Lecture 14:

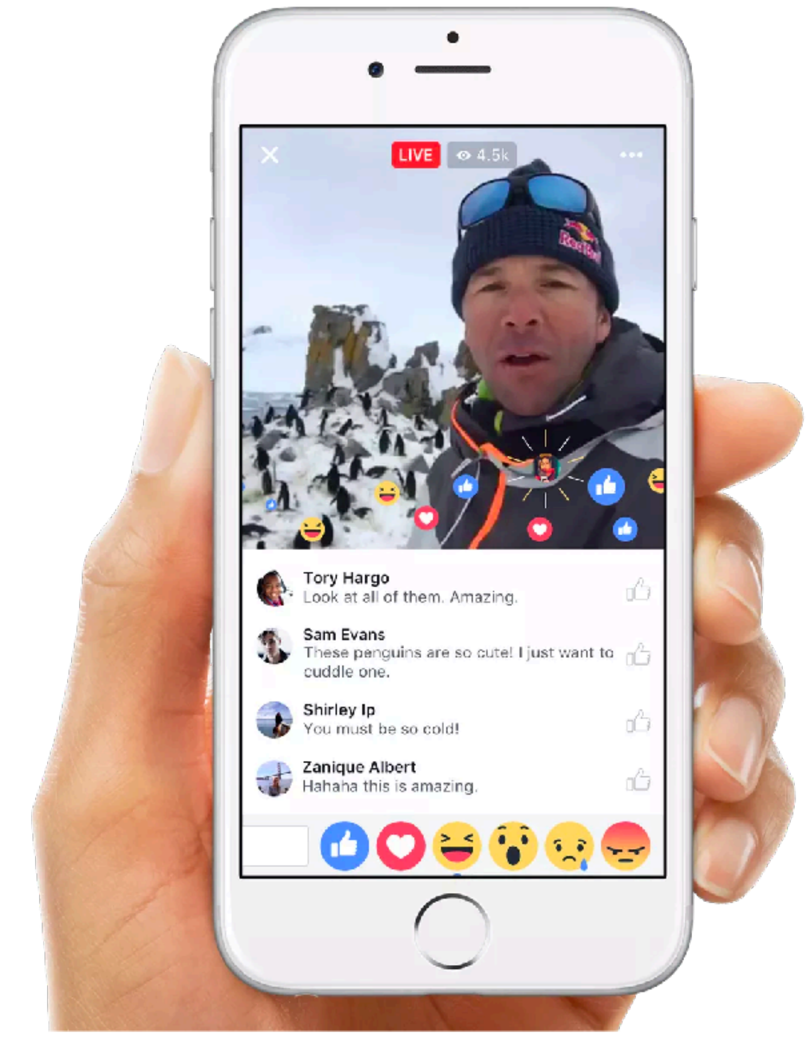
Processing Video at Cloud Scale

Visual Computing Systems
Stanford CS348V, Winter 2018

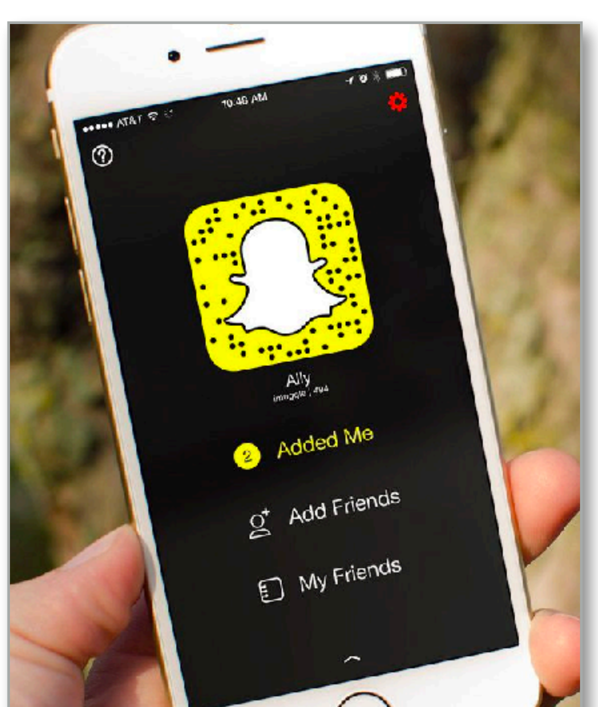
Big video data

Facebook 2016:
100 million hours of video watched per day

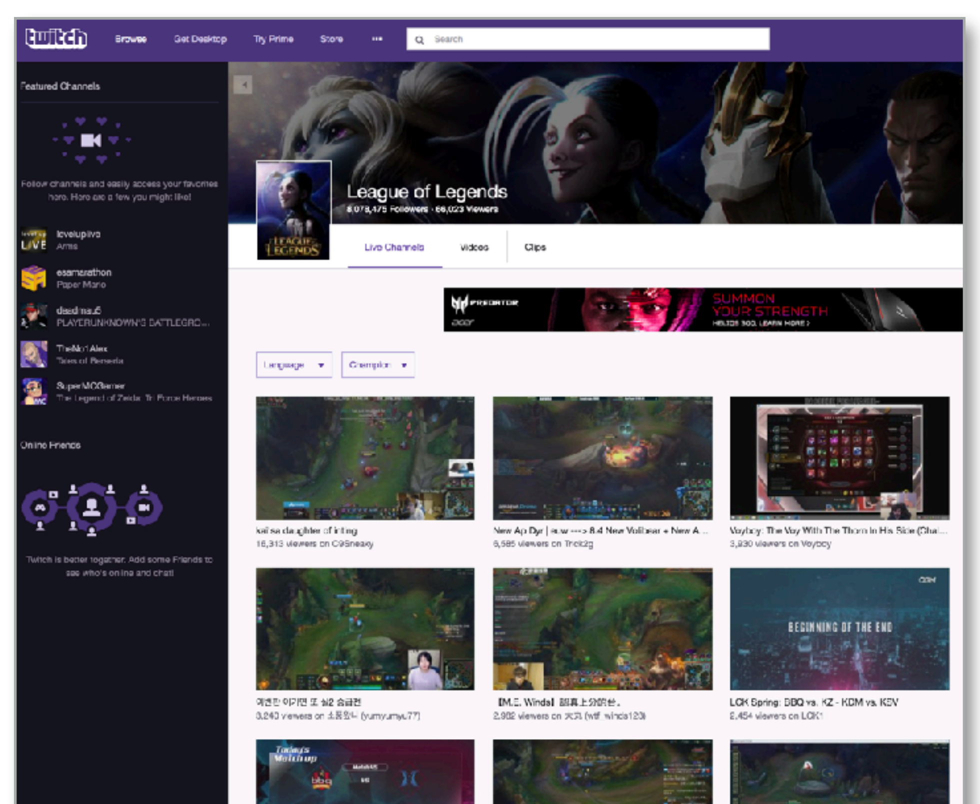
Youtube 2015: 300 hours uploaded per minute [Youtube]



