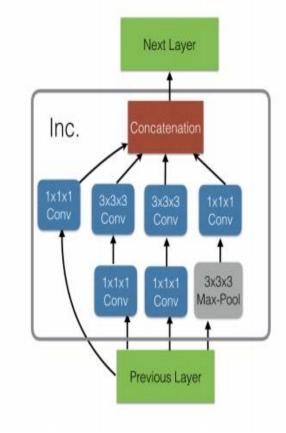
### 13D

Handling space-time together with asymmetric operations

- Inflation
- Bottleneck
- Concept of inception

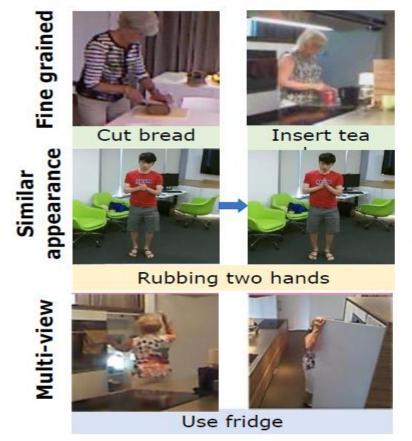


#### Inception Module (Inc.)



### Limitations of 3D CNNs

- Rigid spatio-temporal kernels limiting them to capture subtle motion
- No specific operations to help disambiguate similarity in actions.
- 3D (XYT) CNNs are not viewadaptive.





### References

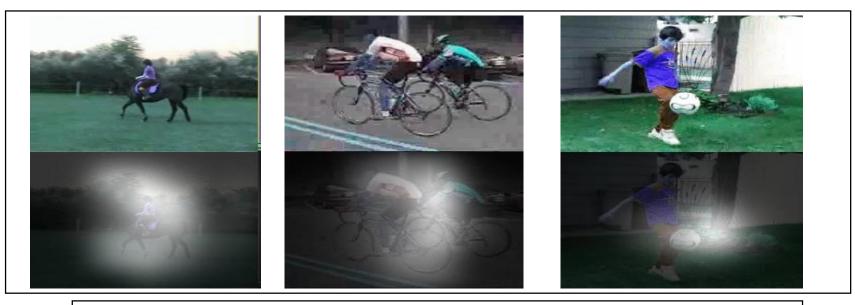
 Quo Vadis, Action Recognition? A New Model and the Kinetics Dataset, CVPR 2017

UCF computer vision video Lectures 2012 (Instructor: Mubarak Shah)

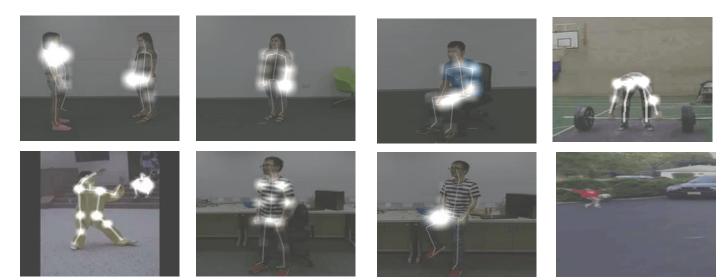
CVPR Tutorial, Human Activity Recognition (M. Ryoo, I. Laptev)

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### Next Week ....



Attention!!!



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