Computer vision tasks and corresponding NNs

Alex Net OpenPose Yolo VGG16 **Mask RCNN U** Net **Keypoints RCNN Faster RCNN Res Net** Joint Instance Object Semantic Classification detection Segmentation Segmentation Detection GRASS, CAT, DOG, DOG, CAT DOG, DOG, CAT TREE, SKY

圖片來源: https://kharshit.github.io/blog/2019/08/23/quick-intro-to-instance-segmentation

Computer vision tasks and corresponding NNs

SlowFast

SORT, ByteTrack
DeepSORT, JDE

Action classification

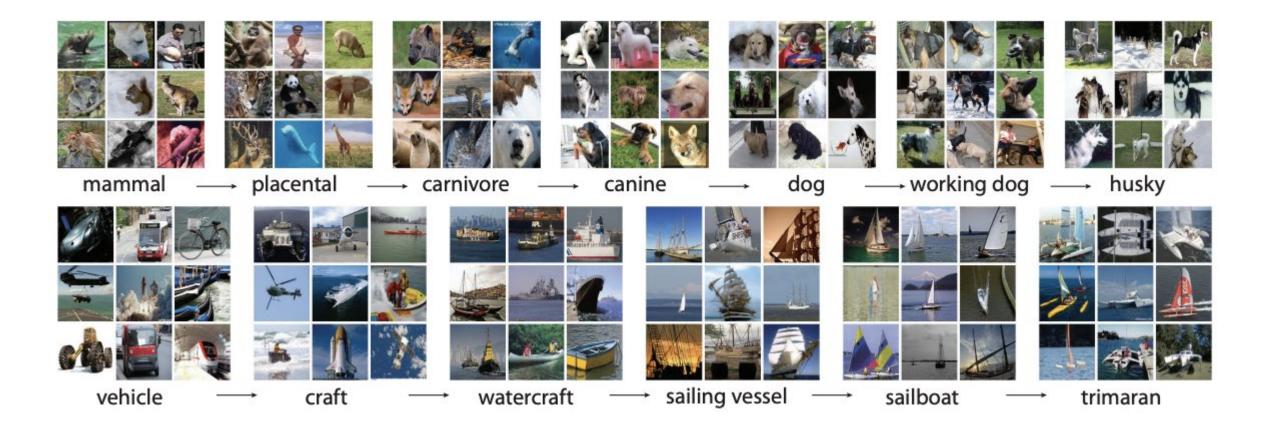


21:10:22 Action = spraying 0.22, cleaning floor 0.18, garbage c ollecting 0.16, 21:10:32 Action =