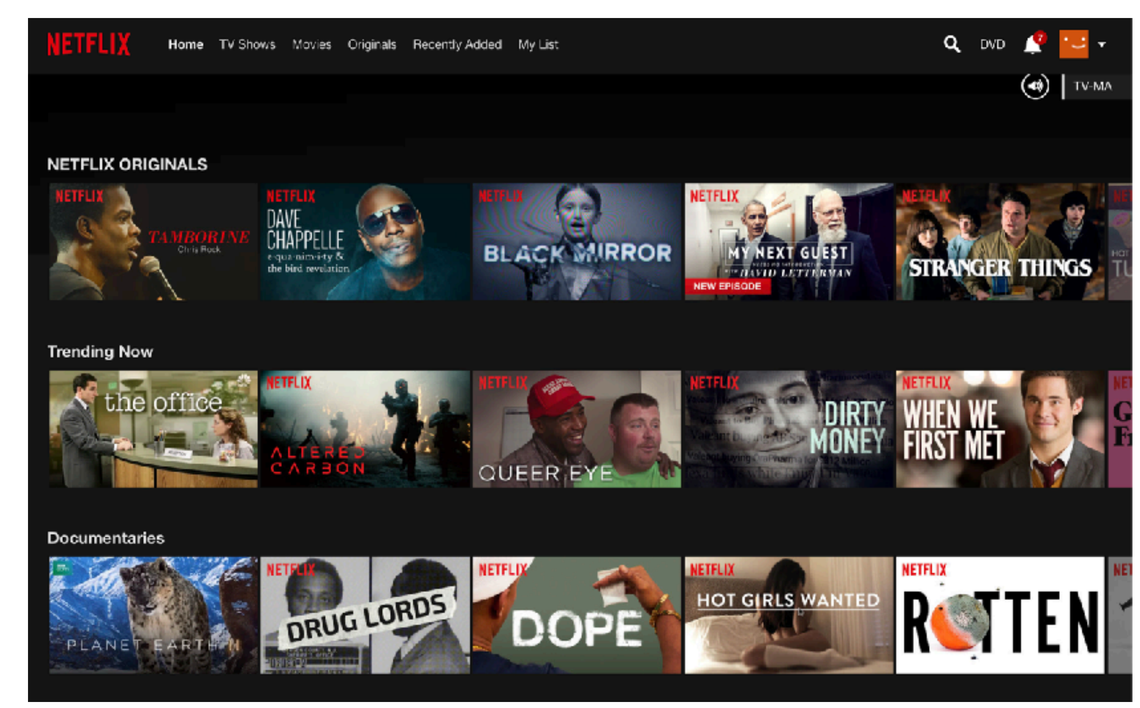
FB Live Video



Snapchat Video



Twitch



Netflix

Today's topic

- Challenges and key ideas of datacenter-scale video processing

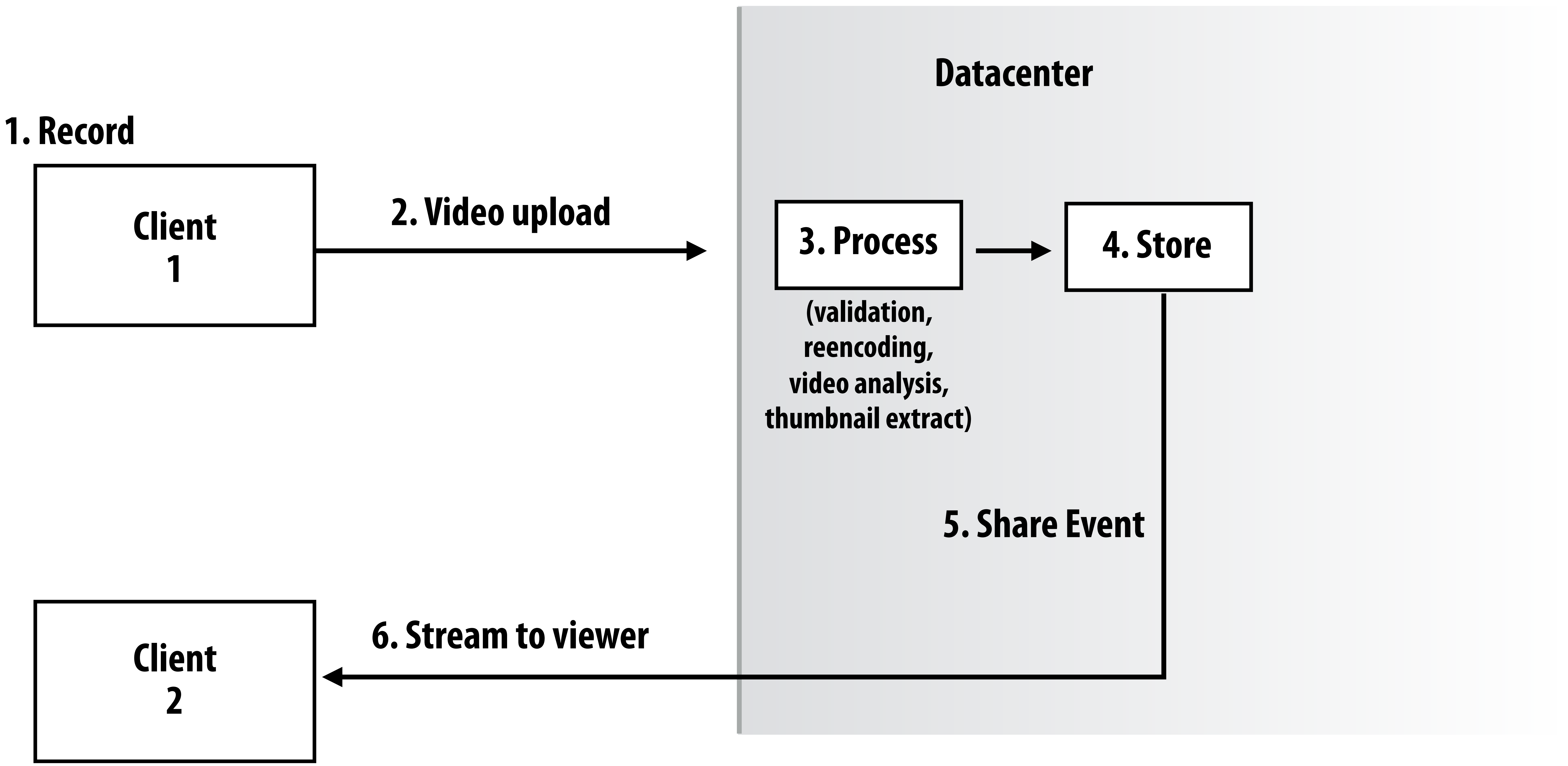
- Three examples:
  - Video upload at Facebook
  - Massively parallel video encoding
  - A data-parallel framework for video processing

Facebook Streaming Video Engine (SVE)

