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Computer Vision; Video



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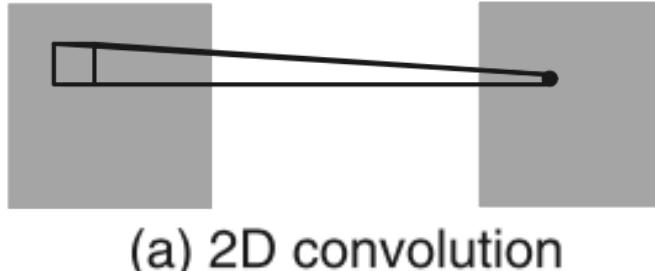
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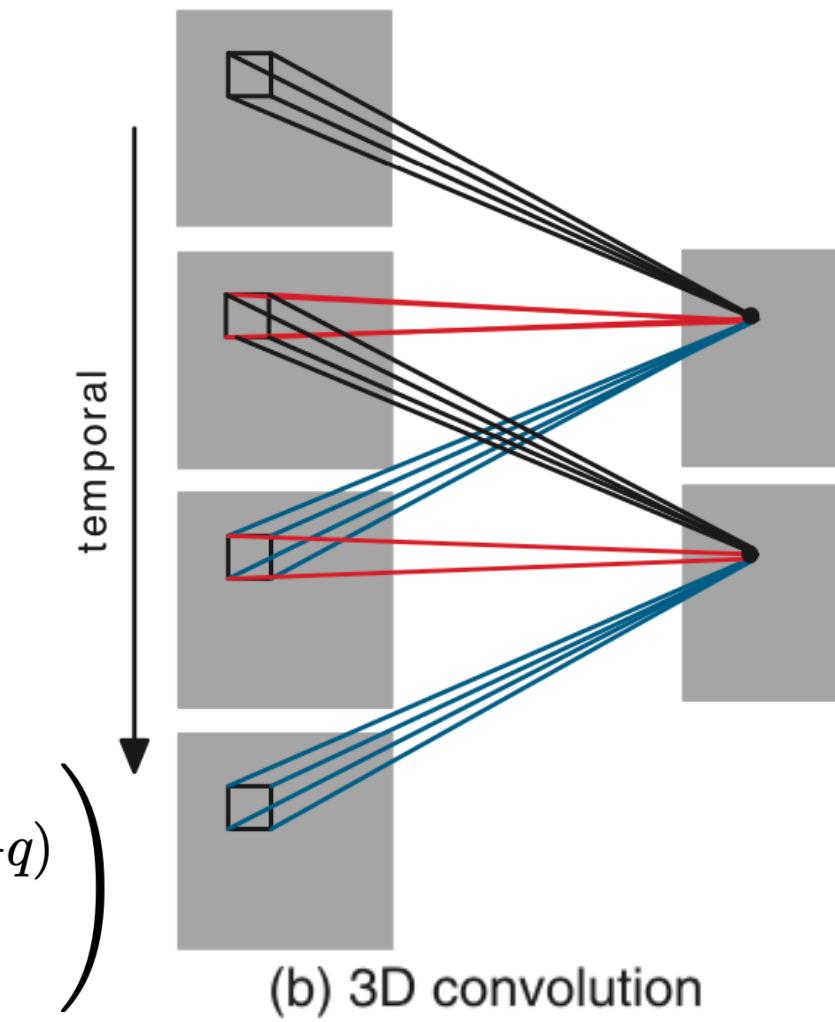
3D Convolutional Neural Networks for Human Action Recognition

- intelligent video surveillance
- customer attributes
- shopping behavior analysis



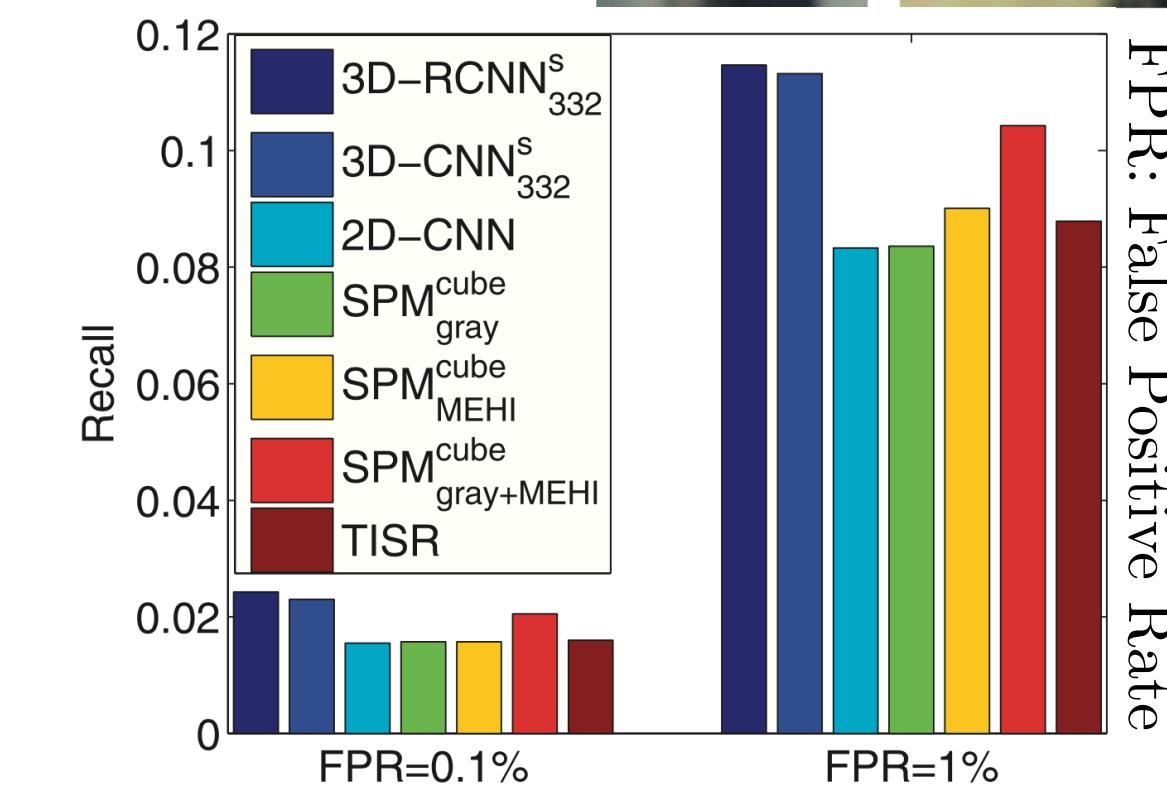
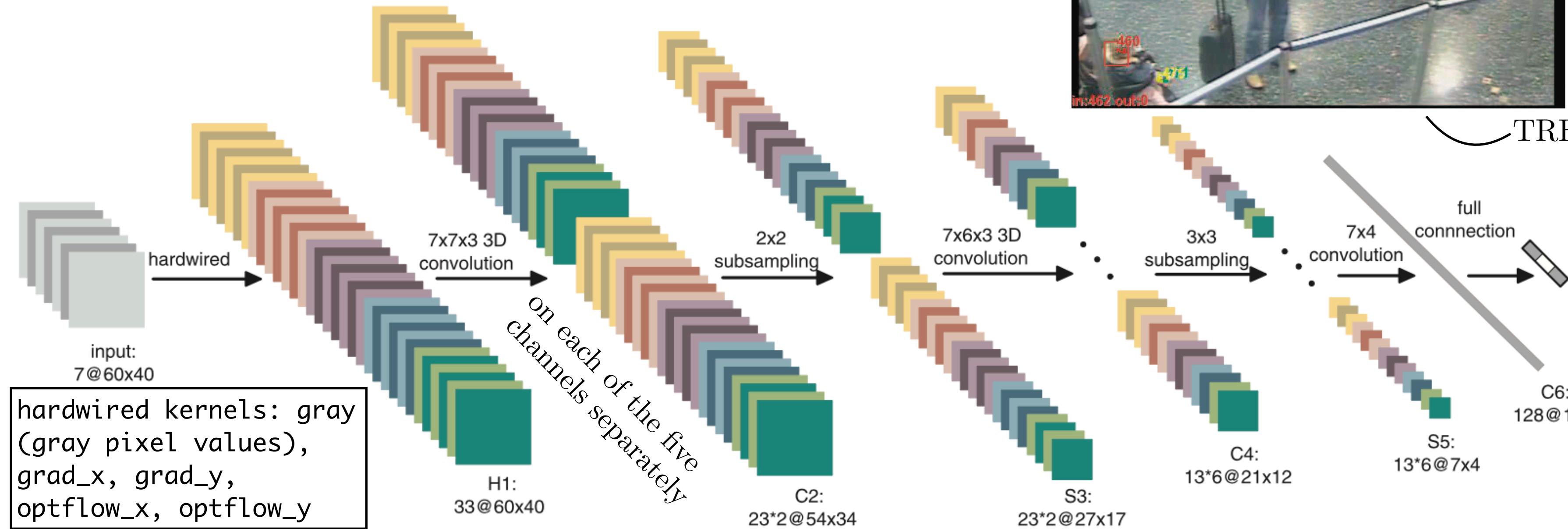
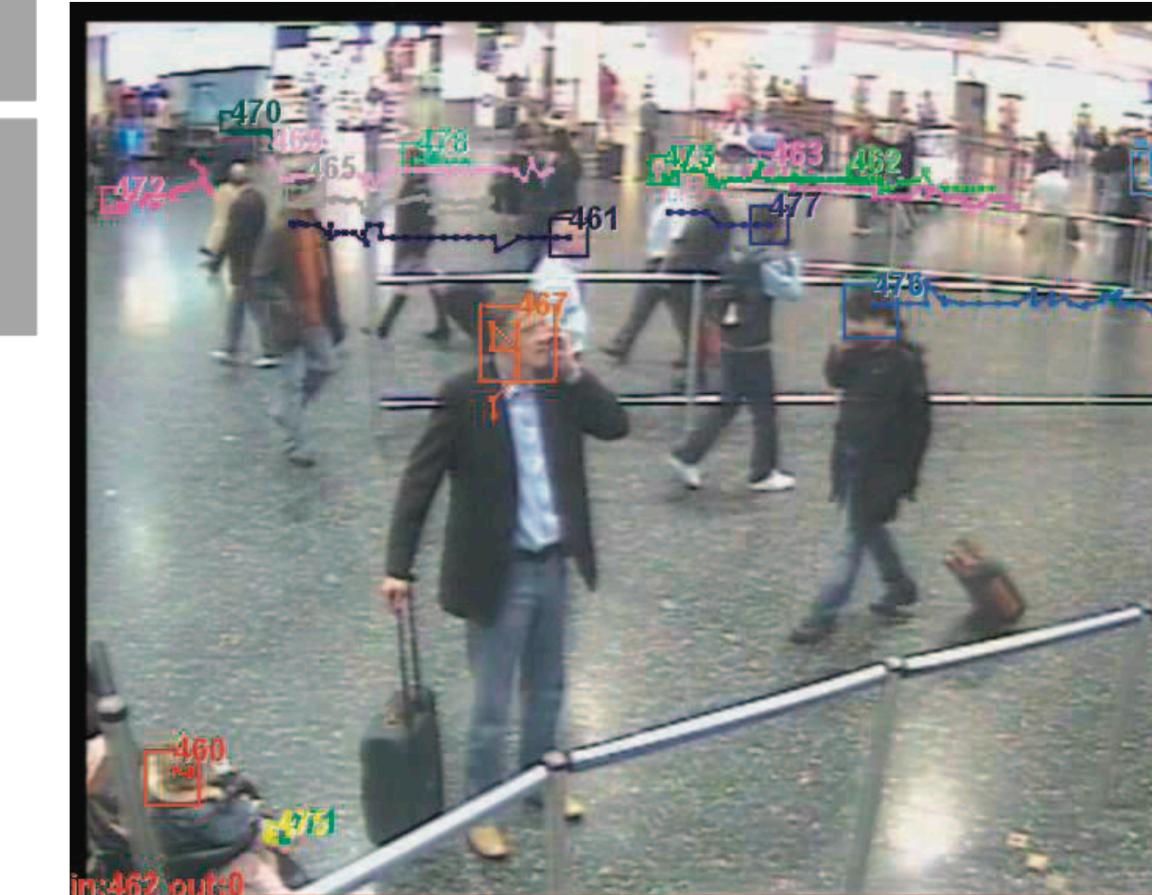
$v_{ij}^{xy} \rightarrow$ value at position (x, y) in the j -th feature map of the i -th layer

$$v_{ij}^{xy} = \tanh \left(b_{ij} + \sum_m \sum_{p=0}^{P_i-1} \sum_{q=0}^{Q_i-1} w_{ijm}^{pq} v_{(i-1)m}^{(x+p)(y+q)} \right)$$



$$v_{ij}^{xyz} = \tanh \left(b_{ij} + \sum_m \sum_{p=0}^{P_i-1} \sum_{q=0}^{Q_i-1} \sum_{r=0}^{R_i-1} w_{ijm}^{pqr} v_{(i-1)m}^{(x+p)(y+q)(z+r)} \right)$$

human detection and tracking





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Large-scale Video Classification with Convolutional Neural Networks



[YouTube Video](#)

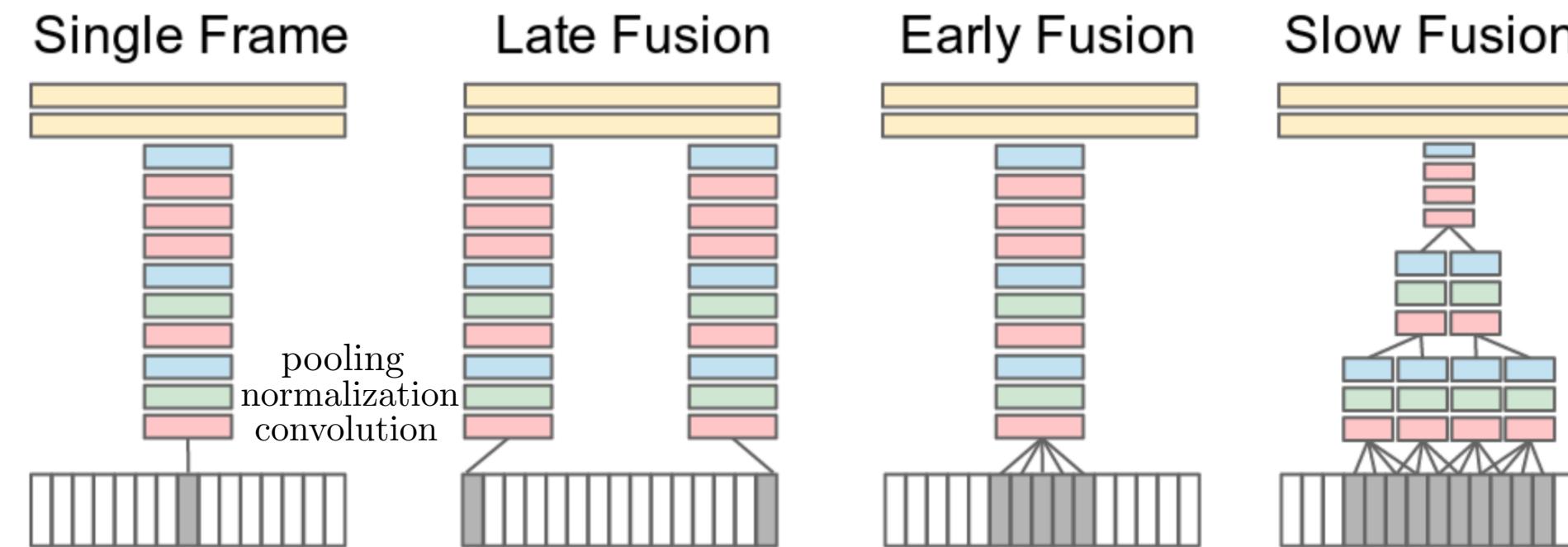
- search
- summarization

Sports-1M dataset: Consists of 1 million YouTube videos belonging to a taxonomy of 487 classes of sports

Context stream: Learns features on low-resolution frames

Fovea stream: Operates on the high-resolution middle portion of the frame

- UCF-101 dataset \leftarrow Transfer Learning
treat every video as a bag of short, fixed-sized clips
each clip contains several contiguous frames in time



Single Frame
 $170 \times 170 \times 3 \rightarrow$ input size
 $C(96, 11, 3) \triangleright N \triangleright P \triangleright C(256, 5, 1) \triangleright N \triangleright P \triangleright C(384, 3, 1) \triangleright C(384, 3, 1) \triangleright C(256, 3, 1) \triangleright P \triangleright FC(4096) \triangleright FC(4096)$
 $P \rightarrow 2 \times 2$ non-overlapping pooling
 $N \rightarrow$ Local Response Normalization

Karpathy, Andrej, et al. "Large-scale video classification with convolutional neural networks." *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*. 2014.