Multiple Object tracking



ImageNet dataset



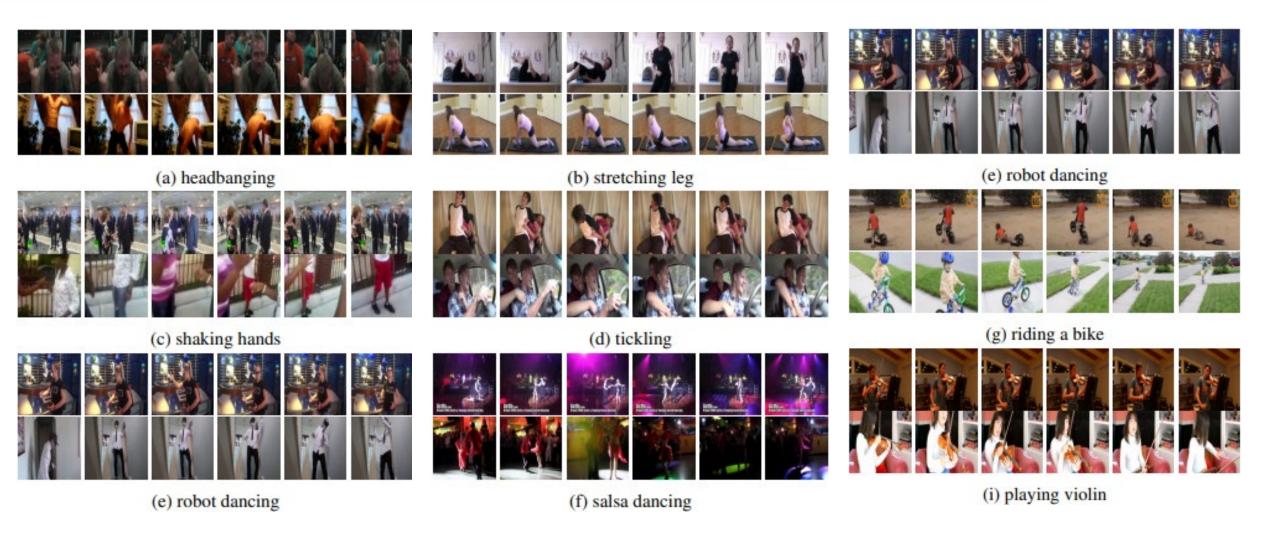
The 1000 categories in ImageNet

```
{0: 'tench, Tinca tinca',
                                                                                                      985: 'daisy',
                                                                                               986
     1: 'goldfish, Carassius auratus',
                                                                                                      986: "yellow lady's slipper, yellow lady-slipper, Cypripedium calc
                                                                                               987
     2: 'great white shark, white shark, man-eater, man-eating shark, Carcharodon carcha
                                                                                               988
                                                                                                      987: 'corn',
                                                                                                      988: 'acorn',
     3: 'tiger shark, Galeocerdo cuvieri',
                                                                                               989
     4: 'hammerhead, hammerhead shark',
                                                                                                      989: 'hip, rose hip, rosehip',
                                                                                               990
     5: 'electric ray, crampfish, numbfish, torpedo',
                                                                                               991
                                                                                                      990: 'buckeye, horse chestnut, conker',
     6: 'stingray',
                                                                                               992
                                                                                                      991: 'coral fungus',
                                                                                                      992: 'agaric',
     7: 'cock',
                                                                                               993
                                                                                                      993: 'gyromitra',
     8: 'hen',
                                                                                               994
                                                                                                      994: 'stinkhorn, carrion fungus',
     9: 'ostrich, Struthio camelus',
                                                                                               995
10
     10: 'brambling, Fringilla montifringilla',
                                                                                                      995: 'earthstar',
11
                                                                                               996
                                                                                                      996: 'hen-of-the-woods, hen of the woods, Polyporus frondosus, Gri
     11: 'goldfinch, Carduelis carduelis',
                                                                                               997
12
                                                                                                      997: 'bolete',
     12: 'house finch, linnet, Carpodacus mexicanus',
                                                                                               998
13
                                                                                                      998: 'ear, spike, capitulum',
     13: 'junco, snowbird',
                                                                                               999
      14: 'indigo hunting indigo finch indigo hind Doccoming cyango'
                                                                                                      999: 'toilet tissue, toilet paper, bathroom tissue'}
                                                                                              1000
```

Coco dataset and 80 categories included in Coco

person	fire hydrant	elephant	skis	wine glass	broccoli	dining table	toaster
bicycle	stop sign	bear	snowboard	cup	carrot	toilet	sink
car	parking meter	zebra	sports ball	fork	hot dog	tv	refrigerator
motorcycle	bench	giraffe	kite	knife	pizza	laptop	book
airplane	bird	backpack	baseball bat	spoon	donut	mouse	clock
bus	cat	umbrella	baseball glove	bowl	cake	remote	vase
train	dog	handbag	skateboard	banana	chair	keyboard	scissors
truck	horse	tie	surfboard	apple	couch	cell phone	teddy bear
boat	sheep	suitcase	tennis racket	sandwich	potted plant	microwave	hair drier
traffic light	cow	frisbee	bottle	orange	bed	oven	toothbrush

Kinects-400 data set



https://www.deepmind.com/open-source/kinetics

400 categories in Kinects-400

- 1. abseiling (1146)
- 2. air drumming (1132)
- 3. answering questions (478)
- 4. applauding (411)
- 5. applying cream (478)
- 6. archery (1147)
- 7. arm wrestling (1123)
- 8. arranging flowers (583)
- 9. assembling computer (542)
- 10. auctioning (478)
- 11. baby waking up (611)
- 12. baking cookies (927)
- 13. balloon blowing (826)
- 14. bandaging (569)

- 386. watering plants (680)
- 387. waxing back (537)
- 388. waxing chest (760)
- 389. waxing eyebrows (720)
- 390. waxing legs (948)
- 391. weaving basket (743)
- 392. welding (759)
- 393. whistling (416)
- 394. windsurfing (1114)
- 395. wrapping present (861)
- 396. wrestling (488)