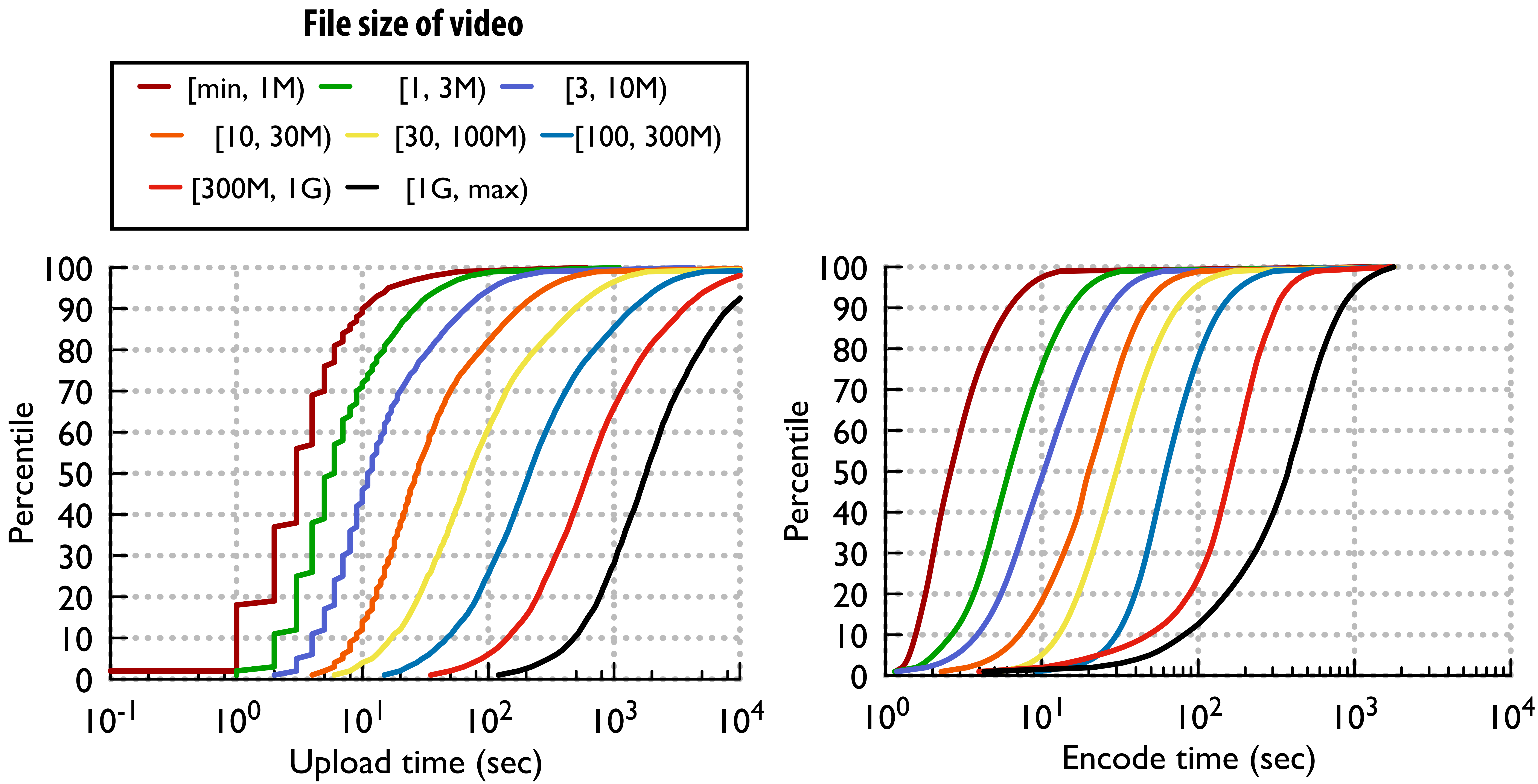
- Designed for non-streaming video upload (not Facebook Live)
  - Facebook video posts
  - FB Messenger video shares
  - Instagram Stories
  - 360 videos

- Goals/requirements:
  - Low latency: minimize latency of start of upload to sharable state
    - Particularly for FB Messanger uploads
  - Flexible (support variety of applications, with different processing pipelines after upload)
  - Robust to faults and overload