Early Fusion

$11 \times 11 \times 3 \times T \rightarrow$ filters on the first convolutional layer

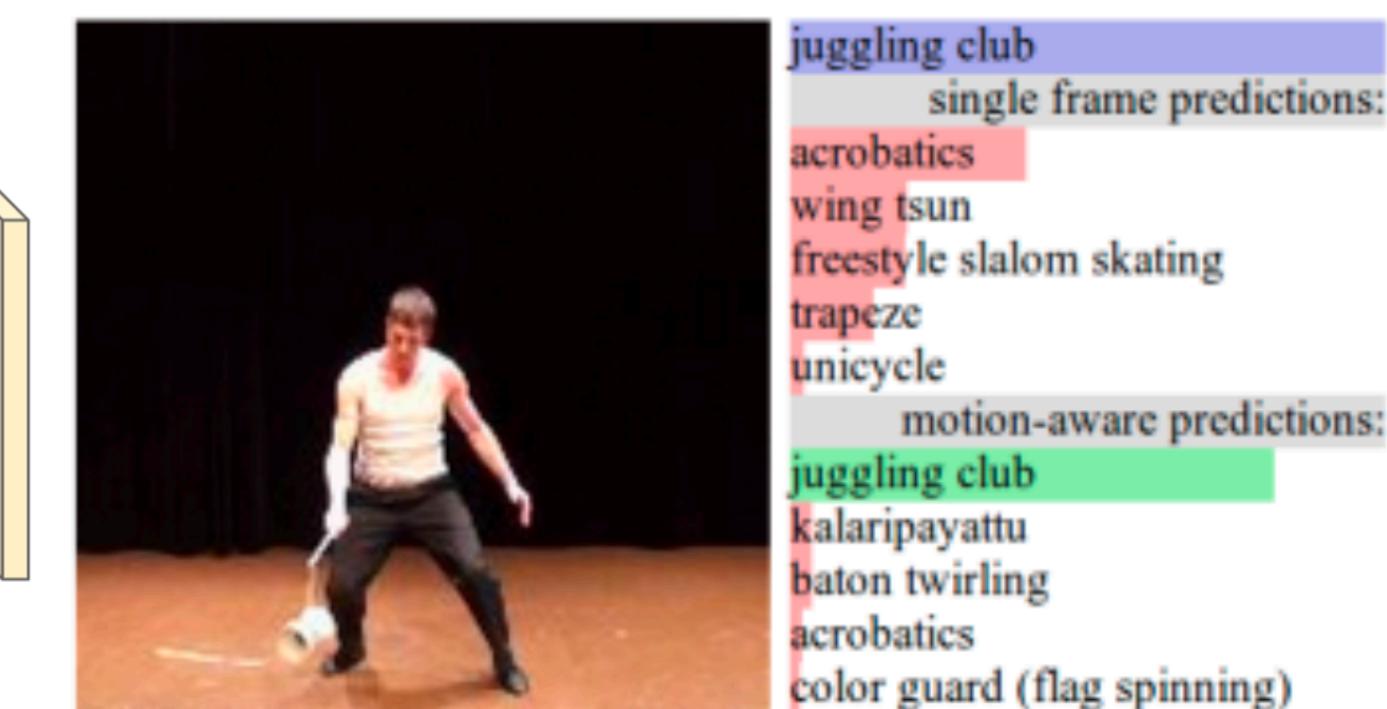
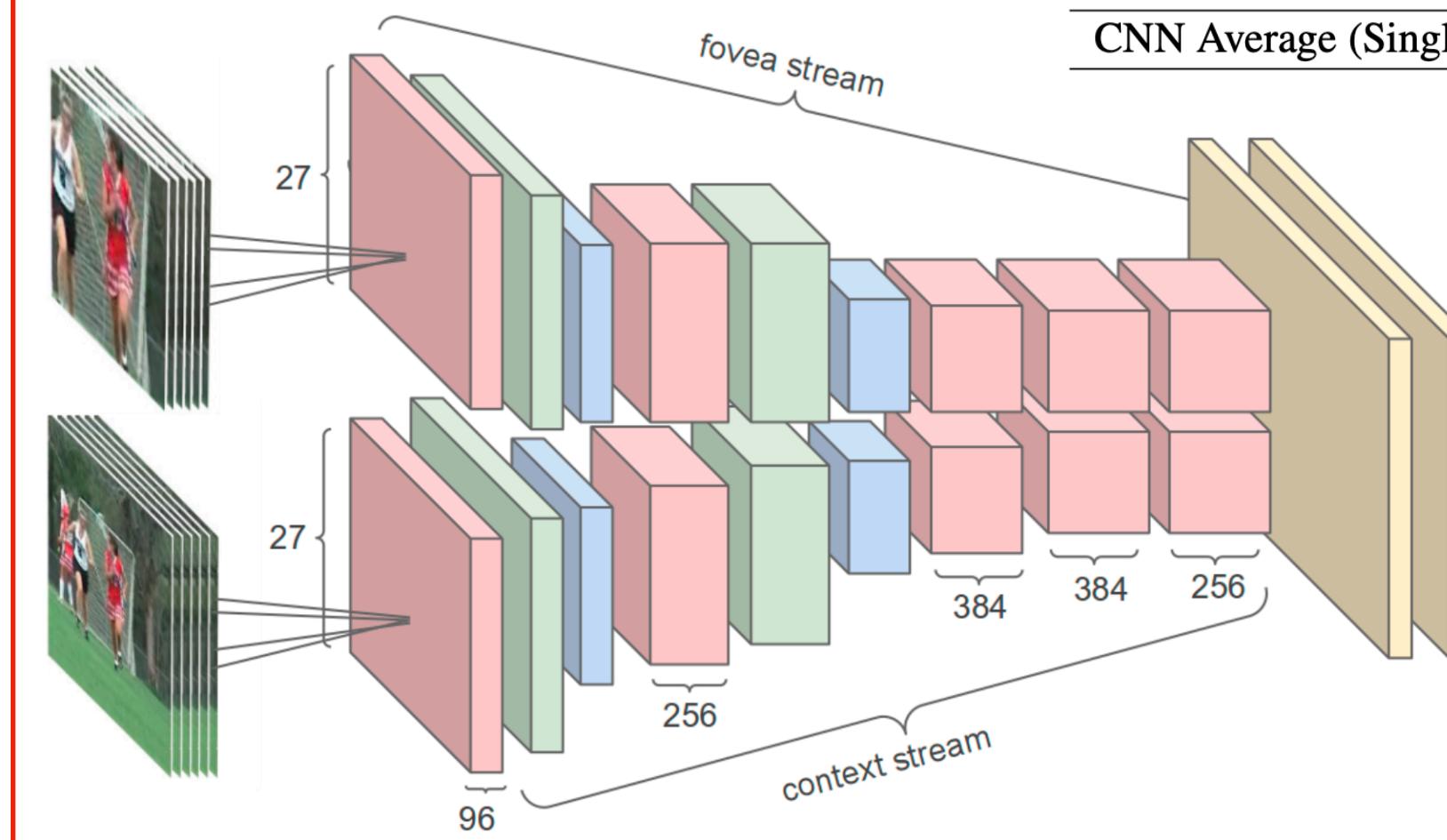
$T = 10$ ($\approx 1/3$ of a second)

Late Fusion

Place two separate single-frame networks up to last convolutional layer $C(256, 3, 1)$ with shared parameters a distance of 15 frames apart and then merge the two streams in the first fully connected layer

Multi-resolution CNNs

(context stream)
 $178 \times 178 \xrightarrow{89 \times 89 \text{ downsampled}}$
 $89 \times 89 \text{ center crop}$
(fovea stream)





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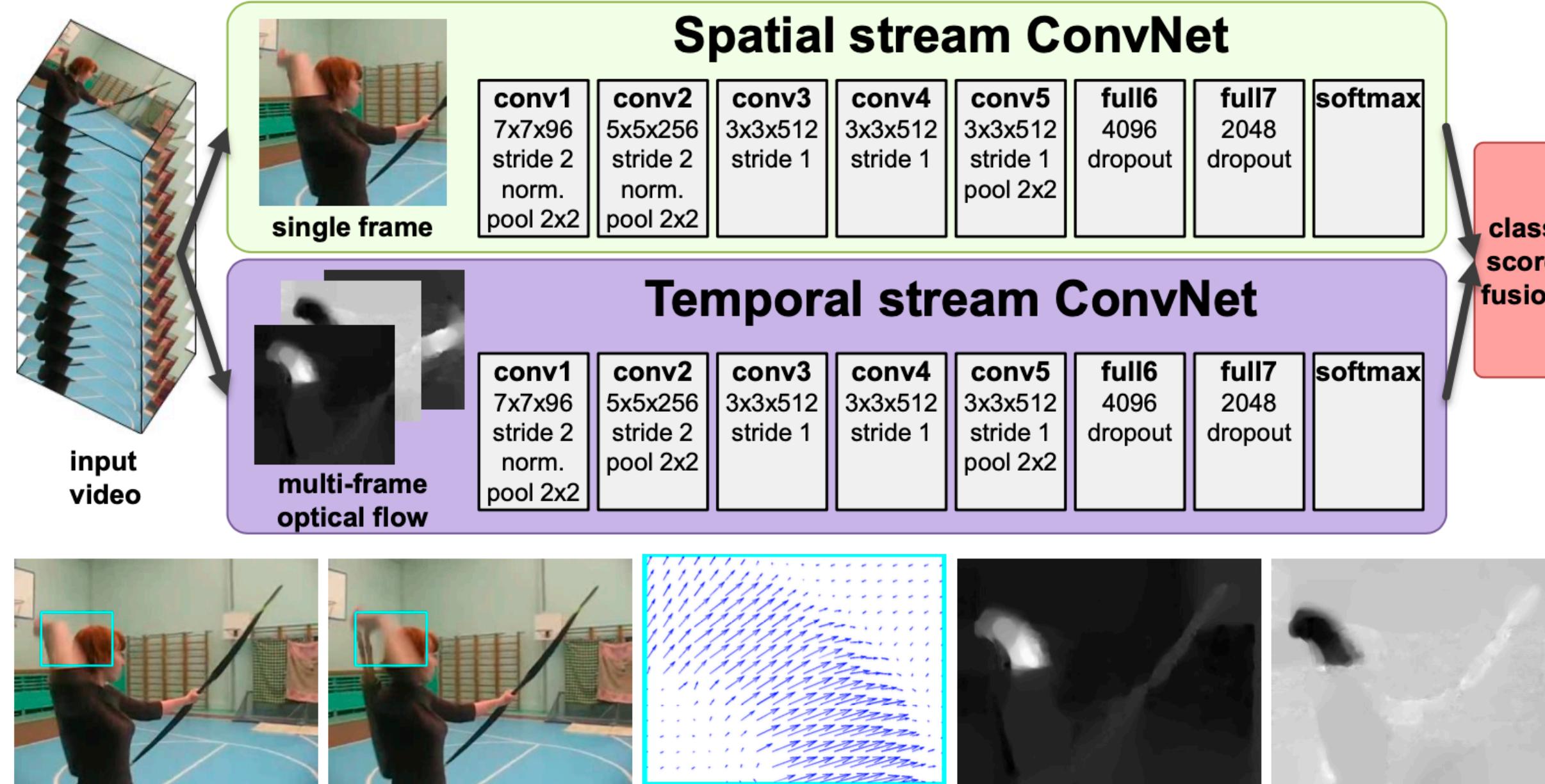
Two-Stream Convolutional Networks for Action Recognition in Videos



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- UCF-101
- HMDB-51

Video can naturally be decomposed into spatial and temporal components



A dense optical flow can be seen as a set of displacement vector fields d_t between the pairs of consecutive frames t and $t + 1$

$d_t(u, v) \rightarrow$ displacement vector at the point (u, v)

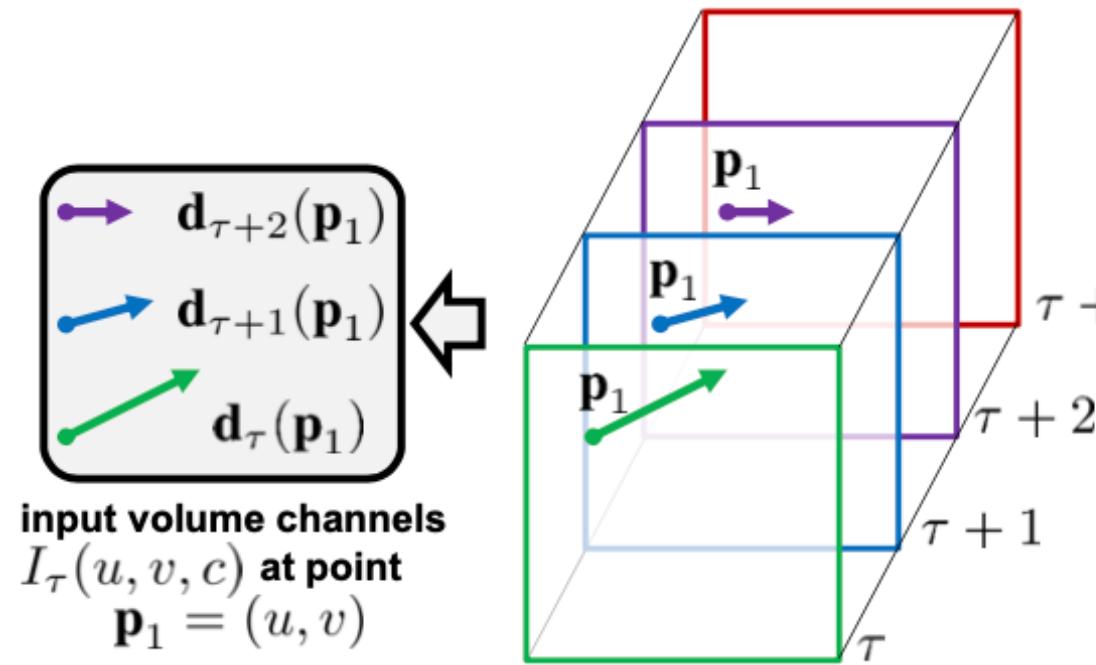
moves the point to the corresponding point in the following frame $t + 1$

$d_t^x, d_t^y \rightarrow$ horizontal and vertical components of the vector field

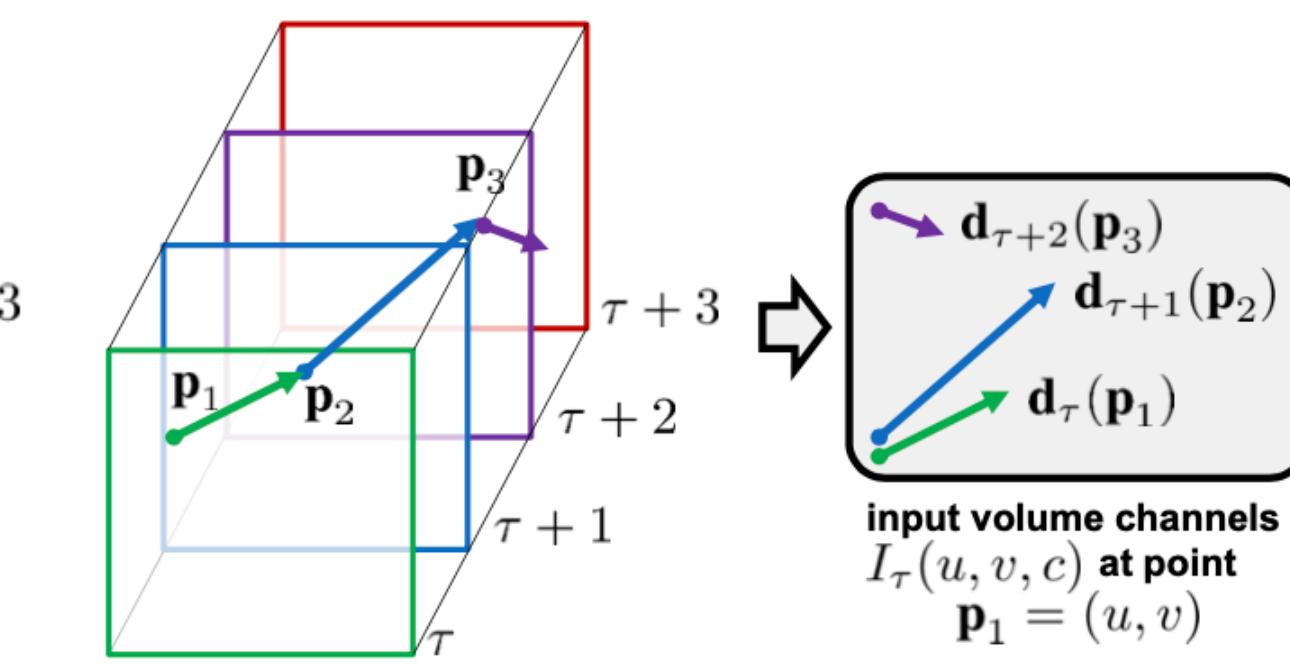
Optical flow stacking

Stack the flow channels d_t^x, d_t^y of L consecutive frames to form a total of $2L$ input channels

$$\begin{aligned}\tau &\rightarrow \text{an arbitrary frame} \\ I_\tau &\in \mathbb{R}^{w \times h \times 2L} \rightarrow \text{input volume} \\ I_\tau(u, v, 2k - 1) &= d_{\tau+k-1}^x(\mathbf{p}_k) \\ I_\tau(u, v, 2k) &= d_{\tau+k-1}^y(\mathbf{p}_k)\end{aligned}$$



$$\begin{aligned}\mathbf{p}_k &= \mathbf{p}_{k-1} + \mathbf{d}_{\tau+k-2}(\mathbf{p}_{k-1}), k > 1 \\ I_\tau(u, v, 2k - 1) &= d_{\tau+k-1}^x(\mathbf{p}_k) \\ I_\tau(u, v, 2k) &= d_{\tau+k-1}^y(\mathbf{p}_k)\end{aligned}$$