- 397. writing (735)
- 398. yawning (398)
- 399. yoga (1140)
- 400. zumba (1093)

Pre-trained NN for CV tasks

Torchvision Detectron2	terchvision Detectron2	Alex Net, VGG16, Res Net Faster RCNN, Keypoints RCNN
PyTorch Hub	O PyTorch Hub	SlowFast
GitHub	GitHub	SORT, DeepSORT, JDE, ByteTrack
MicroSoft CV recipes	COMPUTER VISION BEST PRACTICES FOR COMPUTER VISION	https://github.com/microsoft/computervisi on-recipes

Our own CV tasks

	Fine-tuned pre-trained NN	CV task
HW3	ImageNet pre-trained VGG19	
HW4	COCO pre-trained FasterRCNN	
HW5	Kinects-400 pre-trained SlowFast	

Video classification

SlowFast (1).ipynb

Load pre-trained NN

```
import torch
model = torch.hub.load('facebookresearch/pytorchvideo', 'slowfast_r50', pretrained=True)
```

Kinects 400 labels

Download the id to label mapping for the Kinetics 400 dataset on which the torch hub models were trained. This will be used to get the category label names from the predicted class ids.

```
json_url = "https://dl.fbaipublicfiles.com/pyslowfast/dataset/class_names/kinetics_classnames.json
json_filename = "kinetics_classnames.json"
try: urllib.URLopener().retrieve(json_url, json_filename)
except: urllib.request.urlretrieve(json_url, json_filename)
```

Kinects 400 labels

```
{"\"sharpening knives\"": 290, "\"eating ice cream\"": 115, "\"cutting nails\"": 81, "\"changing
wheel\"": 53, "\"bench pressing\"": 19, "deadlifting": 88, "\"eating carrots\"": 111, "marching": 192,
"\"throwing discus\"": 358, "\"playing flute\"": 231, "\"cooking on campfire\"": 72, "\"breading or
breadcrumbing\"": 33, "\"playing badminton\"": 218, "\"ripping paper\"": 276, "\"playing saxophone\"":
244, "\"milking cow\"": 197, "\"juggling balls\"": 169, "\"flying kite\"": 130, "capoeira": 43, "\"making
jewelry\"": 187, "drinking": 100, "\"playing cymbals\"": 228, "\"cleaning gutters\"": 61, "\"hurling
(sport)\"": 161, "\"playing organ\"": 239, "\"tossing coin\"": 361, "wrestling": 395, "\"driving car\"":
103, "headbutting": 150, "\"gymnastics tumbling\"": 147, "\"making bed\"": 186, "abseiling": 0,
"\"holding snake\"": 155, "\"rock climbing\"": 278, "\"cooking egg\"": 71, "\"long jump\"": 182, "\"bee
keeping\"": 17, "\"trimming or shaving beard\"": 365, "\"cleaning shoes\"": 63, "\"dancing gangnam
style\"": 86, "\"catching or throwing softball\"": 50, "\"ice skating\"": 164, "jogging": 168, "\"eating
spaghetti\"": 116, "bobsledding": 28, "\"assembling computer\"": 8, "\"playing cricket\"": 227,
"\"playing monopoly\"": 238, "\"golf putting\"": 143, "\"making pizza\"": 188, "\"javelin throw\"": 166,
"\"peeling potatoes\"": 211, "clapping": 57, "\"brushing hair\"": 36, "\"flipping pancake\"": 129,
```

Input format

```
side_size = 256
mean = [0.45, 0.45, 0.45]
std = [0.225, 0.225, 0.225]
crop_size = 256
num_frames = 32
sampling_rate = 2
frames_per_second = fps
slowfast_alpha = 4
num_clips = 10
num_crops = 3
```

```
# The duration of the input clip is also specific to the model.
clip_duration = (num_frames * sampling_rate)/frames_per_second
```

```
start_sec = 0
end_sec = start_sec + clip_duration
```

Class practice

• Record a 10-second video that includes $2\sim3$ actions defined in Kinects-400 (or find one from Internet). Let SlowFast recognize the actions in this video.