Basic video sharing pipeline



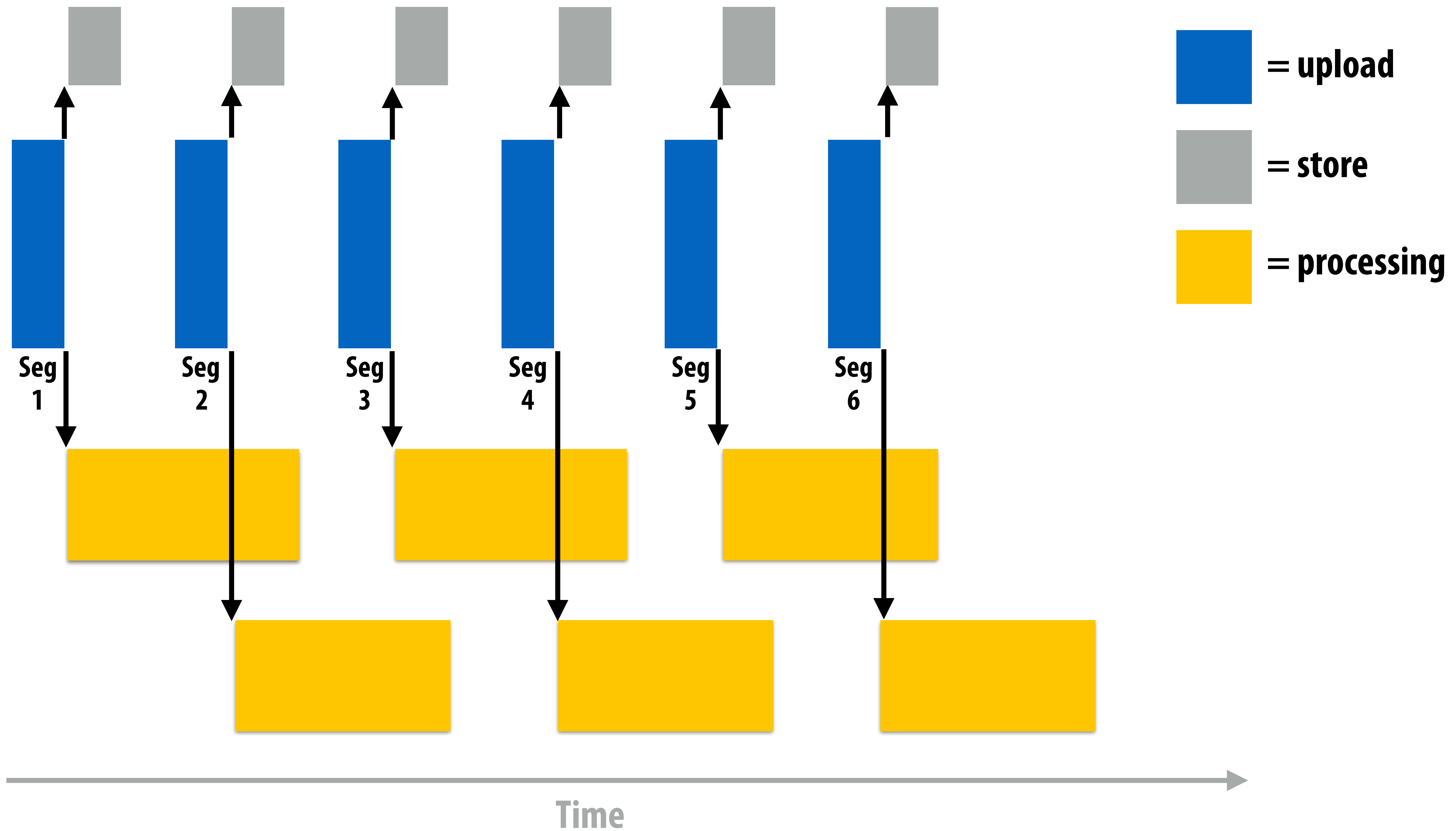
Video upload and processing times *



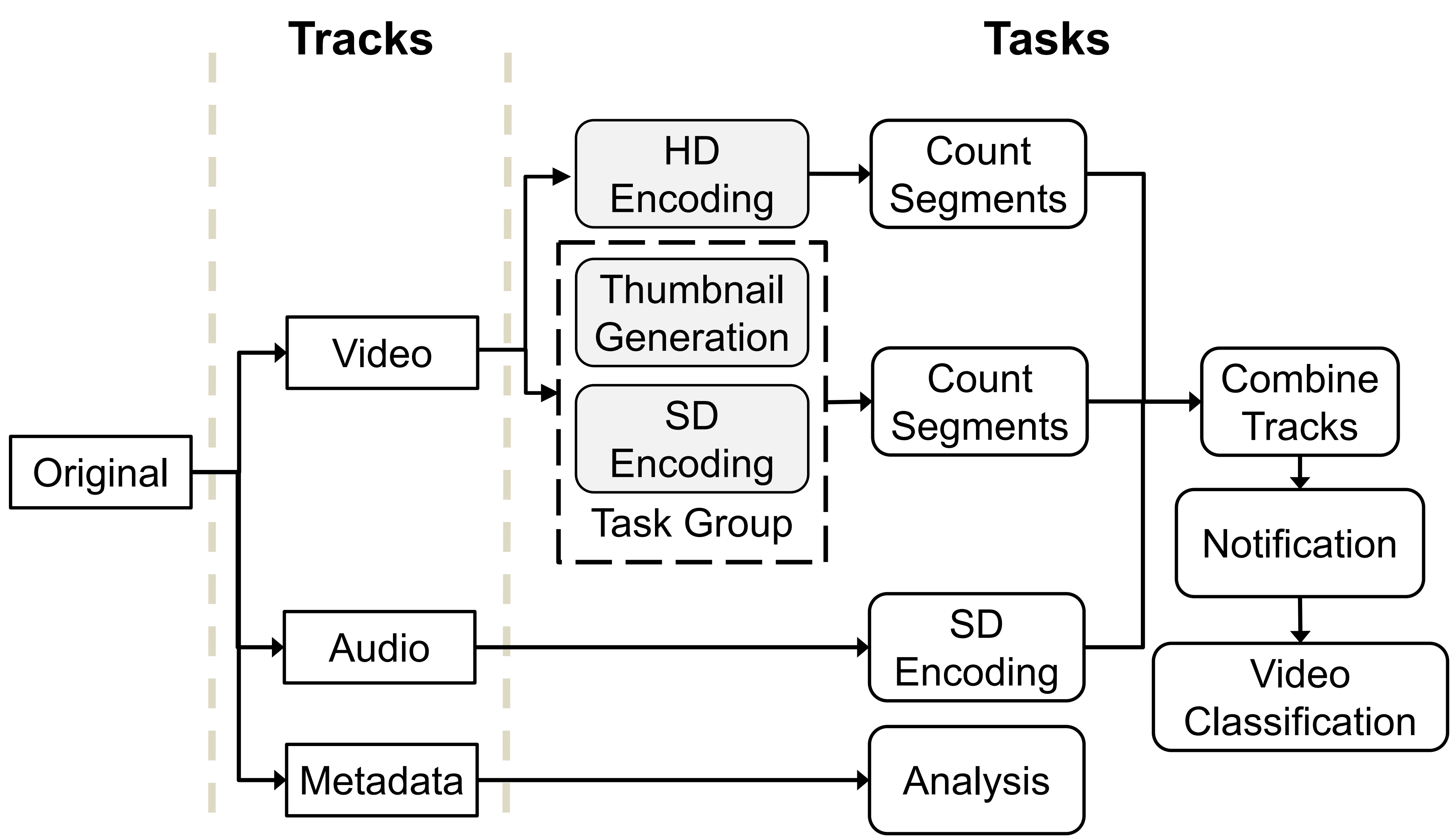
* Serialized times (SVE system will parallelize encoding across segments as discussed in a few slides)

Pipelining upload and processing

- Client application partitions video into segments prior to upload
- Client application optionally downsamples video (skipped if video recorded at low enough resolution, internet connection is fast, or device does not support HW accelerated encode)
- Upload and processing of video is pipelined (upload and processing is mostly parallelized)
- Processing itself can be parallelized across segments



DAG representation of processing



Simple DAG:

Encodes HD and SD version of uploaded video

DAG node = "task"

Each task is executed serially on one video segment

Overall DAG execution can be parallelized

(across tracks and segments)