Bi-directional optical flow forward & backward flows

| Training setting | Dropout ratio | | Spatial ConvNet |
|---------------------------|---------------|--------------|-----------------|
| | 0.5 | 0.9 | |
| From scratch | 42.5% | 52.3% | |
| Pre-trained + fine-tuning | 70.8% | 72.8% | |
| Pre-trained + last layer | 72.7% | 59.9% | |

| Temporal ConvNet | Mean subtraction | |
|---|------------------|--------------|
| | off | on |
| Single-frame optical flow ($L = 1$) | - | 73.9% |
| Optical flow stacking (1) ($L = 5$) | - | 80.4% |
| Optical flow stacking (1) ($L = 10$) | 79.9% | 81.0% |
| Trajectory stacking (2) ($L = 10$) | 79.6% | 80.2% |
| Optical flow stacking (1) ($L = 10$), bi-dir. | - | 81.2% |

| Method | UCF-101 | HMDB-51 |
|---|--------------|--------------|
| Improved dense trajectories (IDT) [26, 27] | 85.9% | 57.2% |
| IDT with higher-dimensional encodings [20] | 87.9% | 61.1% |
| IDT with stacked Fisher encoding [21] (based on Deep Fisher Net [23]) | - | 66.8% |
| Spatio-temporal HMAX network [11, 16] | - | 22.8% |
| “Slow fusion” spatio-temporal ConvNet [14] | 65.4% | - |
| Spatial stream ConvNet | 73.0% | 40.5% |
| Temporal stream ConvNet | 83.7% | 54.6% |
| Two-stream model (fusion by averaging) | 86.9% | 58.0% |
| Two-stream model (fusion by SVM) | 88.0% | 59.4% |



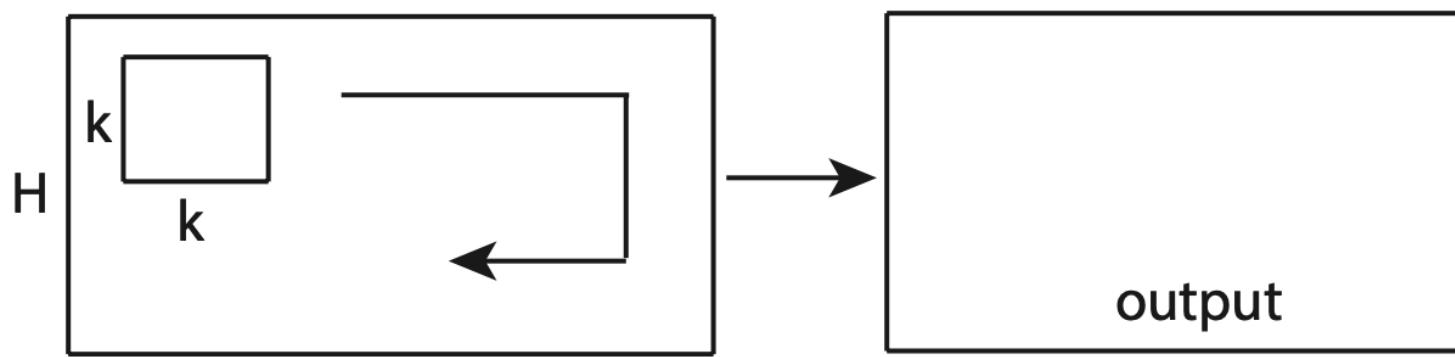
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Learning Spatiotemporal Features with 3D Convolutional Networks

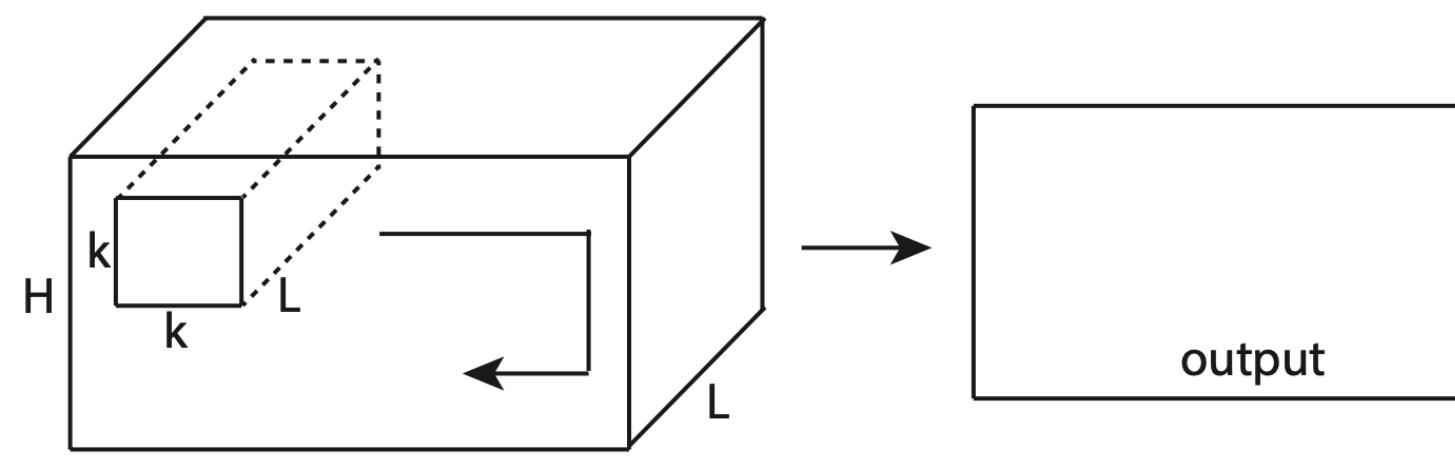


[YouTube Video](#)

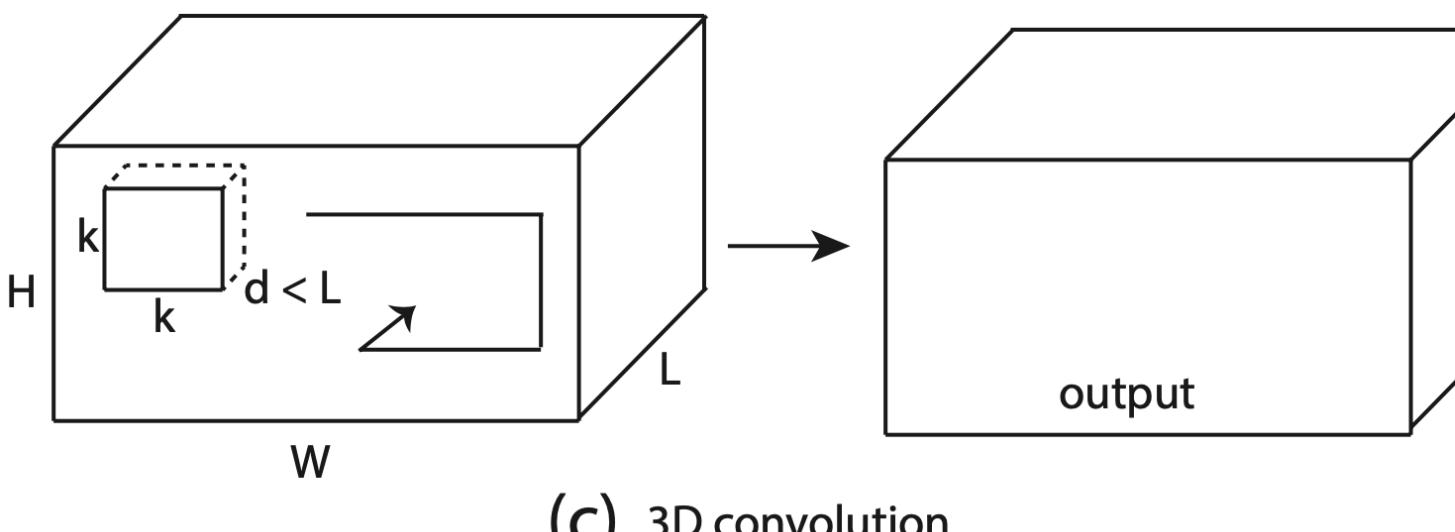
- search – recommendation – ranking
- action recognition
- abnormal event detection (anomaly detection)
- activity understanding
- video retrieval
- event & action detection



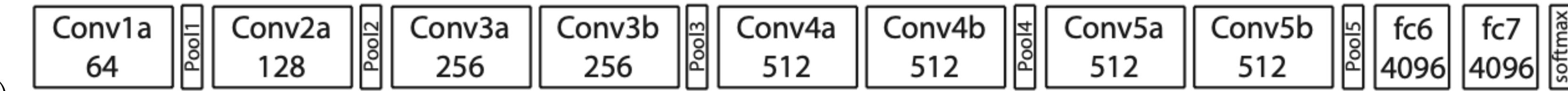
(a) 2D convolution



(b) 2D convolution on multiple frames



(c) 3D convolution



All 3D convolution kernels are $3 \times 3 \times 3$

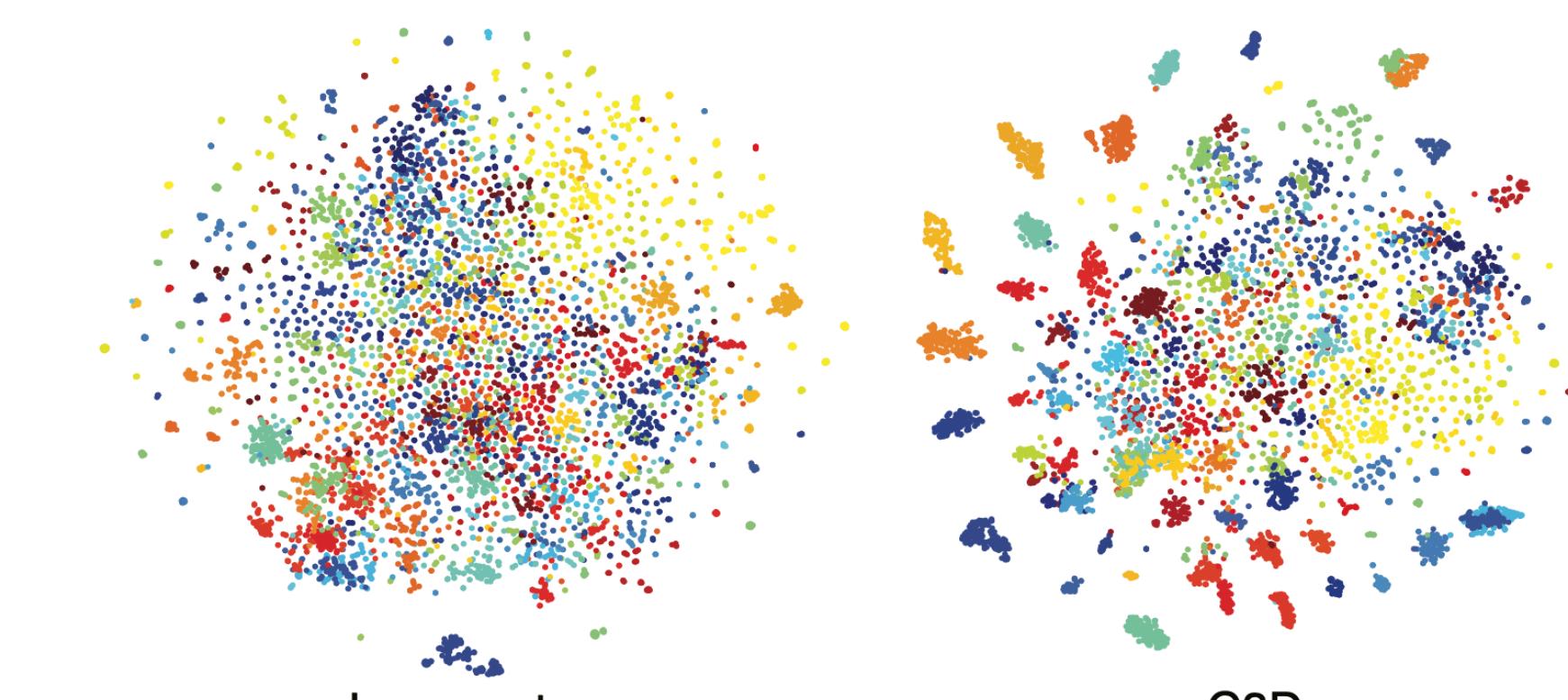
| Dataset Task | Sport1M action recognition | UCF101 action recognition | ASLAN action similarity labeling | YUPENN scene classification | UMD scene classification | Object object recognition |
|--------------|----------------------------|---------------------------|----------------------------------|-----------------------------|--------------------------|---------------------------|
| Method | [29] | [39]([25]) | [31] | [9] | [9] | [32] |
| Result | 90.8 | 75.8 (89.1) | 68.7 | 96.2 | 77.7 | 12.0 |
| C3D | 85.2 | 85.2 (90.4) | 78.3 | 98.1 | 87.7 | 22.3 |

RGB



All possible features (e.g. optical flow, improved Dense Trajectory)

iDT



Imagenet

C3D

Each clip is visualized as a point

| Method Usage | iDT CPU | Brox's CPU | Brox's GPU | C3D GPU |
|--------------|---------|------------|------------|---------|
| RT (hours) | 202.2 | 2513.9 | 607.8 | 2.2 |
| FPS | 3.5 | 0.3 | 1.2 | 313.9 |
| x Slower | 91.4 | 1135.9 | 274.6 | 1 |