Video clips	Actions you classified	Actions classified by SlowFast
0~3		
2~5		
4~7		
6~9		
7~10		

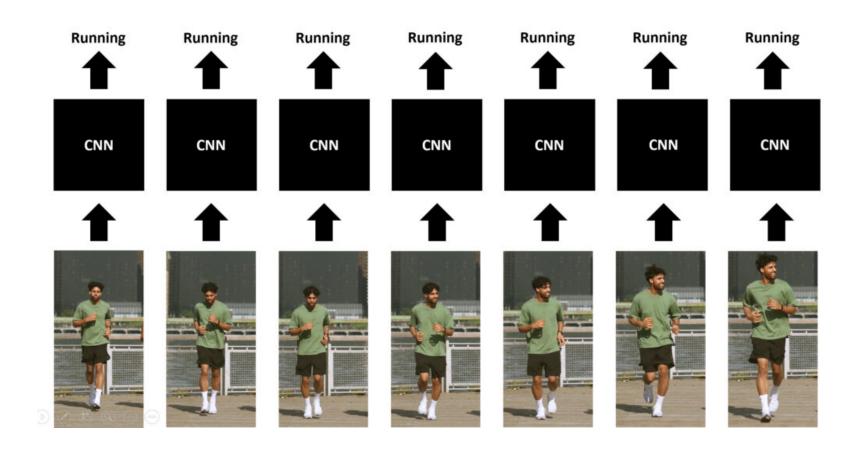
Human activity recognition

Introduction to Video Classification and Human Activity Recognition



Single frame CNN

Videos generally contain a lot of frames, and we do not need to run a classification model on each frame, but only a few of them that are spread out throughout the entire video.



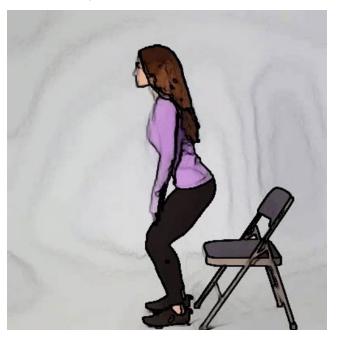
Problem with single frame based action recognition

You need a series of image frames to classify human activity correctly



Sit down or stand up?





Problem with single frame based action recognition

You need a series of image frames to classify human activity correctly





Can image classification be used to predict action?







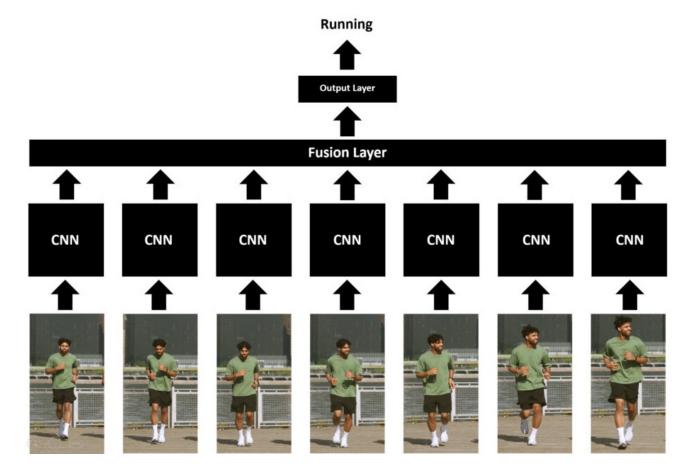






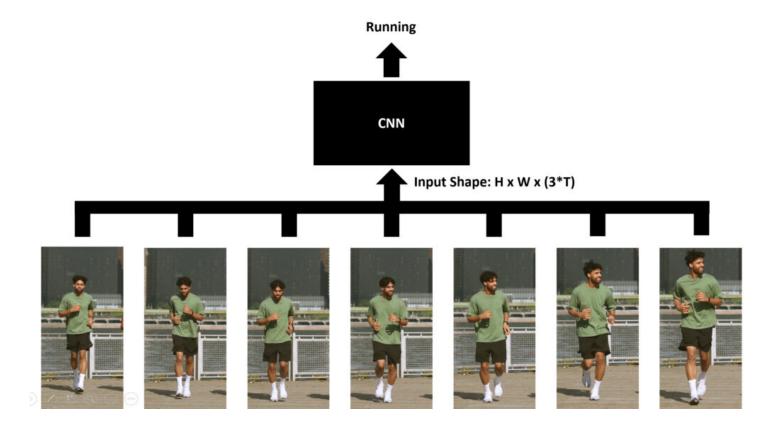
Late fusion

This approach enables the model to learn spatial as well as temporal information about the appearance and movement of the objects in a scene. The Fusion layer is normally implemented using the max pooling, average pooling or flattening technique.