Facebook Video Posts: ~153 tasks

Messanger shares: 18 tasks

Instagram stories: 22 tasks

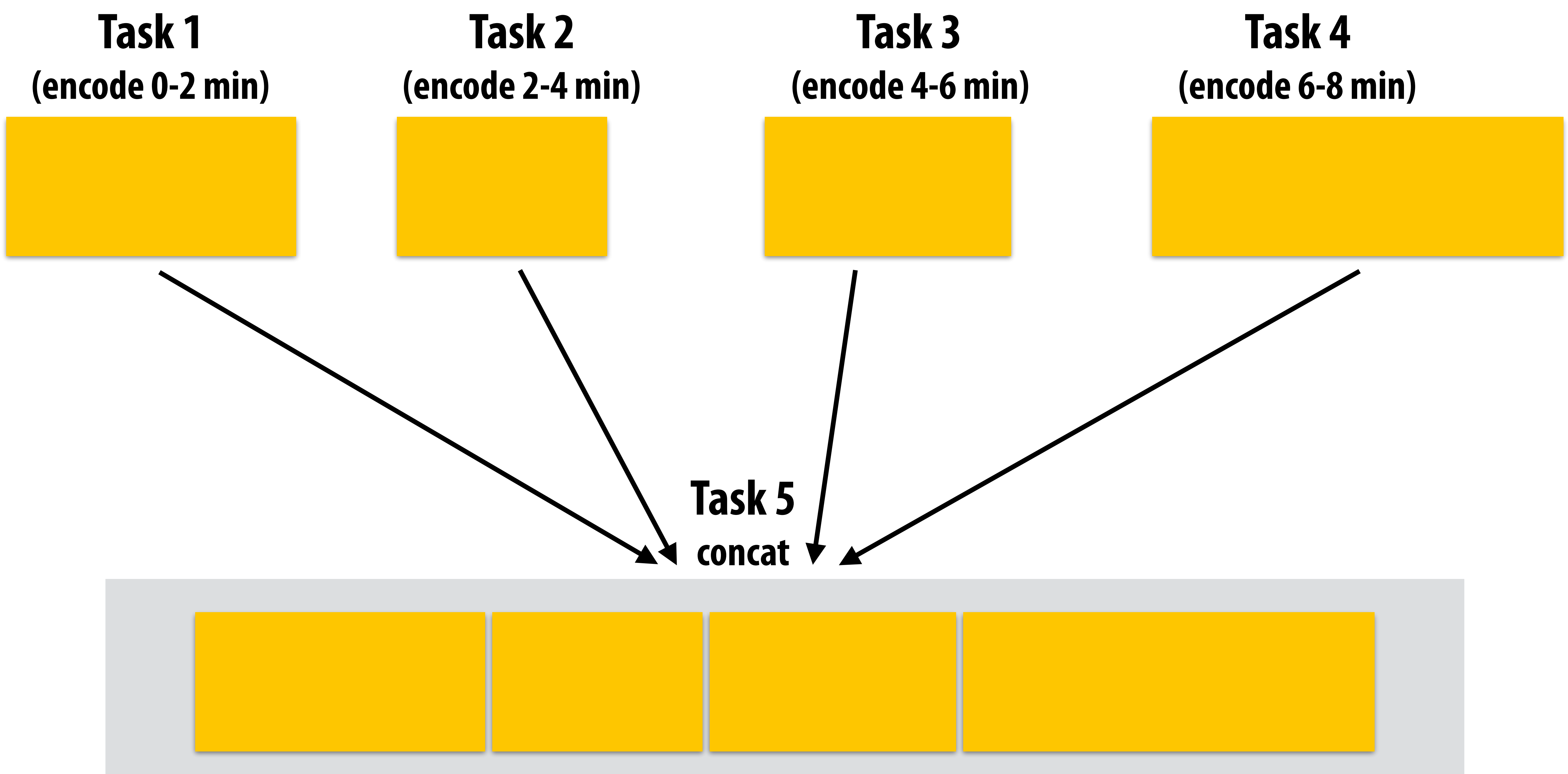
DAG Specification:

Nodes defined on audio, video, metadata tracks:

```
pipeline = create_pipeline(video)

video_track = pipeline.create_video_track()
if video.should_encode_hd
  hd_video = video_track.add(hd_encoding)
   .add(count_segments)
sd_video = video_track.add(
  {sd_encoding, thumbnail_generation},
 ).add(count_segments)

audio_track = pipeline.create_audio_track()
sd_audio = audio_track.add(sd_encoding)

meta_track =
  pipeline.create_metadata_track()
  .add(analysis)

pipeline.sync_point(
  {hd_video, sd_video, sd_audio},
  combine_tracks,
 ).add(notify, 'latency_sensitive')
  .add(video_classification)
```

Coarse-grained parallel video encoding

- Parallelized across segments (Iframe inserted at start of segment)
- Concatenate independently encoded bitstreams



Smaller segments = more potential parallelism, worse video compression
Latency-sensitive applications: 10 second segments
Non-latency sensitive, long videos: 2 minute segments (maximize compression)

Overload control

- When FB cannot keep up with upload rate…

- Delay latency-insensitive tasks
- Redirect uploads to new datacenter region
- Delay processing of new uploads

Massively parallel video encoding

Challenge

- Video encoding is inherently sequential (current frame represented in terms of data from previous frames)
- Coarse-grained parallelism is possible, at the cost of reduced compression (additional keyframes)
  - 4K video: keyframe ~ 11MB, interframe ~ 10s of KB
- Growing interest in “Serverless computing”

AWS Lambda

Google
CLOUD FUNCTIONS
Create small, single-purpose functions that respond to events in the cloud

Today’s AWS Lambda Pricing
\$0.000002 per request + \$0.00001667 per GB/sec

Memory (MB)	Free tier seconds per month	Price per 100ms (\$)
128	3,200,000	0.000000208
192	2,133,333	0.000000313
256	1,600,000	0.000000417

- Question: Is it possible to parallelize video encode onto thousands of cores?

Expressing a video encoder in a continuation passing style

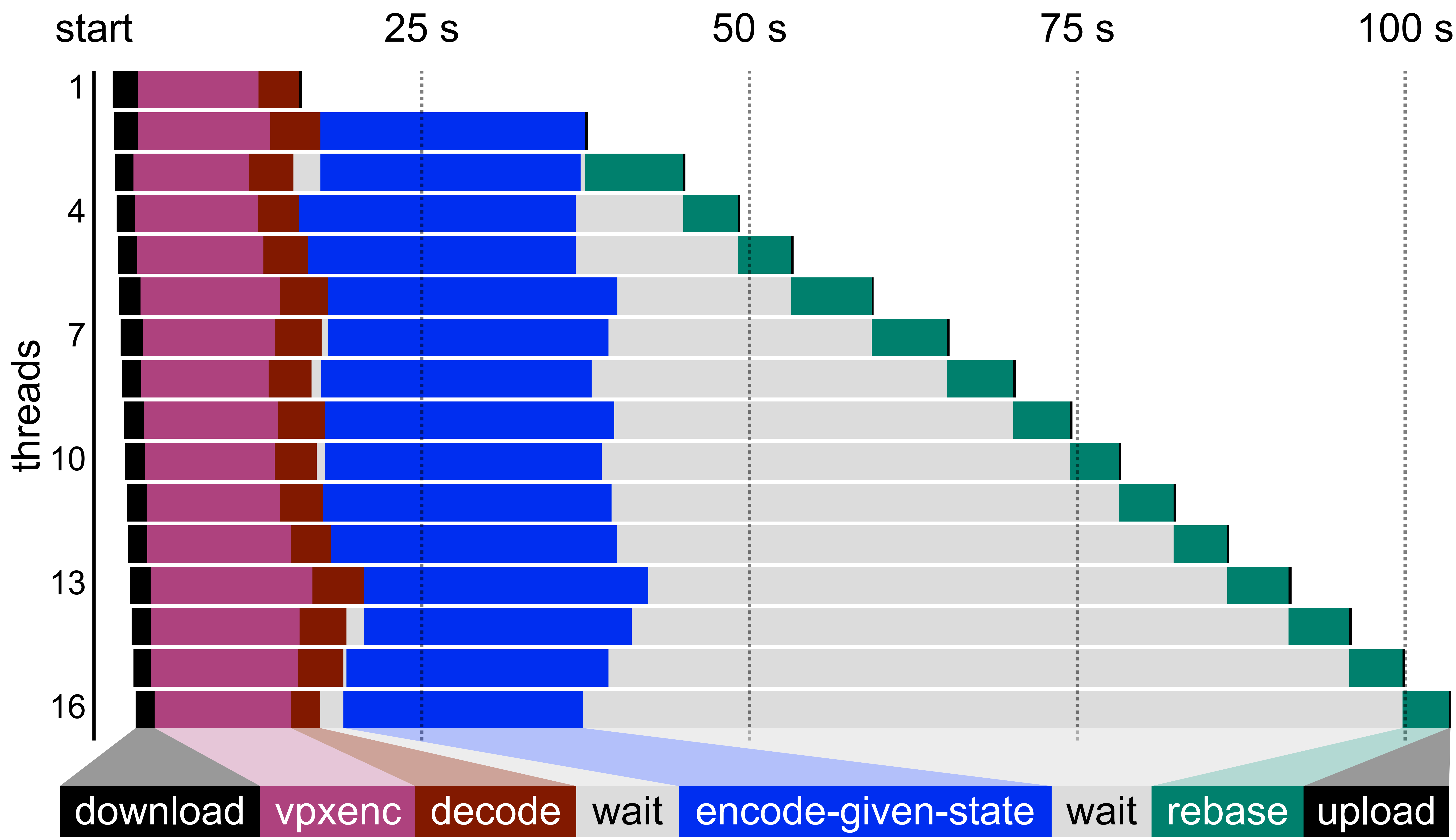
```
// prob model: tables representing encoding of values in video stream
// reference_images contains three prior images
state:= (prob_model, reference_images[3]);

// just a full image
keyframe := image pixels for entire frame

// prediction_modes and motion vectors define how to predict current
// frame given decoder state
// residue is correction to this prediction
interframe := (prediction_modes, motion_vectors, residue)

// decoding a frame generates one image of pixels, and
// an updated decoder state
decode(state, compressed_frame) -> (new_state, image)

// generate an interframe approximating image given the current
// decoder state.  This operation requires expensive motion estimation.
encode-given-state(state, image, quality_param) -> interframe

// use prediction info from interframe to estimate prediction for
// image given new state, store new residue in new_interface
// Note: rebase is cheap because it does not perform motion estimation
rebase(new_state, image, interframe) -> new_interframe
```