Runtime analysis on UCF101

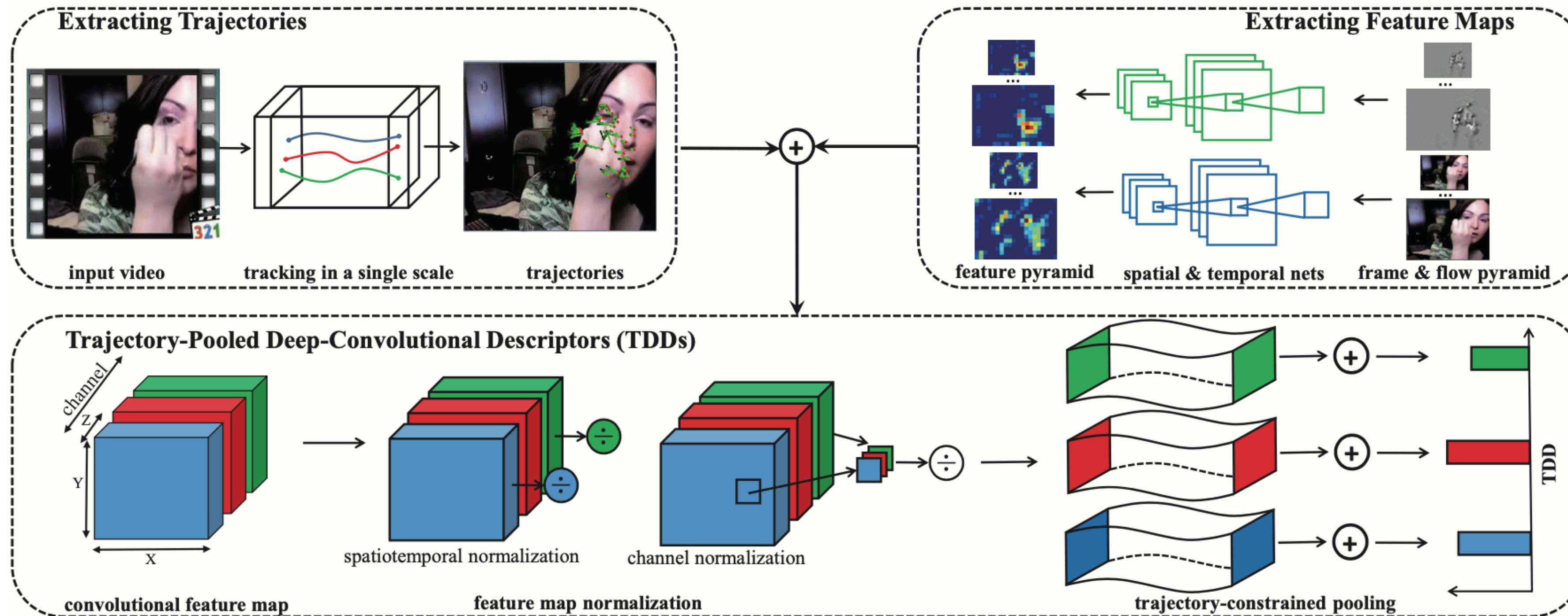
| Method | Accuracy (%) |
|--|--------------|
| Imagenet + linear SVM | 68.8 |
| iDT w/ BoW + linear SVM | 76.2 |
| Deep networks [18] | 65.4 |
| Spatial stream network [36] | 72.6 |
| LRCN [6] | 71.1 |
| LSTM composite model [39] | 75.8 |
| C3D (1 net) + linear SVM | 82.3 |
| C3D (3 nets) + linear SVM | 85.2 |
| iDT w/ Fisher vector [31] | 87.9 |
| Temporal stream network [36] | 83.7 |
| Two-stream networks [36] | 88.0 |
| LRCN [6] | 82.9 |
| LSTM composite model [39] | 84.3 |
| Conv. pooling on long clips [29] | 88.2 |
| LSTM on long clips [29] | 88.6 |
| Multi-skip feature stacking [25] | 89.1 |
| C3D (3 nets) + iDT + linear SVM | 90.4 |

Action recognition results on UCF101



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Action Recognition with Trajectory-Pooled Deep-Convolutional Descriptors



| Algorithm | HMDB51 | UCF101 |
|--------------------------|--------------|--------------|
| HOG [31, 32] | 40.2% | 72.4% |
| HOF [31, 32] | 48.9% | 76.0% |
| MBH [31, 32] | 52.1% | 80.8% |
| HOF+MBH [31, 32] | 54.7% | 82.2% |
| iDT [31, 32] | 57.2% | 84.7% |
| Spatial net [24] | 40.5% | 73.0% |
| Temporal net [24] | 54.6% | 83.7% |
| Two-stream ConvNets [24] | 59.4% | 88.0% |
| Spatial conv4 | 48.5% | 81.9% |
| Spatial conv5 | 47.2% | 80.9% |
| Spatial conv4 and conv5 | 50.0% | 82.8% |
| Temporal conv3 | 54.5% | 81.7% |
| Temporal conv4 | 51.2% | 80.1% |
| Temporal conv3 and conv4 | 54.9% | 82.2% |
| TDD | 63.2% | 90.3% |
| TDD and iDT | 65.9% | 91.5% |

– video surveillance – human computer interaction – video content analysis

Trajectory-pooled Deep-convolutional Descriptor (TDD)

$V \rightarrow$ video

$T(V) = \{T_1, \dots, T_K\} \rightarrow$ set of trajectories

$T_k = \{(x_1^k, y_1^k, z_1^k), \dots, (x_P^k, y_P^k, z_P^k)\} \rightarrow$ trajectory k

$C(V) = \{C_1^s, \dots, C_M^s, C_1^t, \dots, C_M^t\} \rightarrow$ convolutional feature maps (Two-Stream CNNs)

$C_m^s \in \mathbb{R}^{H_m \times W_m \times L \times N_m} \rightarrow$ m -th layer feature map of spatial network

$C_m^t \in \mathbb{R}^{H_m \times W_m \times L \times N_m} \rightarrow$ m -th layer feature map of temporal network

$L \rightarrow$ duration of the video, $N_m \rightarrow$ number of channels

Trajectory Pooling

$$D(T_k, \tilde{C}_m^a) = \sum_{p=1}^P \tilde{C}_m^a((\overline{r_m \times x_p^k}), (\overline{r_m \times y_p^k}), z_p^k) \quad a \in \{s, t\}$$

$r_m \rightarrow$ map size ratio with respective to input size

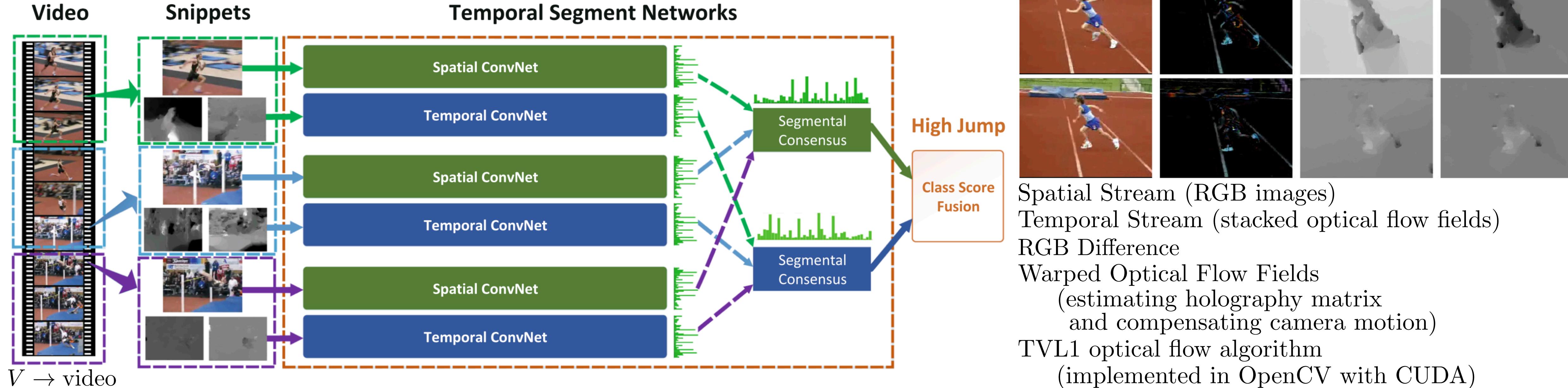
$(\cdot) \rightarrow$ rounding operation spatiotemporal normalization

$$\begin{aligned} \tilde{C}_m^a(x, y, z, n) &= C_m^a(x, y, z, n) / \max_{x, y, z} C_m^a(x, y, z, n) \\ \tilde{C}_m^a(x, y, z, n) &= C_m^a(x, y, z, n) / \max_n C_m^a(x, y, z, n) \end{aligned}$$

Temporal Segment Networks: Towards Good Practices for Deep Action Recognition

Security and behavior analysis

An extension of the two-stream convolutional networks to model long range temporal structure



$\{S_1, S_2, \dots, S_K\} \rightarrow K = 3$ segments of equal durations

$(T_1, T_2, \dots, T_K) \rightarrow \text{sequence of snippets}$

$T_k \rightarrow \text{snippet randomly sampled from its corresponding segment } S_k$

$\text{TSN}(T_1, T_2, \dots, T_K) = \mathcal{H}(\mathcal{G}(\mathcal{F}(T_1; \mathbf{W}), \mathcal{F}(T_2; \mathbf{W}), \dots, \mathcal{F}(T_K; \mathbf{W})))$

$\mathcal{F}(T_k; \mathbf{W}) \rightarrow \text{ConvNet (outputs class scores for all classes)}$

$\mathcal{G} \rightarrow \text{segmental consensus function}$

$\mathcal{H} \rightarrow \text{prediction function (softmax)}$

$\mathbf{G} = \mathcal{G}(\mathcal{F}(T_1; \mathbf{W}), \mathcal{F}(T_2; \mathbf{W}), \dots, \mathcal{F}(T_K; \mathbf{W}))$

$G_i = g(\mathcal{F}_i(T_1), \dots, \mathcal{F}_i(T_K)) \rightarrow \text{aggregation function (averaging)}$

$$\mathcal{L}(y, \mathbf{G}) = - \sum_{i=1}^C y_i \left(G_i - \log \sum_{j=1}^C \exp G_j \right)$$

UCF101 dataset (split 1)

| Component | Basic Two-stream [1] | Cross-Modality pre-training |
|-------------------------|----------------------|-----------------------------|
| Accuracy | 90.0 % | 91.5 |
| Partial BN with dropout | | Temporal segment networks |
| 92.0 % | 93.5 % | |

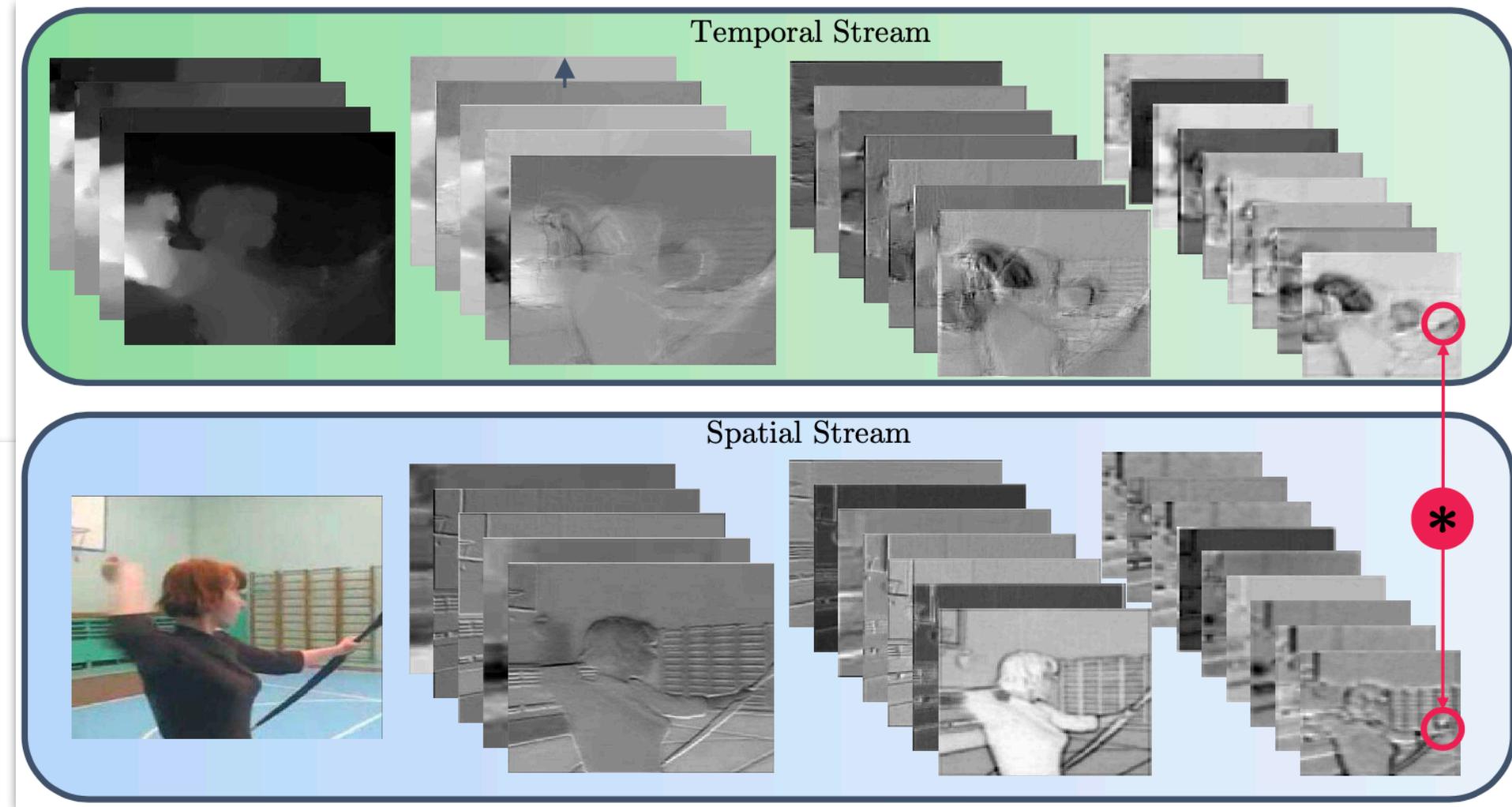
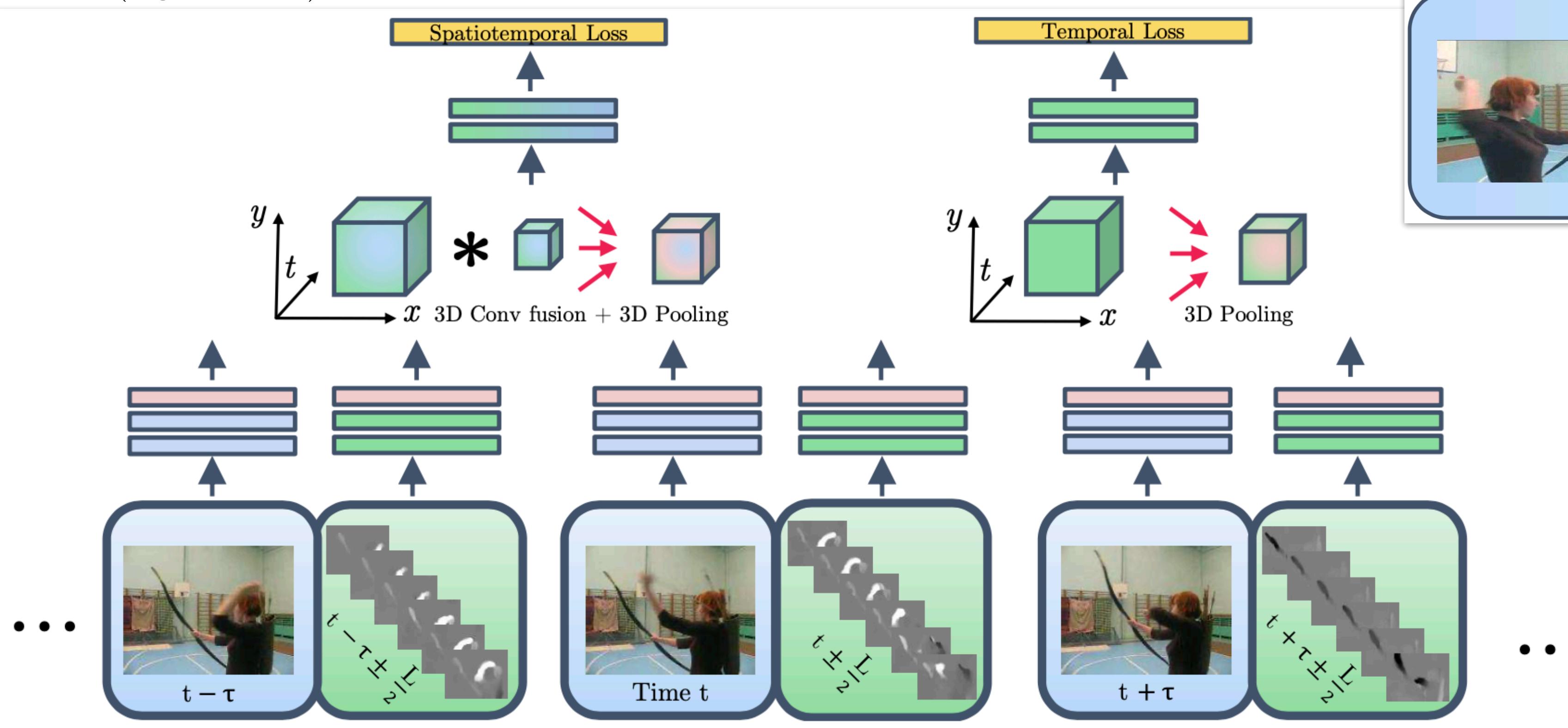


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Convolutional Two-Stream Network Fusion for Video Action Recognition

Two main drawbacks of the two-stream architecture:

- unable learn the pixel-wise correspondences between spatial and temporal features (since fusion is only on the classification scores)
- limited in temporal scale as the spatial ConvNet operates only on single frames and the temporal ConvNet only on a stack of L temporally adjacent optical flow frames (e.g. $L = 10$).