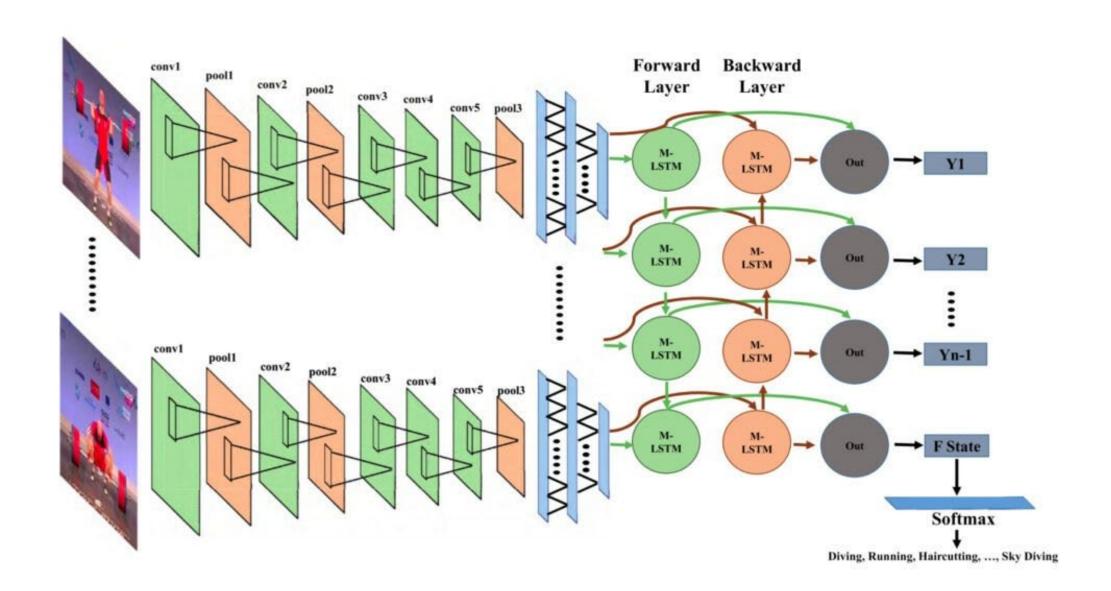


Early fusion

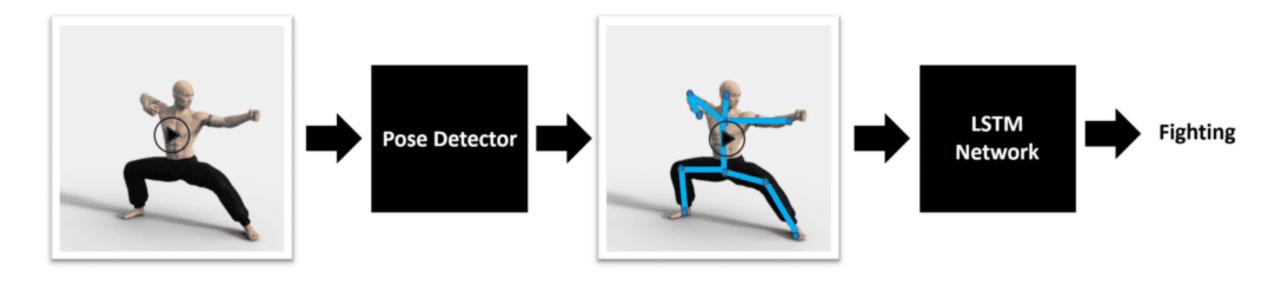
The temporal dimension and the channel (RGB) dimension of the video are fused at the start before passing it to the model which allows the first layer to operate over frames and learn to identify local pixel motions between adjacent frames.