Massively parallel video encoding using "rebase"

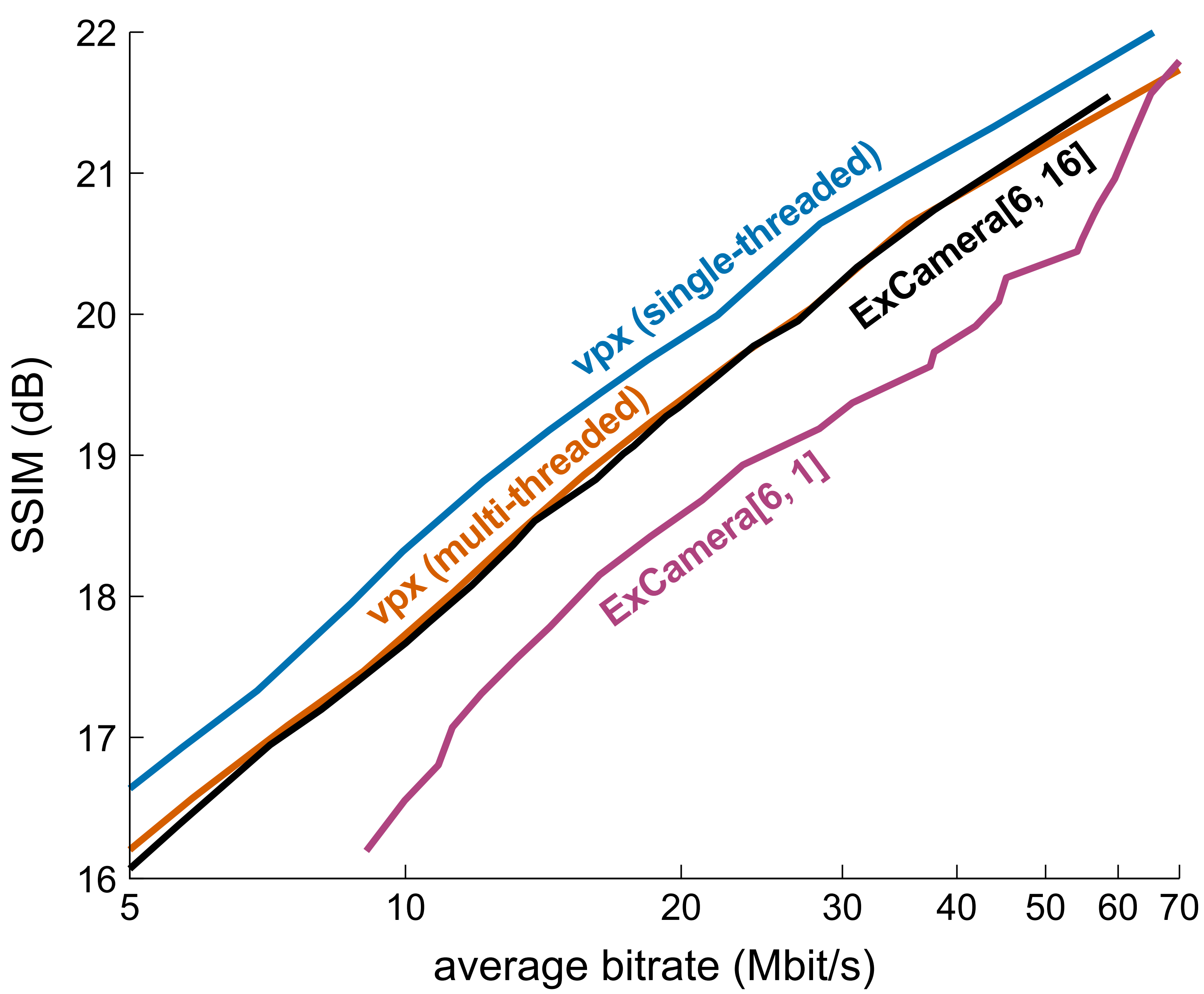
```
// N = frames per thread
// x = threads to use
ParallelEncode[N,x]

In parallel, each thread encodes N consecutive frames of video
(generates 1 keyframe + N-1 interframes)

In parallel, each thread decodes its N frames of video
Thread t passes its final decoder state to thread t+1.

In parallel, each thread executes encode-given-state() on its first frame
using the decoder state it receives, replacing what was a keyframe with an
interframe that is dependent on decoding the prior thread's output.
(requires the original image)

In sequence, each thread rebases its remaining frames based on state after
decoding first frame.  When complete, thread t sends final decoder state
to thread t+1
```

Computation schedule for ParallelEncode[16,6]

Using 16 threads to encode 16 x 6 = 96 frames of video



Leverage wide parallelism + preserve reasonable video quality



ExCamera results are on 3600 cores

System	Bitrate at 20 dB SSIM (lower is better)	Encode time (lower is better)
ExCamera[6,16][1]	27.4 Mbps	2.6 minutes
ExCamera[6,1][2]	43.1 Mbps	0.5 minutes
`vpxenc` multi-threaded	27.2 Mbps	149 minutes
`vpxenc` single-threaded	22.0 Mbps	453 minutes

Scanner

Motivating questions

If I wanted to grab a few terabytes of video, store it in a database, and perform pixel-level analyses on frames from the collection using a cluster of high-compute-density nodes, what system should I use?

If large-scale, frame-level processing was widely available, what are new types of questions a data analyst might ask about increasingly abundant video datasets?