- How to fuse the two networks?
- Where to fuse the networks?
- How to fuse the networks temporally?

| Method | UCF101 | HMDB51 |
|--|--------|--------|
| Spatiotemporal ConvNet [11] | 65.4% | - |
| LRCN [6] | 82.9% | - |
| Composite LSTM Model [25] | 84.3% | 44.0 |
| C3D [30] | 85.2% | - |
| Two-Stream ConvNet [22] | 88.0% | 59.4% |
| Factorized ConvNet [26] | 88.1% | 59.1% |
| Two-Stream Conv Pooling [17] | 88.2% | - |
| Ours (S:VGG-16, T:VGG-M) | 90.8% | 62.1% |
| Ours (S:VGG-16, T:VGG-16, single tower after fusion) | 91.8% | 64.6% |
| Ours (S:VGG-16, T:VGG-16) | 92.5% | 65.4% |

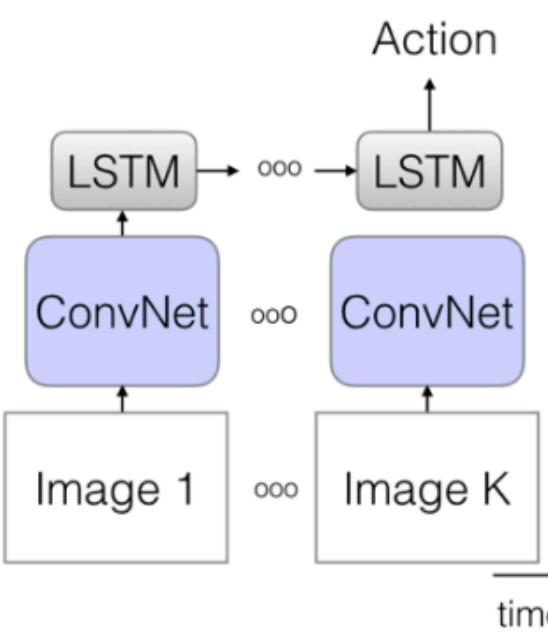
$TL \rightarrow$ total temporal receptive field

Feichtenhofer, Christoph, Axel Pinz, and Andrew Zisserman. "Convolutional two-stream network fusion for video action recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.

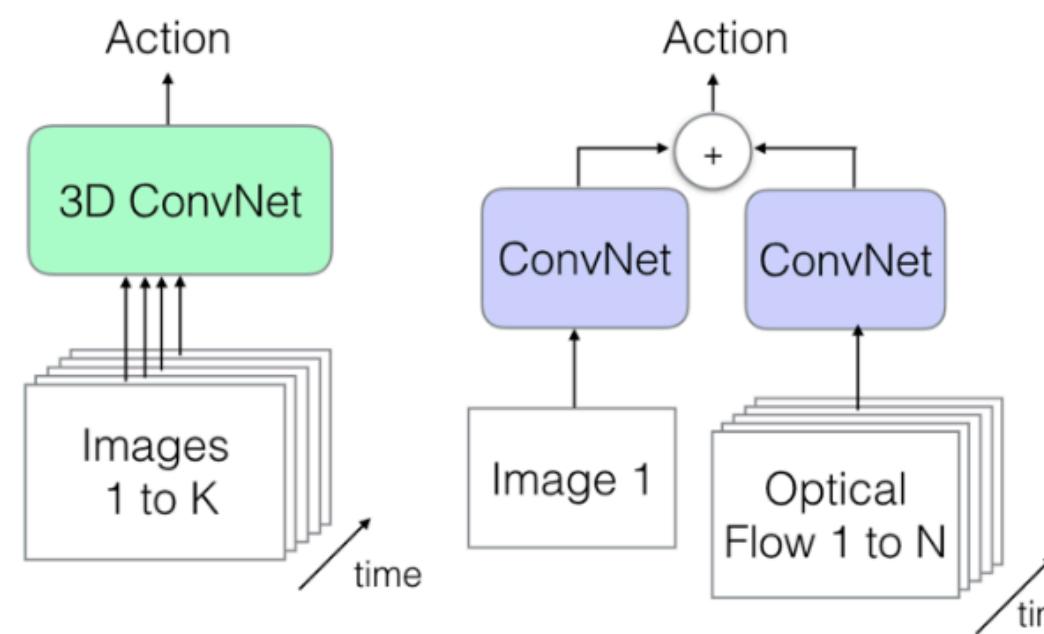
Quo Vadis, Action Recognition? A New Model and the Kinetics Dataset


[YouTube Video](#)

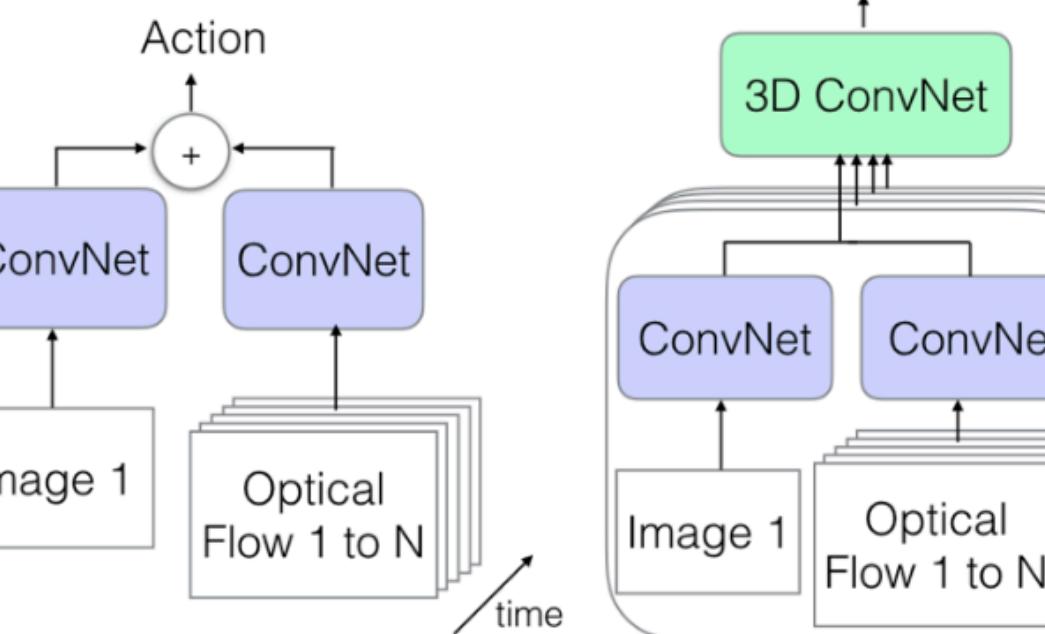
a) LSTM



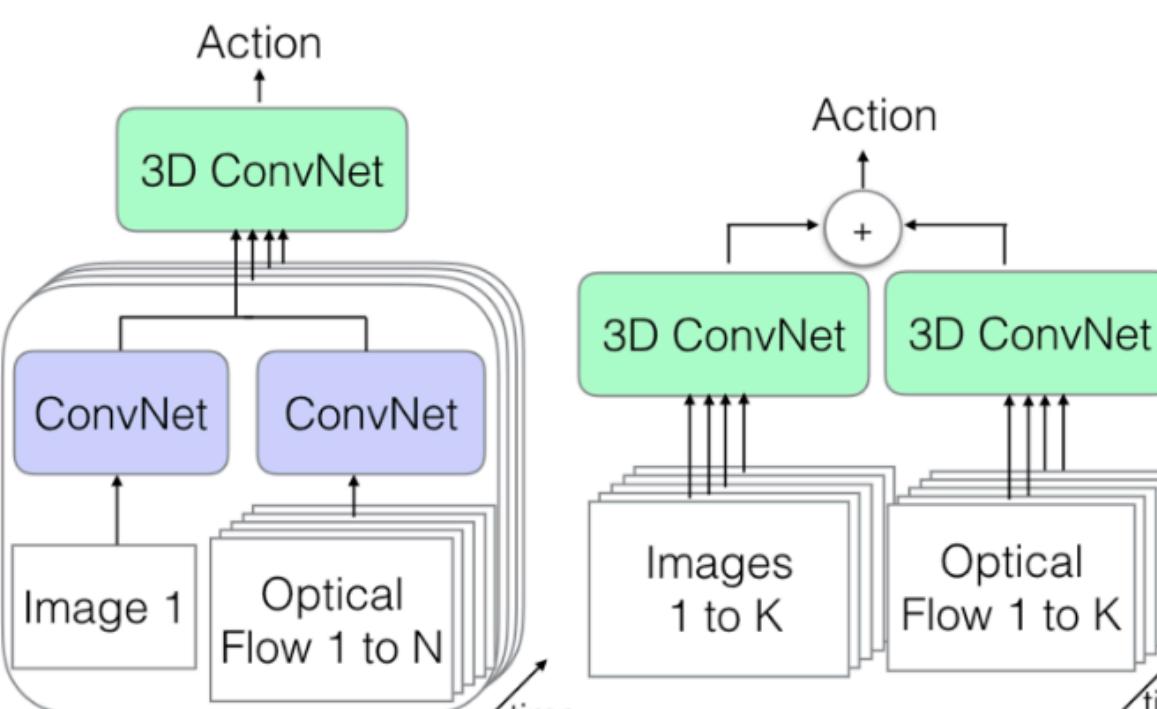
b) 3D-ConvNet



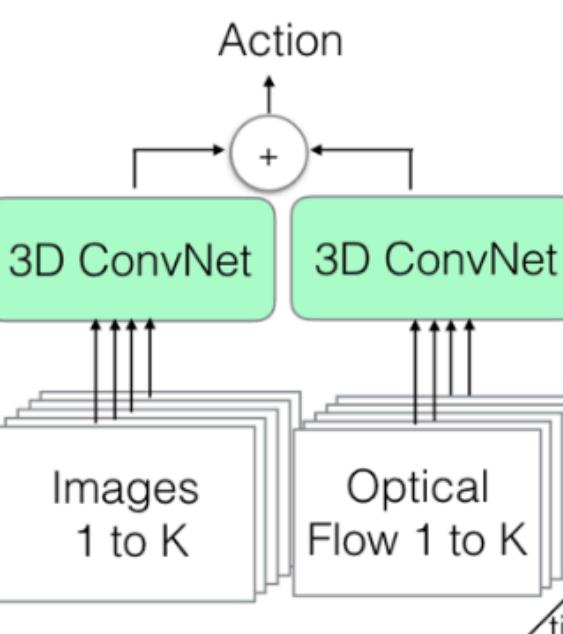
c) Two-Stream



d) 3D-Fused Two-Stream



e) Two-Stream 3D-ConvNet



Two-stream Inflated 3D ConvNet (I3D)

Repeating the weights of the 2D filters N times along the time dimension, and rescaling them by dividing by N .

Train the two networks separately and average their predictions at test time.

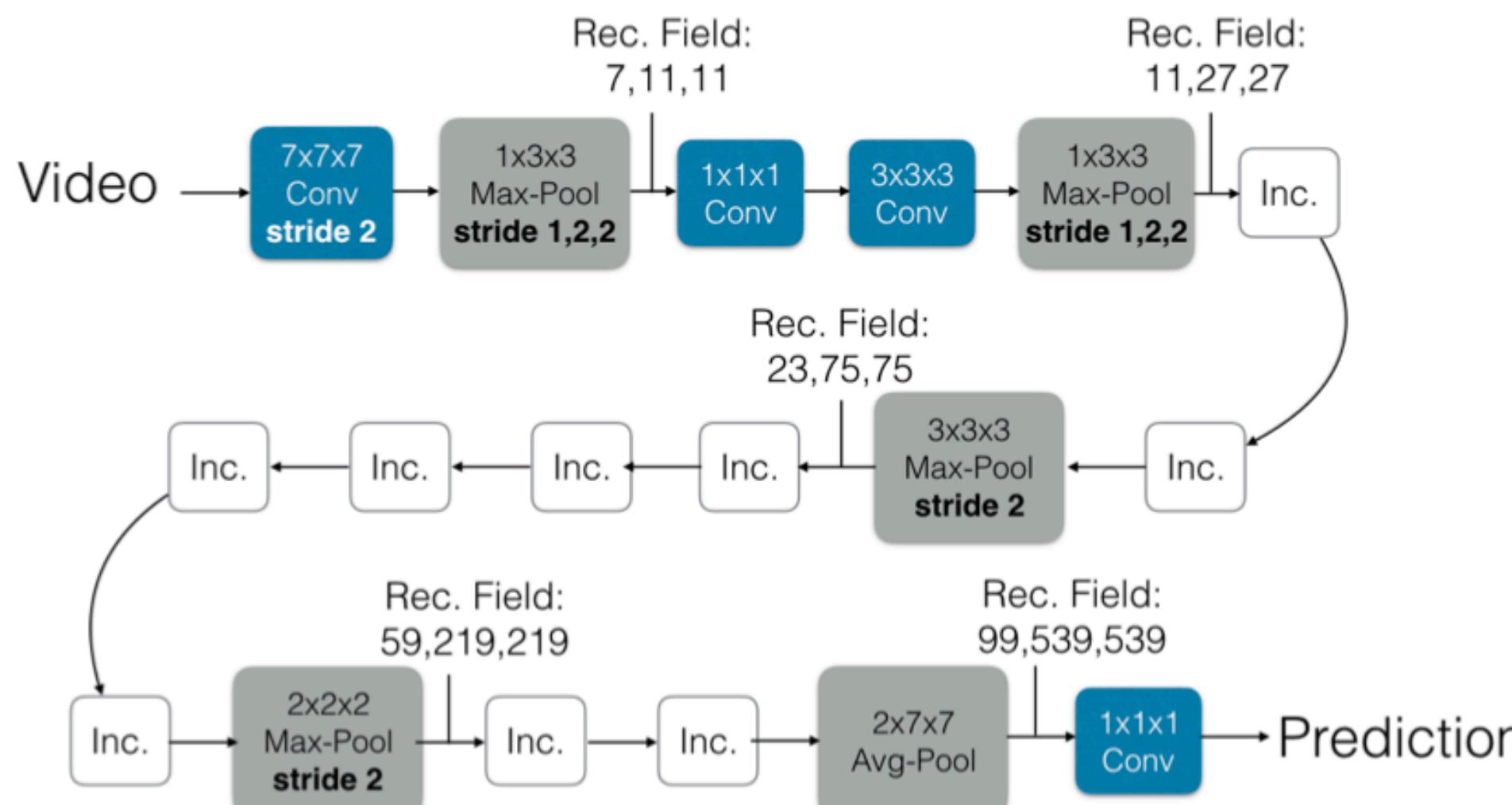
The Kinetics Human Action Video Dataset

The list of action classes covers: Person Actions (singular), e.g. drawing, drinking, laughing, punching; Person-Person Actions, e.g. hugging, kissing, shaking hands; and, Person-Object Actions, e.g. opening presents, mowing lawn, washing dishes.