CNN + LSTM

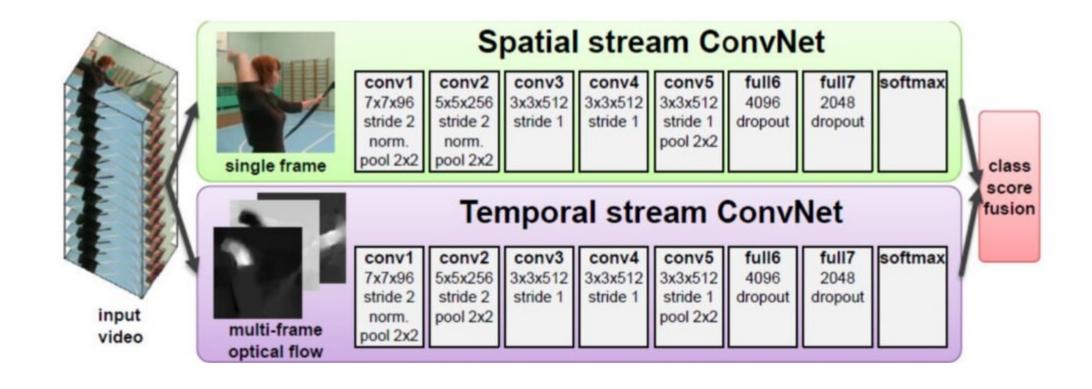


Pose detection + LSTM



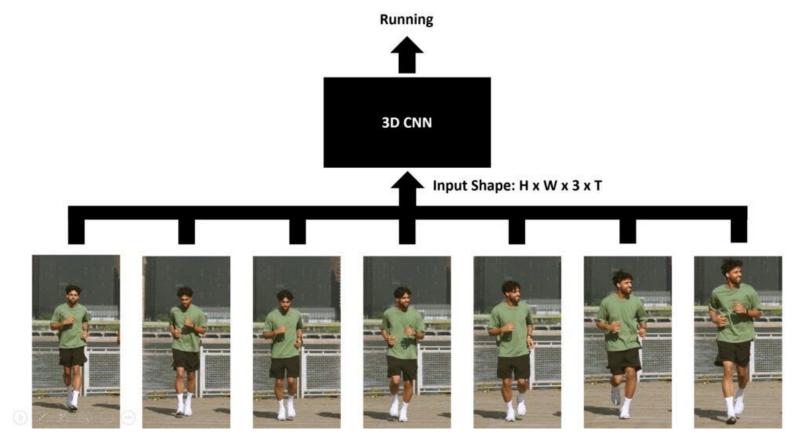
Optical flow + CNN

Optical flow is the pattern of visible motion of objects, edges and helps calculate the motion vector of every pixel in a video frame. The stream on the bottom called the Temporal stream takes every adjacent frame's optical flows after merging them using the early fusion technique and then using the motion information to make a prediction.



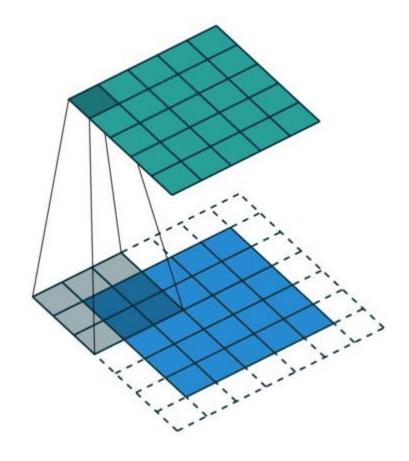
3D CNN slow fusion

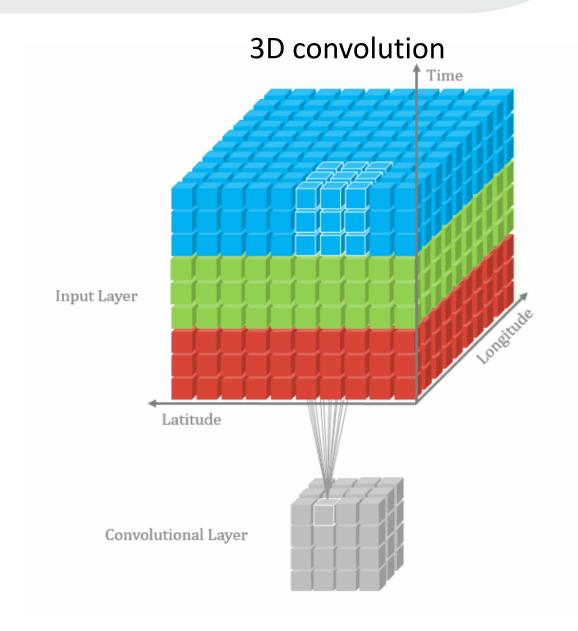
This approach uses a 3D convolution network that allows you to process temporal information and spatial by using a 3 Dimensional CNN. This method is also called the Slow Fusion approach. Unlike Early and Late fusion, this method fuses the temporal and spatial information slowly at each CNN layer throughout the entire network.