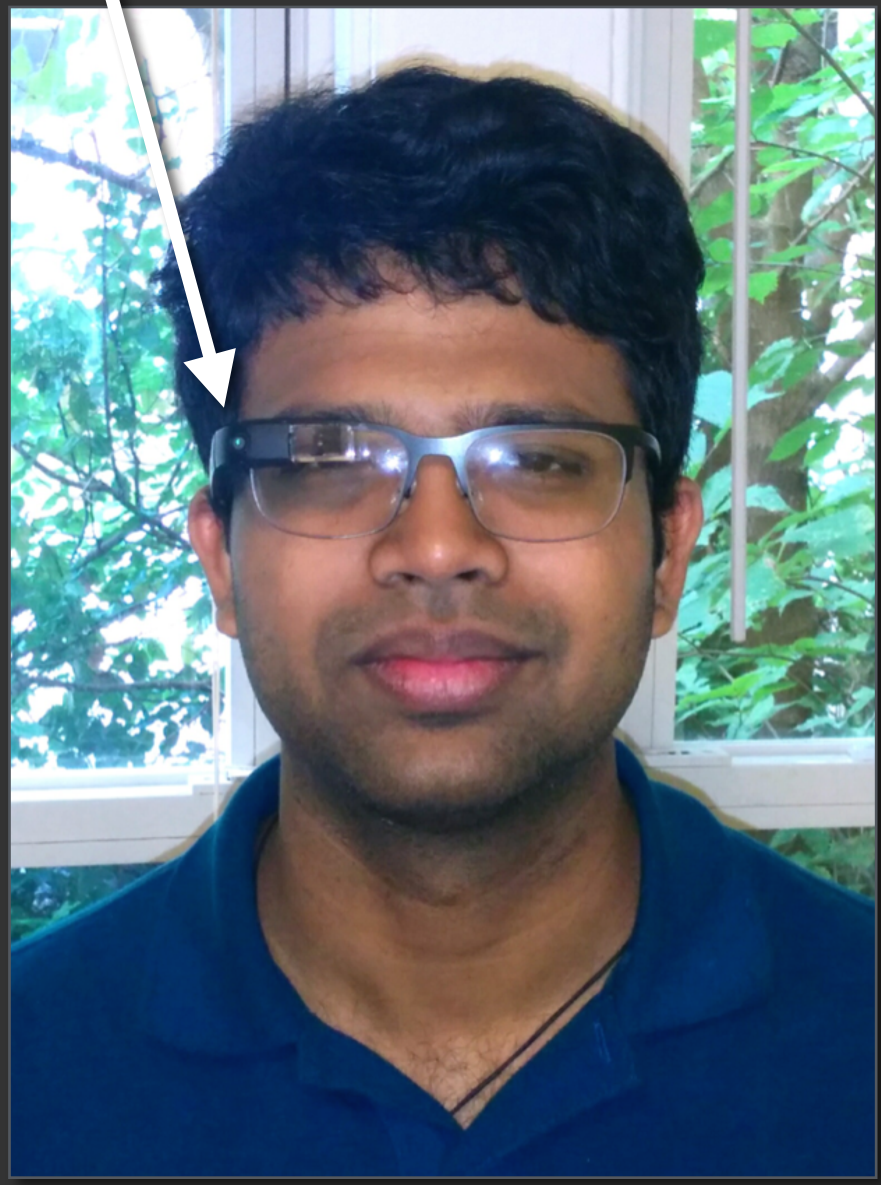
What are the software tools needed to conduct visual data mining on large video collections?

“KrishnaCam” egocentric video dataset

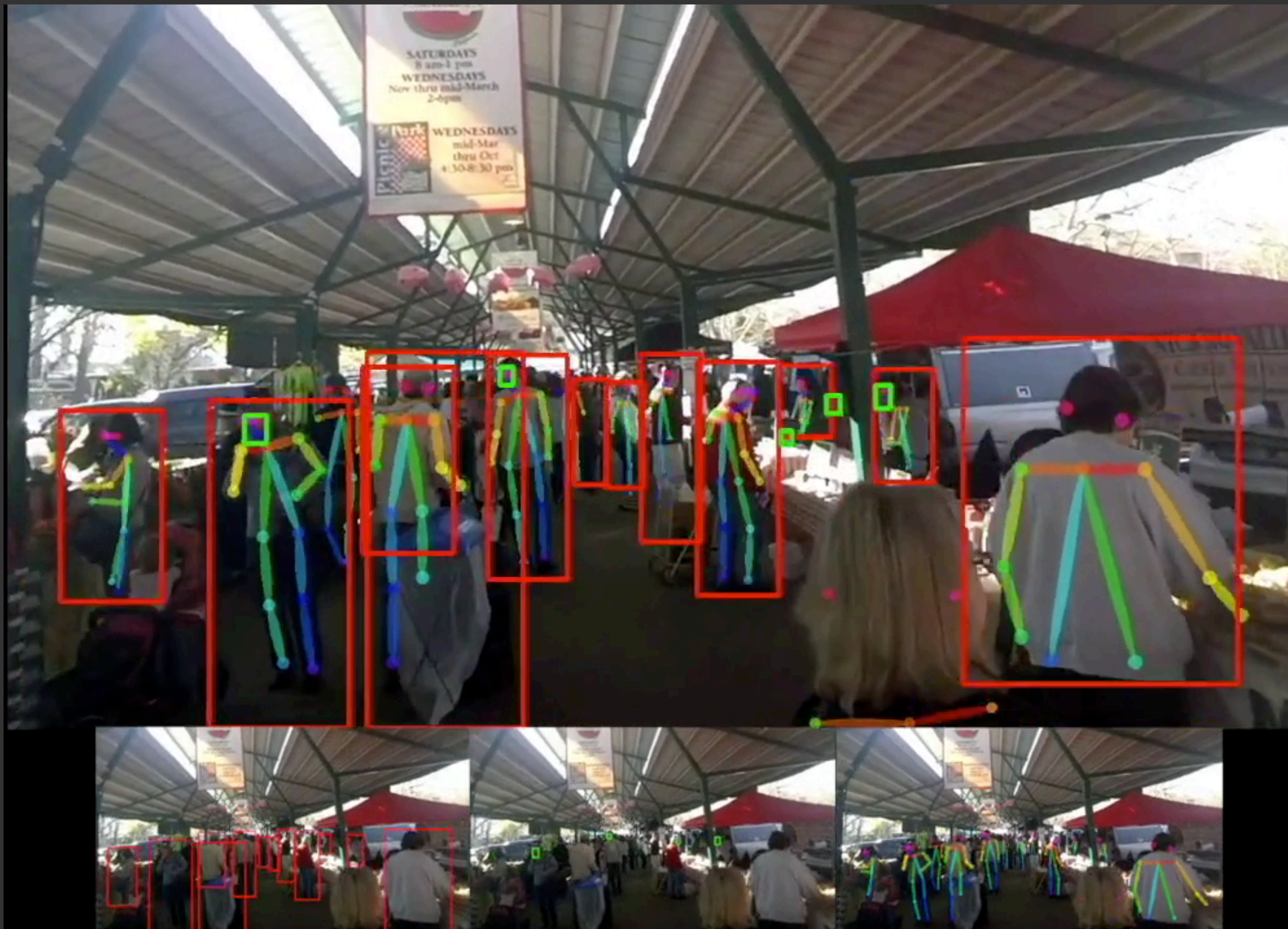
[Singh 2016]