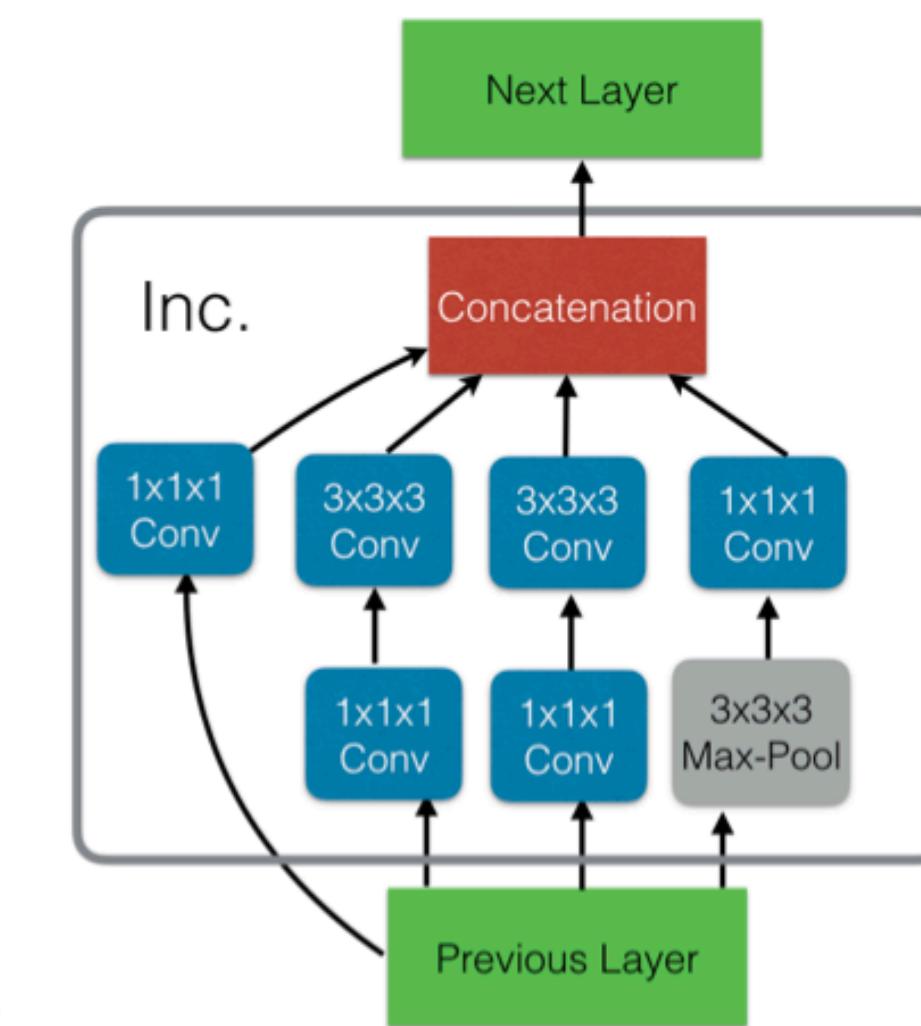
– 400 human action classes – 400 or more clips per class

$K \rightarrow$ total number of frames in a video
 $N \rightarrow$ a subset of neighboring frames of the video

Inflated Inception-V1



Inception Module (Inc.)



| Model | UCF-101 | HMDB-51 |
|---|-------------|-------------|
| Two-Stream [25] | 88.0 | 59.4 |
| IDT [30] | 86.4 | 61.7 |
| Dynamic Image Networks + IDT [2] | 89.1 | 65.2 |
| TDD + IDT [31] | 91.5 | 65.9 |
| Two-Stream Fusion + IDT [8] | 93.5 | 69.2 |
| Temporal Segment Networks [32] | 94.2 | 69.4 |
| ST-ResNet + IDT [7] | 94.6 | 70.3 |
| Deep Networks [15], Sports 1M pre-training | 65.2 | - |
| C3D one network [29], Sports 1M pre-training | 82.3 | - |
| C3D ensemble [29], Sports 1M pre-training | 85.2 | - |
| C3D ensemble + IDT [29], Sports 1M pre-training | 90.1 | - |
| RGB-I3D, miniKinetics pre-training | 91.8 | 66.4 |
| RGB-I3D, Kinetics pre-training | 95.4 | 74.5 |
| Flow-I3D, miniKinetics pre-training | 94.7 | 72.4 |
| Flow-I3D, Kinetics pre-training | 95.4 | 74.6 |
| Two-Stream I3D, miniKinetics pre-training | 96.9 | 76.3 |
| Two-Stream I3D, Kinetics pre-training | 97.9 | 80.2 |

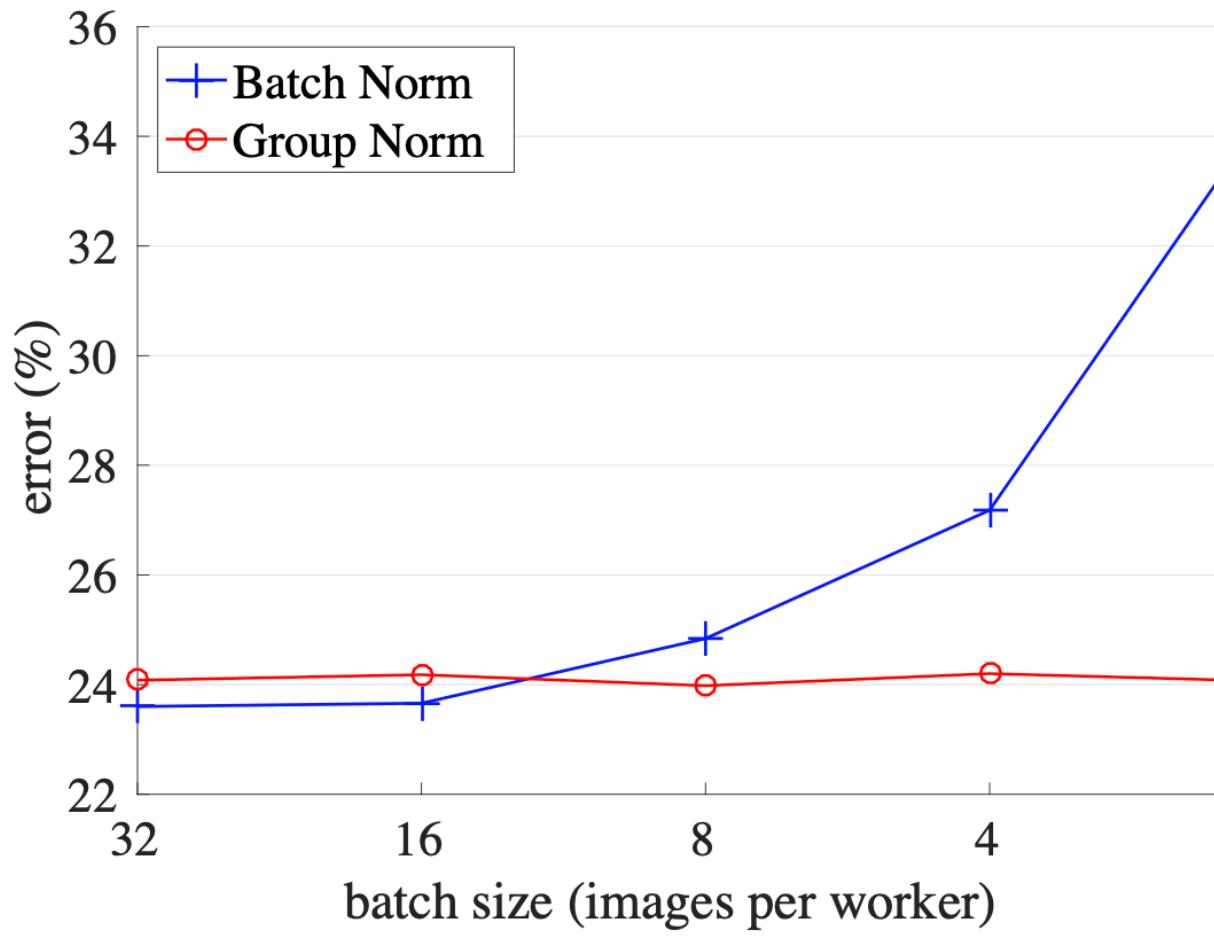


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Group Normalization



$$\hat{x}_i = \frac{1}{\sigma_i} (x_i - \mu_i)$$

$x \rightarrow$ the feature computed by a layer

$i = (i_N, i_C, i_H, i_W) \rightarrow$ an index

$N \rightarrow$ batch axis

$C \rightarrow$ channel axis

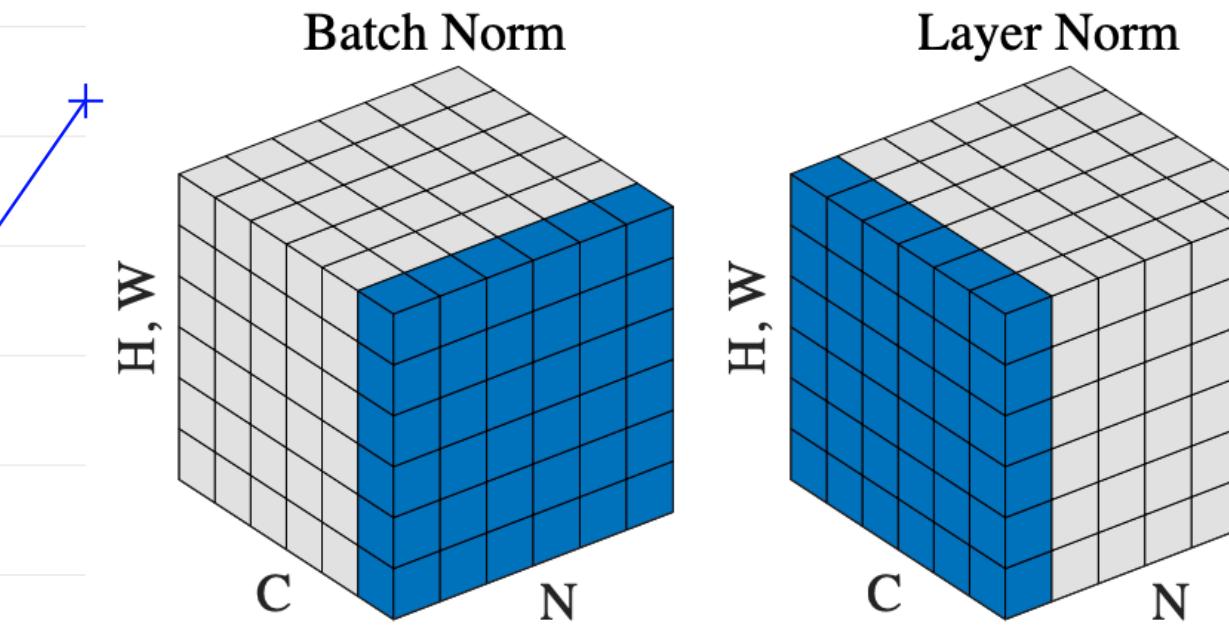
$H \rightarrow$ height axis

$W \rightarrow$ width axis

$$\mu_i = \frac{1}{m} \sum_{k \in \mathcal{S}_i} x_k, \quad \sigma_i = \sqrt{\frac{1}{m} \sum_{k \in \mathcal{S}_i} (x_k - \mu_i)^2 + \epsilon},$$

$\mathcal{S}_i \rightarrow$ set of pixels in which the mean and std are computed
 $|\mathcal{S}_i| = m$

Batch Norm $\Rightarrow \mu \& \sigma$ computed
 $\mathcal{S}_i = \{k : k_C = i_C\}$ along (N, H, W) axes



Layer Norm

$\mathcal{S}_i = \{k : k_N = i_N\}$
 $\Rightarrow \mu \& \sigma$ computed along (C, H, W) axes

Instance Norm

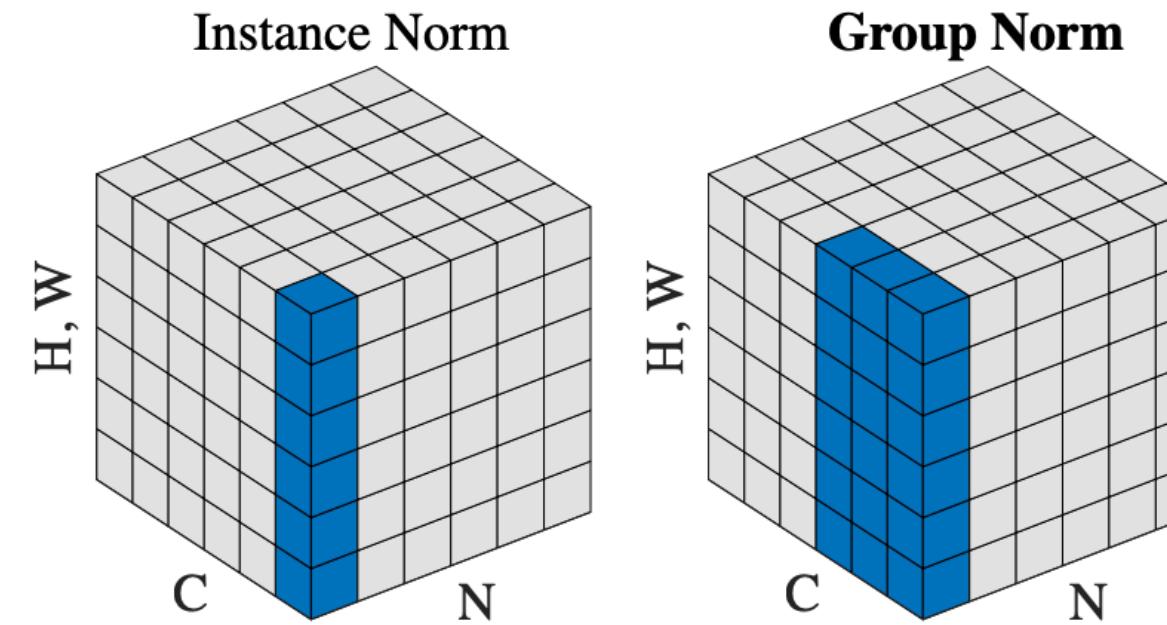
$\mathcal{S}_i = \{k : k_N = i_N, k_C = i_C\}$
 $\Rightarrow \mu \& \sigma$ computed along (H, W) axes for each sample and for each channel

Shift & Scale

$y_i = \gamma \hat{x}_i + \beta$
per channel γ and β
(indexed by i_C)

Group Norm

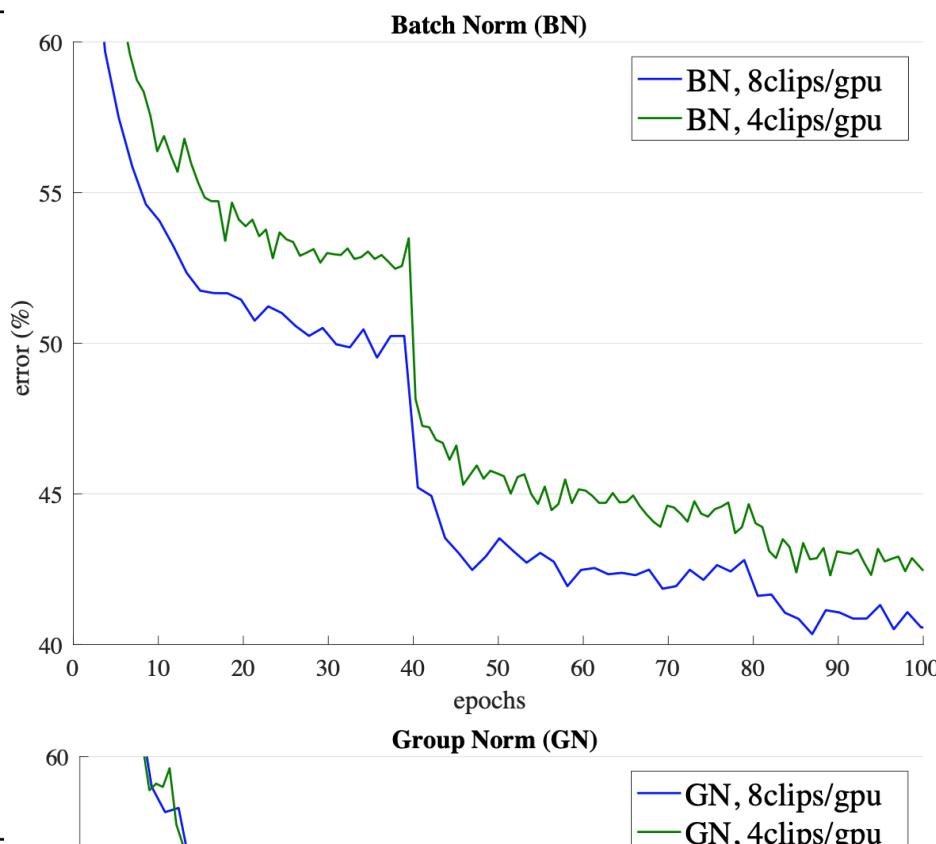
$\mathcal{S}_i = \{k : k_N = i_N, \left\lfloor \frac{k_C}{C/G} \right\rfloor = \left\lfloor \frac{i_C}{C/G} \right\rfloor\}$ $\Rightarrow \mu \& \sigma$ computed along (H, W) axes and a group of C/G channels
 $G = 32 \rightarrow$ number of groups
 $C/G \rightarrow$ number of channels per group