3D convolution

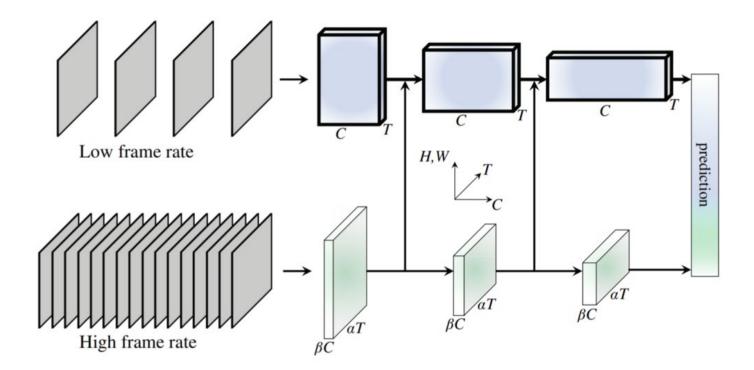
2D convolution





SlowFast

The stream on top, called the slow branch, operates on a low temporal frame rate video and has a lot of channels at every layer for detailed processing for each frame. On the other hand, the stream on the bottom, also known as the fast branch, has low channels and operates on a high temporal frame rate version of the same video.



SlowFast

SlowFast Networks for Video Recognition

Christoph Feichtenhofer Haoqi Fan Jitendra Malik Kaiming He
Facebook AI Research (FAIR)

Prepare input image frames

```
side_size = 256
mean = [0.45, 0.45, 0.45]
std = [0.225, 0.225, 0.225]
crop_size = 256
num frames = 32
sampling_rate = 2
frames_per_second = fps
slowfast_alpha = 4
num_clips = 10
num_crops = 3
```

```
transform = ApplyTransformToKey(
    key="video",
    transform=Compose(
            UniformTemporalSubsample(num_frames),
            Lambda (lambda x: x/255.0),
            NormalizeVideo(mean, std),
            ShortSideScale(
                size=side_size
            CenterCropVideo(crop size),
            PackPathway()
```

Slow and fast pathway

```
class PackPathway(torch.nn.Module):
   Transform for converting video frames as a list of tensors.
    11 11 11
   def init (self):
        super().__init__()
   def forward(self, frames: torch.Tensor):
       fast pathway = frames
        # Perform temporal sampling from the fast pathway.
        slow pathway = torch.index select(
            frames,
            1,
            torch.linspace(
                0, frames.shape[1] - 1, frames.shape[1] // slowfast_alpha
            ).long(),
        frame_list = [slow_pathway, fast_pathway]
        return frame list
```

HW 5 – Action recognition with SlowFast

- Due next week, group of 1~3
- Shoot a 30 sec video with action sequence of various lengths, e.g., walk (5 sec) \rightarrow sit (3 sec) \rightarrow stand (4 sec) \rightarrow jump (10 sec) \rightarrow wave hands (8 sec)
- Show your action table and SlowFast results, with fixed sampling rate = 2, and num_frames=32, 48, 64 (assuming fps=30, then clip duration ≈ 1 , 2, 4 sec)

Actions in input video

Time period	Actions performed
1-5	walk
5-8	sit

No of frames=32 \rightarrow clip duration \approx 2 sec

Time period	Actions recognized by SlowFast
1-2	(Show only top labels with larger probability)
2-4	
•••	

No of frames=48 \rightarrow clip duration \approx 3 sec

Time period	Actions recognized by SlowFast	p
1-3	Show top labels	
3-6		

No of frames=64 \rightarrow clip duration \approx 4 sec

Time period	Actions recognized by SlowFast
1-4	Show top labels
4-8	