ImageNet

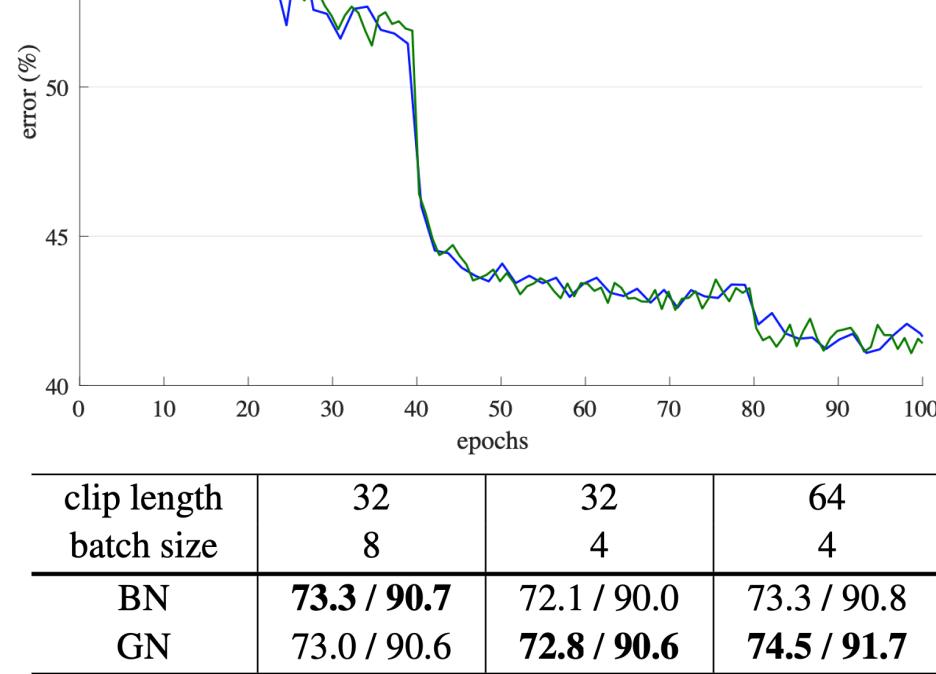
| | BN | LN | IN | GN |
|-------------------|-------------|-------------|-------------|-------------|
| val error | 23.6 | 25.3 | 28.4 | 24.1 |
| Δ (vs. BN) | - | 1.7 | 4.8 | 0.5 |
| batch size | 32 | 16 | 8 | 4 |
| BN | 23.6 | 23.7 | 24.8 | 27.3 |
| GN | 24.1 | 24.2 | 24.0 | 24.1 |
| Δ | 0.5 | 0.5 | -0.8 | -3.1 |
| | | | | -10.6 |

Video Classification in Kinetics



Detection and segmentation ablation results in COCO

| backbone | AP ^{bbox} | AP ₅₀ ^{bbox} | AP ₇₅ ^{bbox} | AP ^{mask} | AP ₅₀ ^{mask} | AP ₇₅ ^{mask} |
|----------|--------------------|----------------------------------|----------------------------------|--------------------|----------------------------------|----------------------------------|
| BN* | 37.7 | 57.9 | 40.9 | 32.8 | 54.3 | 34.7 |
| GN | 38.8 | 59.2 | 42.2 | 33.6 | 55.9 | 35.4 |

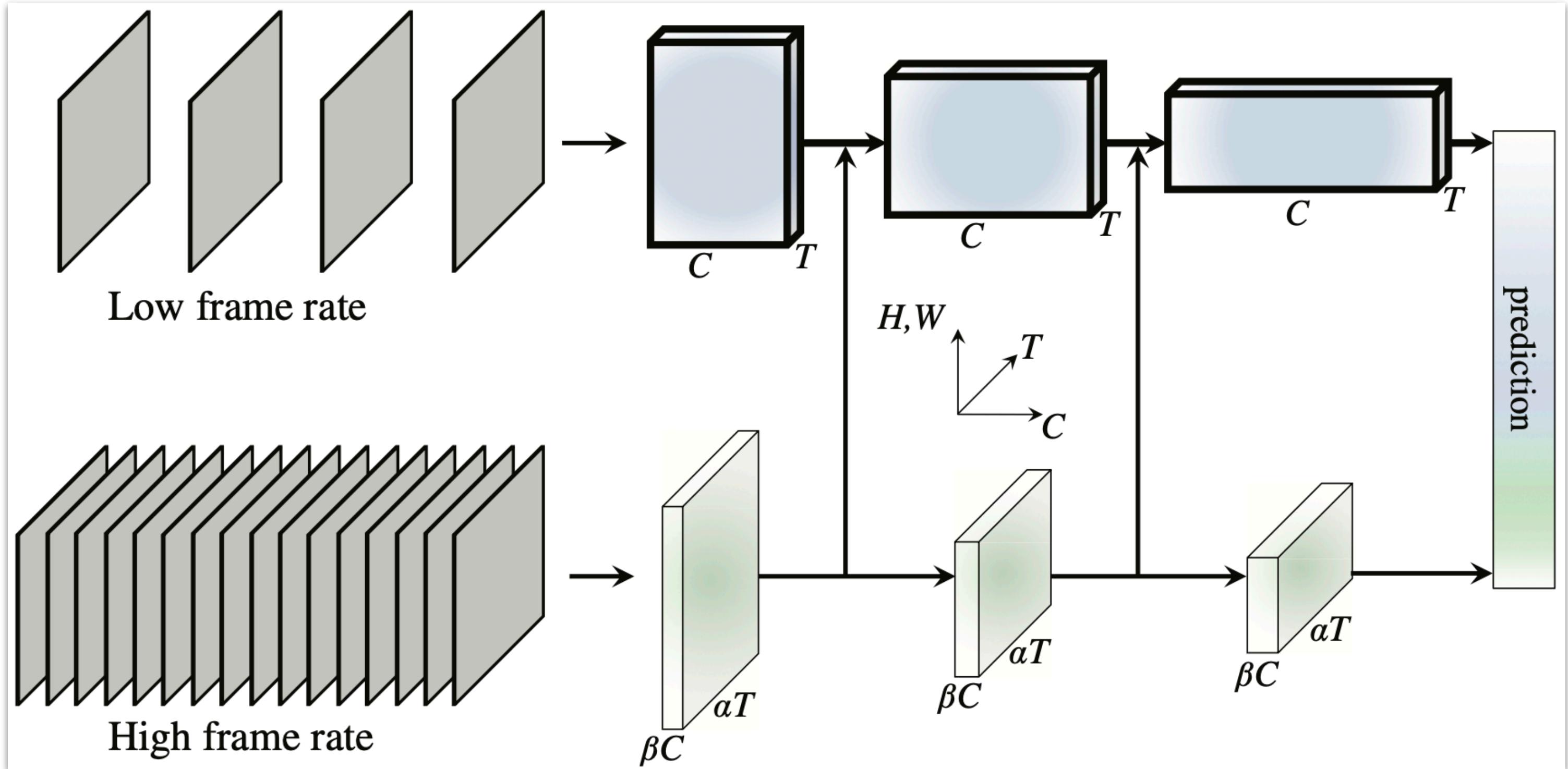




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SlowFast Networks for Video Recognition

– Kinetics – Charades – AVA dataset



$\alpha > 1 \rightarrow$ frame rate ratio between Fast and Slow pathways

$\beta < 1 \rightarrow$ ratio of Fast pathway channels to Slow ones

Fast pathway: high frame rate, high temporal resolution features (no temporal downsampling layers), and low channel capacity

Lateral connections

$\{T, S^2, C\}, \{\alpha T, S^2, \beta C\} \rightarrow$ shapes of the Slow and Fast pathways

Time-strided convolution: Perform a 3D convolution of a 5×1^2 kernel with $2\beta C$ output channels and stride = α . Concatenation is employed for fusion.

| stage | Slow pathway | Fast pathway | output sizes $T \times S^2$ |
|-------------------|---|--|---|
| raw clip | - | - | 64×224^2 |
| data layer | stride 16, 1^2 | stride $2, 1^2$ | <i>Slow</i> : 4×224^2 <i>Fast</i> : 32×224^2 |
| conv ₁ | $1 \times 7^2, 64$ stride 1, 2^2 | $5 \times 7^2, 8$ stride 1, 2^2 | <i>Slow</i> : 4×112^2 <i>Fast</i> : 32×112^2 |
| pool ₁ | 1×3^2 max stride 1, 2^2 | 1×3^2 max stride 1, 2^2 | <i>Slow</i> : 4×56^2 <i>Fast</i> : 32×56^2 |
| res ₂ | $\left[\begin{array}{l} 1 \times 1^2, 64 \\ 1 \times 3^2, 64 \\ 1 \times 1^2, 256 \end{array} \right] \times 3$ | $\left[\begin{array}{l} \underline{3} \times 1^2, 8 \\ \underline{1} \times 3^2, 8 \\ 1 \times 1^2, 32 \end{array} \right] \times 3$ | <i>Slow</i> : 4×56^2 <i>Fast</i> : 32×56^2 |
| res ₃ | $\left[\begin{array}{l} 1 \times 1^2, 128 \\ 1 \times 3^2, 128 \\ 1 \times 1^2, 512 \end{array} \right] \times 4$ | $\left[\begin{array}{l} \underline{3} \times 1^2, 16 \\ \underline{1} \times 3^2, 16 \\ 1 \times 1^2, 64 \end{array} \right] \times 4$ | <i>Slow</i> : 4×28^2 <i>Fast</i> : 32×28^2 |
| res ₄ | $\left[\begin{array}{l} \underline{3} \times 1^2, 256 \\ \underline{1} \times 3^2, 256 \\ 1 \times 1^2, 1024 \end{array} \right] \times 6$ | $\left[\begin{array}{l} \underline{3} \times 1^2, 32 \\ \underline{1} \times 3^2, 32 \\ 1 \times 1^2, 128 \end{array} \right] \times 6$ | <i>Slow</i> : 4×14^2 <i>Fast</i> : 32×14^2 |
| res ₅ | $\left[\begin{array}{l} \underline{3} \times 1^2, 512 \\ \underline{1} \times 3^2, 512 \\ 1 \times 1^2, 2048 \end{array} \right] \times 3$ | $\left[\begin{array}{l} \underline{3} \times 1^2, 64 \\ \underline{1} \times 3^2, 64 \\ 1 \times 1^2, 256 \end{array} \right] \times 3$ | <i>Slow</i> : 4×7^2 <i>Fast</i> : 32×7^2 |
| | | global average pool, concat, fc | # classes |

dimensions of kernels are denoted by $\{T \times S^2, C\}$ for temporal, spatial, and channel sizes. Strides are denoted as $\{\text{temporal stride}, \text{spatial stride}^2\}$. Here the speed ratio is $\alpha = 8$ and the channel ratio is $\beta = 1/8$. τ is 16. The **green** colors mark *higher* temporal resolution, and **orange** colors mark *fewer* channels, for the Fast pathway. Non-degenerate temporal filters are underlined. Residual blocks are shown by brackets. The backbone is ResNet-50.



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Learning Multi-Domain Convolutional Neural Networks for Visual Tracking

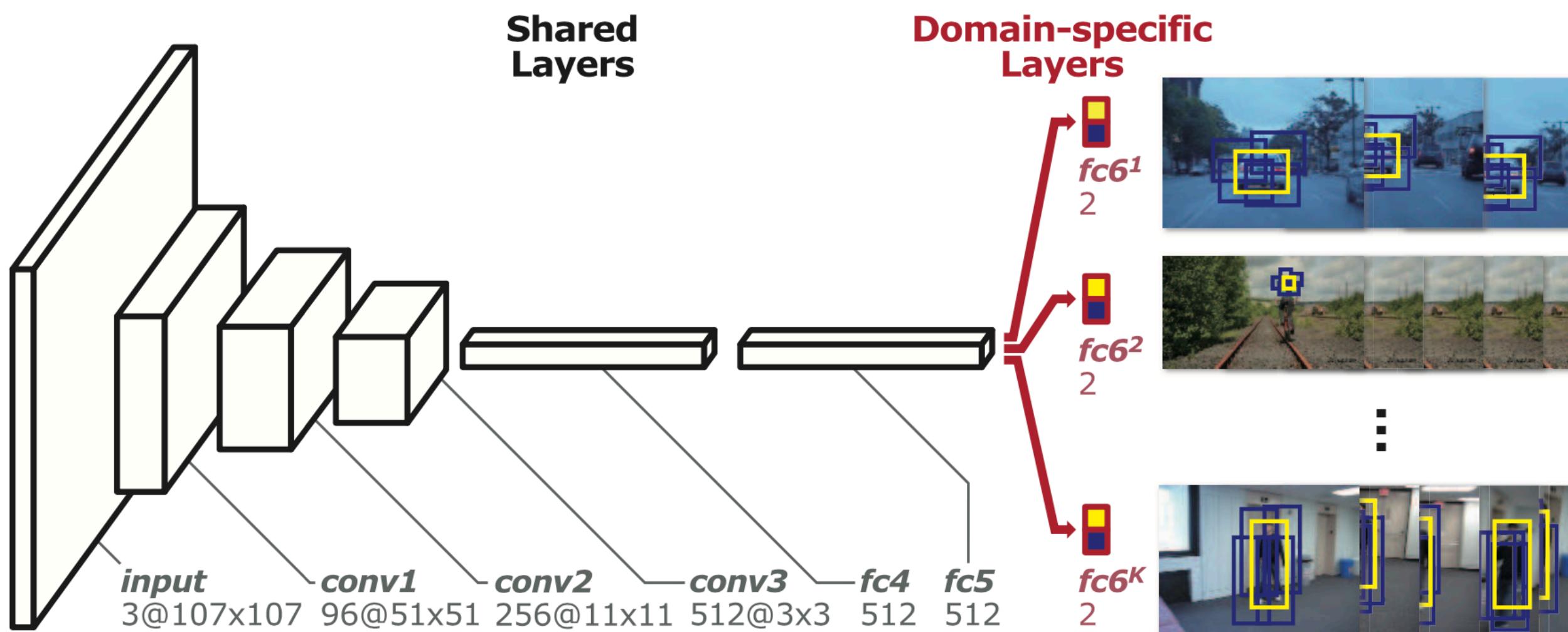
Multi-Domain Network (MDNet)

Each video is regarded as a separate domain!

Offline multi-domain learning

Collect 50 positive and 200 negative samples from every frame, where positive and negative examples have ≥ 0.7 and ≤ 0.5 IoU overlap ratios with ground-truth bounding boxes, respectively.

Yellow and blue bounding boxes denote the positive and negative samples in each domain, respectively.



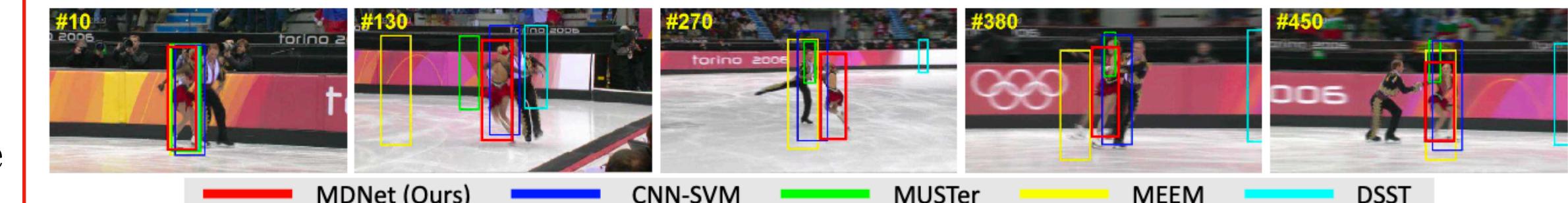
Online tracking algorithm

Fine-tune a new fc6 branch (corresponding to a new test video) and the shared fc4 and fc5 while keeping the conv layers fixed (on the first frame).

Input: Initial target state x_1

Output: Estimate target states x_t^*

<https://www.youtube.com/watch?v=zYM7G5qd090&t=102s>



$x_t^1, \dots, x_t^N \rightarrow N$ target candidates sampled around the previous target state x_{t-1}^*

$f^+(x_t^i), f^-(x_t^i) \rightarrow$ positive and negative scores

$x_t^* = \arg \max_{x_t^i} f^+(x_t^i) \rightarrow$ optimal target state

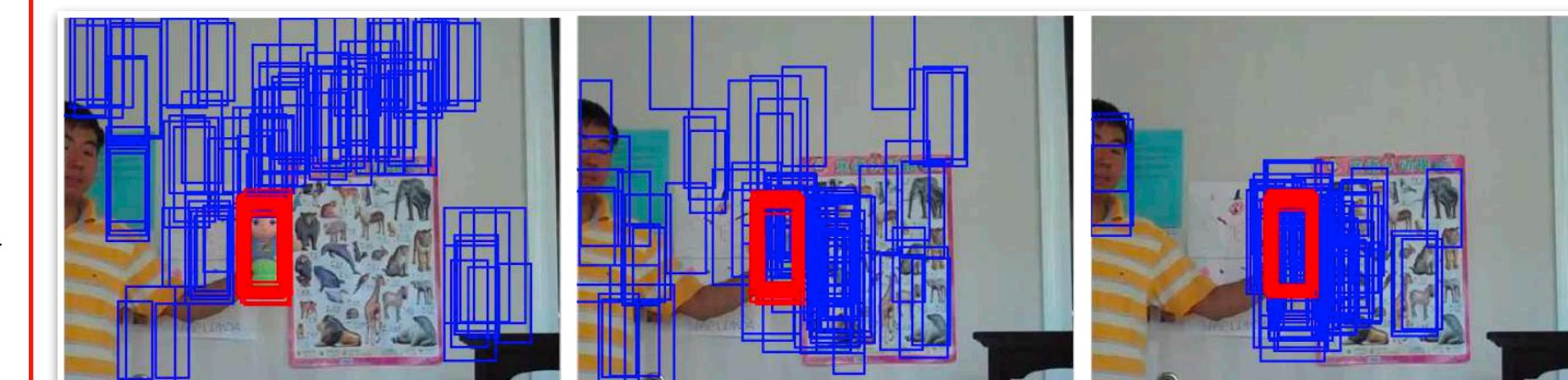
If $f^+(x_t^*) > 0.5$ then accept x_t^* as the target state and adjust it according to a simple linear bounding box regressor trained on the first frame only.

If $f^+(x_t^*) < 0.5$ then update fc4, fc5 and fc6.

Hard Minibatch Mining

Minibatch consists of M^+ positives and M_h^- hard negatives.

The hard negative examples are identified by testing $M^- (\gg M_h^-)$ negative samples and selecting the ones with top M_h^- scores.



The evaluation is based on two metrics: center location error and bounding box overlap ratio.



Boulder

Fully-Convolutional Siamese Networks for Object Tracking

<https://www.youtube.com/watch?v=zS6kil8DgDY>



Frame 1 (init.)

Frame 50

Frame 100

Frame 200

Deep Similarity Learning for Tracking

$z \rightarrow$ an exemplar image (i.e., initial appearance of the object)

$x \rightarrow$ candidate image of the same size

$f(z, x) \rightarrow$ return a high score if two images depict the same object
and a low score otherwise

To find the position of the object in a new image, we can then exhaustively test all possible locations and choose the candidate with the maximum similarity to the past appearance of the object.

$f \rightarrow$ learned from a dataset of videos with labeled object trajectories

$f(z, x) = g(\varphi(z), \varphi(x)) \rightarrow$ Siamese network

embedding

a simple distance of a similarity metric

Fully-Convolutional Siamese Architecture

$h(L_{k\tau}x) = L_\tau h(x) \iff h$ is fully convolutional with stride k

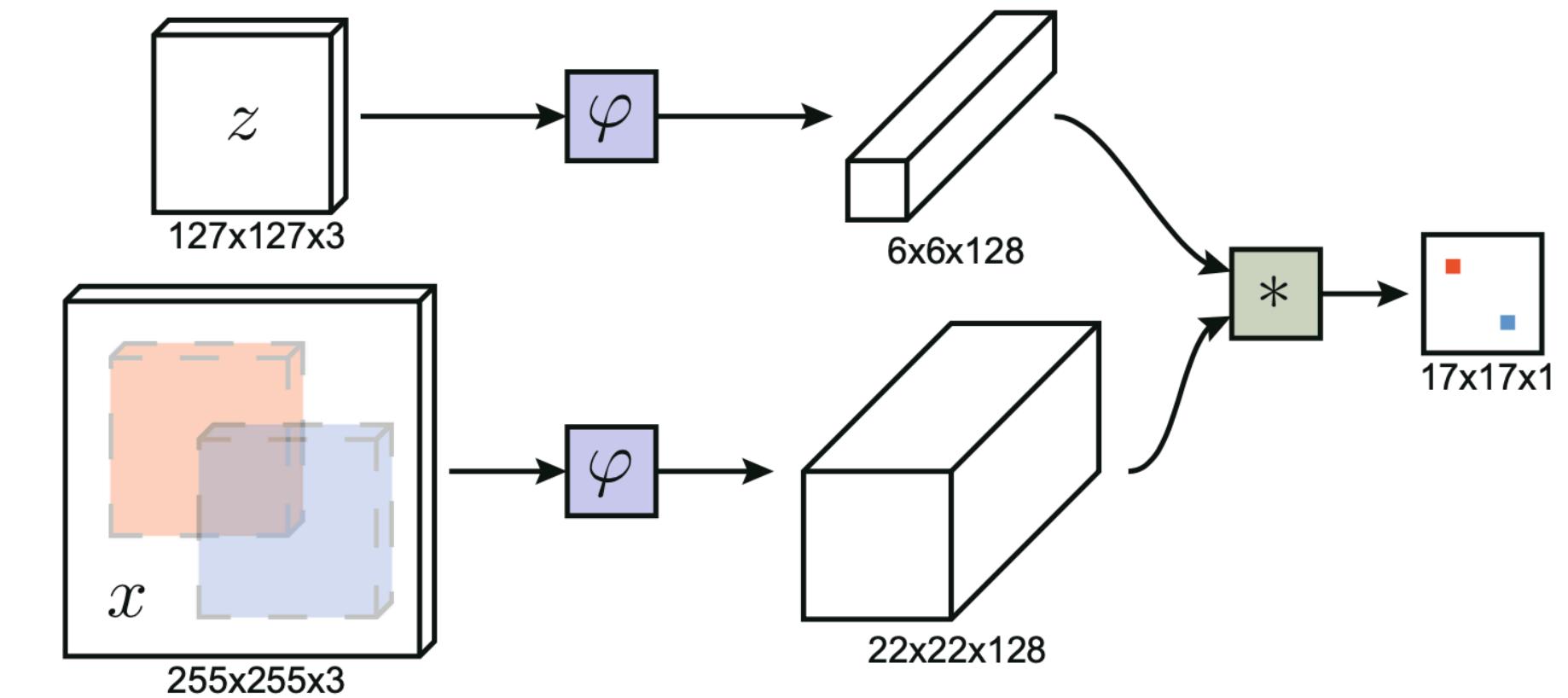
$(L_\tau x)[u] = x[u - \tau]$

$f(z, x) = \varphi(z) * \varphi(x) + b \rightarrow$ score map defined on a finite grid $\mathcal{D} \subset \mathbb{Z}^2$

convolutional embedding function

cross-correlation layer

Advantage: Instead of a candidate image of the same size we can use a much larger search image



During tracking, we use a search image centred at the previous position of the target. The position of the maximum score relative to the centre of the score map, multiplied by the stride of the network, gives the displacement of the target from frame to frame. Multiple scales are searched in a single forward-pass by assembling a mini-batch of scaled images.

Training with Large Search Images

$$L(y, v) = \frac{1}{|\mathcal{D}|} \sum_{u \in \mathcal{D}} \ell(y[u], v[u])$$

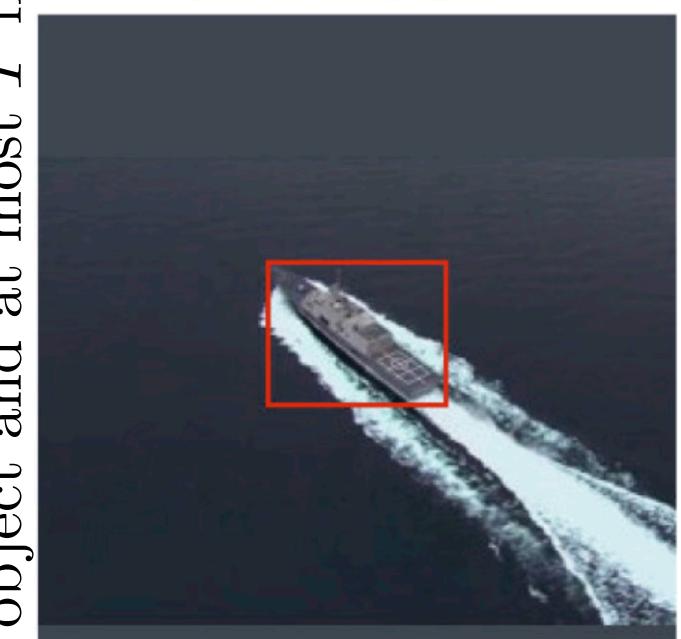
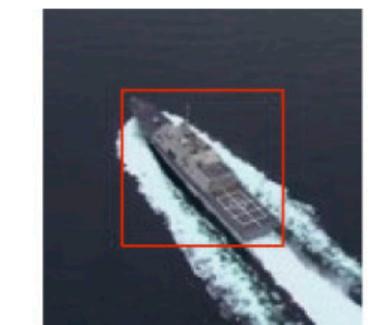
logistic loss

$$\ell(y, v) = \log(1 + \exp(-yv))$$

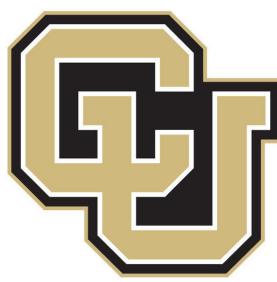
$$y[u] = \begin{cases} +1 & \text{if } k\|u - c\| \leq R \\ -1 & \text{otherwise.} \end{cases}$$

| Dataset (%) | # Videos | # Objects | Accuracy | # Failures | Expected avg. overlap |
|-------------|----------|-----------|--------------|------------|-----------------------|
| 2 | 88 | 60k | 0.484 | 183 | 0.168 |
| 4 | 177 | 110k | 0.501 | 160 | 0.192 |
| 8 | 353 | 190k | 0.484 | 142 | 0.193 |
| 16 | 707 | 330k | 0.522 | 132 | 0.219 |
| 32 | 1413 | 650k | 0.521 | 117 | 0.234 |
| 100 | 4417 | 2m | 0.524 | 87 | 0.274 |

Two frames of a video, both containing the object and at most T frames apart

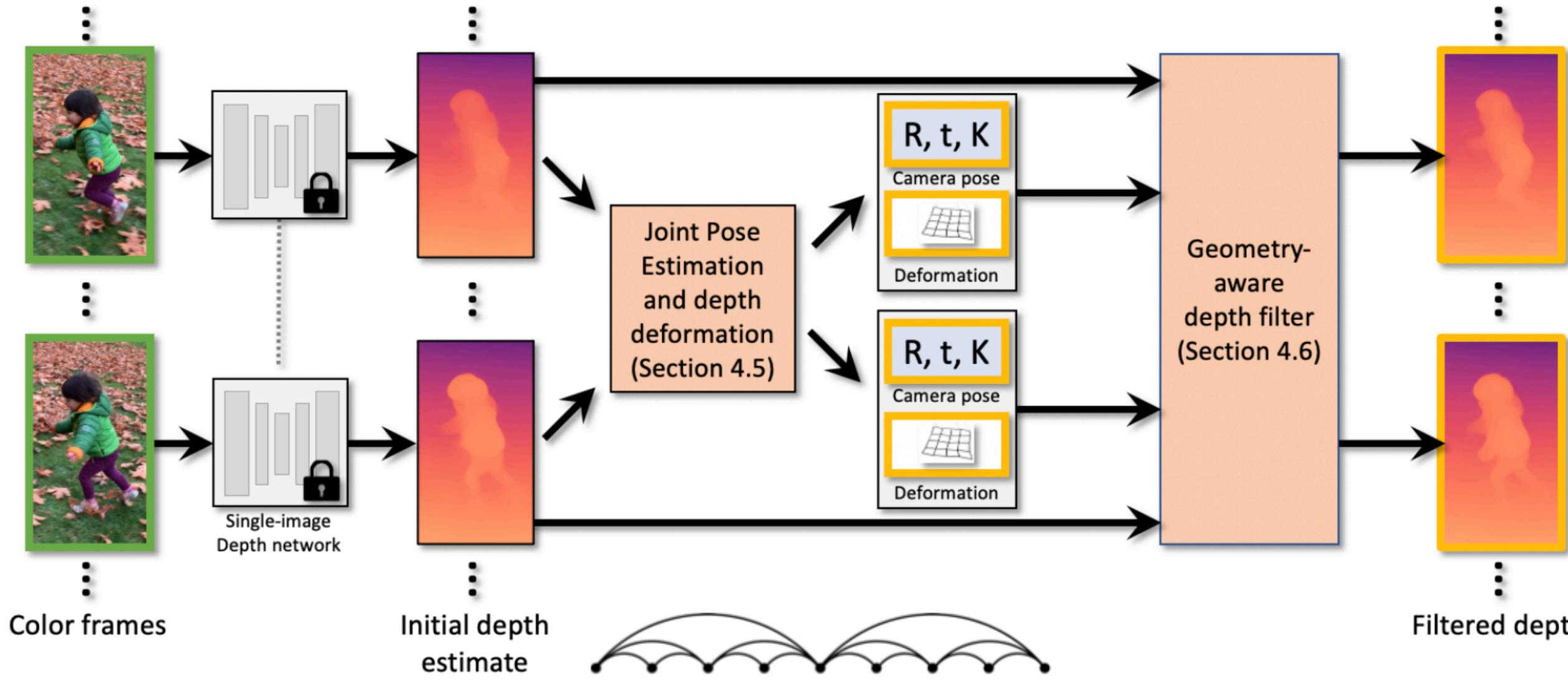


ImageNet Video



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Robust Consistent Video Depth Estimation



$P = \{(i, j) : |i - j| = k, i \bmod k = 0, k = 1, 2, 4, \dots\} \rightarrow$ set of frame pairs

$f_{i \rightarrow j} \rightarrow$ dense optical flow field

mapping a pixel in frame i to its corresponding location in frame j

$m_{i \rightarrow j}^{\text{flow}} \rightarrow$ binary mask (forward-backward consistent flow pixels)

$m_i^{\text{dyn}} \rightarrow$ binary segmentation mask (Mask R-CNN)
indicating likely dynamic pixels ("person", "animal", "vehicle")

Depth Estimation

$p \rightarrow$ 2D pixel coordinate

$c_i(p) = s_i d_i(p) \tilde{p} \rightarrow$ 3D coordinate in frame i 's 3D camera coordinate system

$s_i \rightarrow$ per-frame scale coefficient

$d_i \rightarrow$ CNN-estimated depth map

$\tilde{p} = [p_x, p_y, 1]^T \rightarrow$ homogenous-augmented pixel coordinate

$c_{i \rightarrow j}(p) = K_j R_j^T (R_i K_i^{-1} c_i(p) + t_i - t_j) \rightarrow$ projection of $c_i(p)$ into the camera coordinate system of another frame j

Kopf, Johannes, et al. "Robust Consistent Video Depth Estimation." ArXiv:2012.05901 [Cs], Dec. 2020. arXiv.org, <http://arxiv.org/abs/2012.05901>.

$$R_i, R_j \rightarrow \text{rotation of frames } i \text{ and } j \quad \mathcal{L}^{\text{sim}}(a, b) = \mathcal{L}^{\text{spatial}}(a, b) + \mathcal{L}^{\text{ratio}}(a, b)$$

$$t_i, t_j \rightarrow \text{translation of frames } i \text{ and } j \quad K_i, K_j \rightarrow \text{intrinsics of frames } i \text{ and } j$$

$$\arg \min_{\theta^{\text{depth}}} \sum_{(i,j) \in P} \sum_{p \in m_{i \rightarrow j}^{\text{flow}}} \mathcal{L}_{i \rightarrow j}^{\text{repro}}(p), \quad \text{s.t. fixed } \theta^{\text{cam}}$$

$$\mathcal{L}_{i \rightarrow j}^{\text{repro}}(p) = \mathcal{L}_j^{\text{sim}}(c_{i \rightarrow j}(p), c_j(f_{i \rightarrow j}(p))) \rightarrow \text{reprojection loss}$$

$$\theta^{\text{cam}} = \{R_i, t_i, K_i, s_i\} \rightarrow \text{camera parameters}$$

$$\theta^{\text{depth}} \rightarrow \text{depth CNN parameters}$$

Joint Pose Estimation and Depth Deformation

Reverse the roles of θ^{depth} and θ^{cam} !

Replace s_i with $\phi_i(p) = \sum_k b_k(p) s_i^k$.

$\phi_i(p) \rightarrow$ depth deformation model

$s_i^k \rightarrow$ scale factors (defined on a regular grid across the image)

$b_k(p) \rightarrow$ bilinear coefficients

Geometry-aware Depth Filter

$$d_i^{\text{final}}(p) = \sum_{q \in N(p)} \sum_{j=i-\tau}^{i+\tau} z_{j \rightarrow i}(\tilde{f}_{i \rightarrow j}(q)) w_{i \rightarrow j}(q)$$

$z_{j \rightarrow i} \rightarrow$ reprojected depth (scalar z -component of $c_{j \rightarrow i}$)

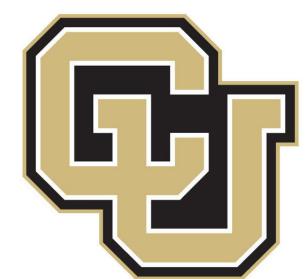
$\tilde{f} \rightarrow$ flow field between far frames

(chaining flow maps between consecutive frames)

$$w_{i \rightarrow j}(q) = \exp(-\lambda_f \mathcal{L}^{\text{ratio}}(c_i(p), c_{j \rightarrow i}(\tilde{f}_{i \rightarrow j}(q))))$$

– Sintel – DAVIS – Cellphone Vides Datasets

$$\mathcal{L}^{\text{ratio}}(a, b) = \frac{\max(a_z, b_z)}{\min(a_z, b_z)} - 1$$



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Questions?

[YouTube Playlist](#)