72 hours of recording over nine months: (Sep 2014 – May 2015)

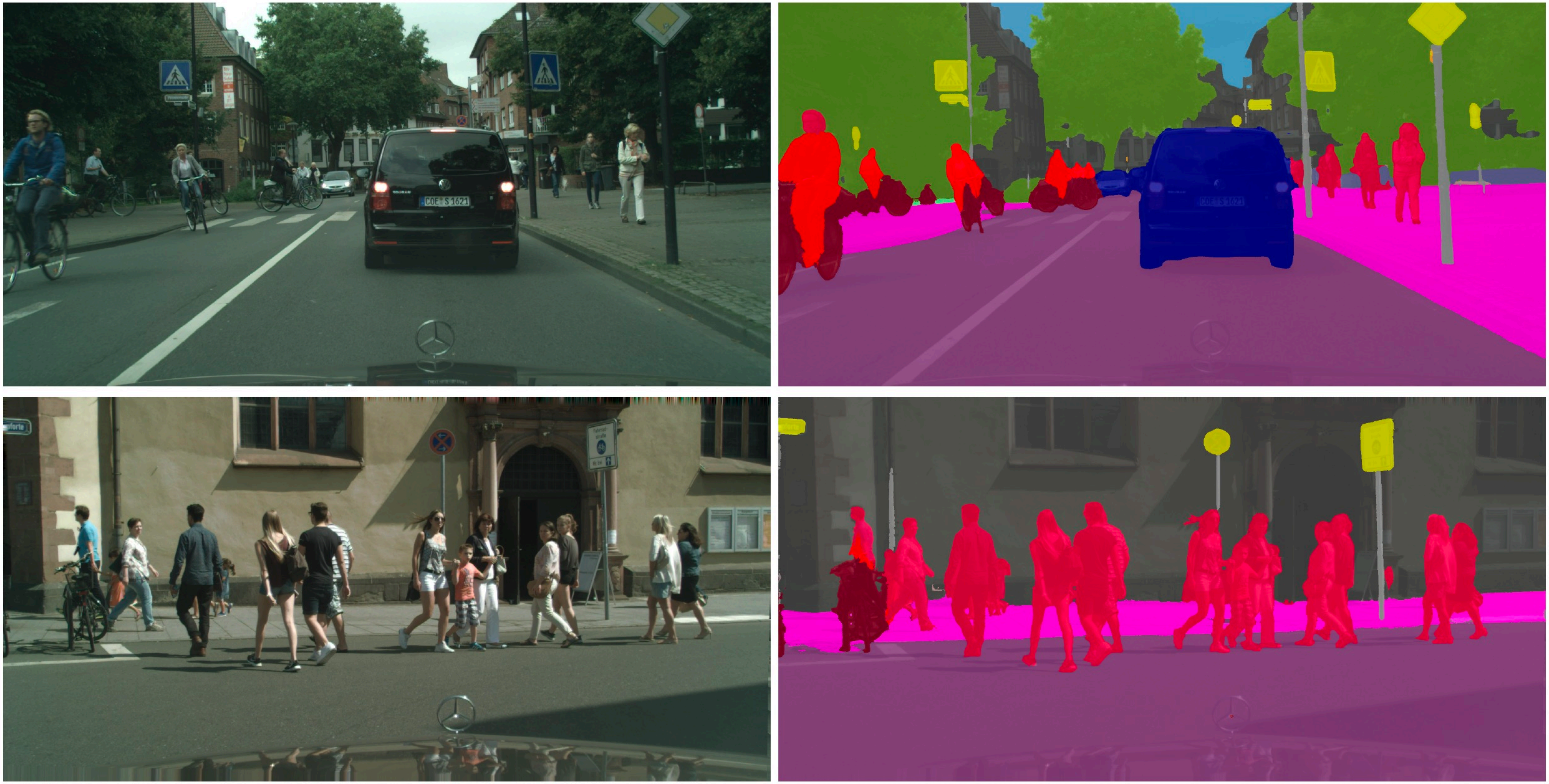
Google Glass



Ensemble of face detectors for KrishnaCam



Large-scale autonomous vehicle datasets



[Image Credit: Kundu et al. 2016]

American TV news dataset

- 3 years of CNN, FOX, MSNBC
- 72,000 hours of video, 12 billion frames

Fareed Zakaria GPS

CNN Newsroom

Situation Room

CNN Newsroom with Poppy Harlow

The Lead with Jake Tapper

America News Headquarters

The Five

The Real Story With Gretchen Carlson

Shepard Smith Reporting

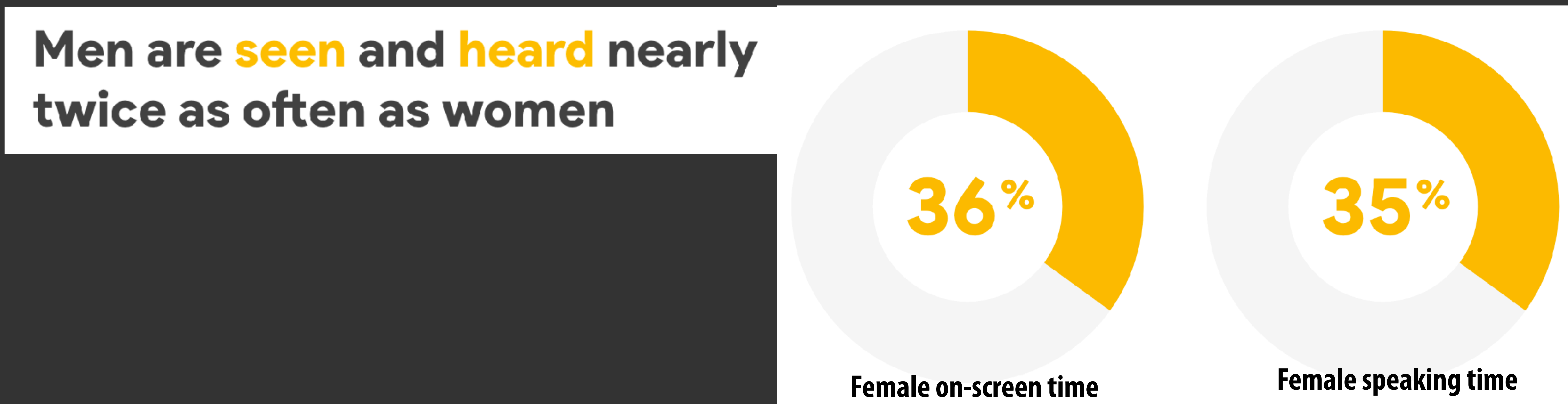
On the Record With Brit Hume

Example questions

- Where are the commercials?
  - Largely to exclude from analysis, but may wish to analyze commercials independently?
- Can we break the video into shots?

Geena Davis Inclusion Quotient (GD-IQ)

Project between Google and The Geena Davis Institute on Gender in Media



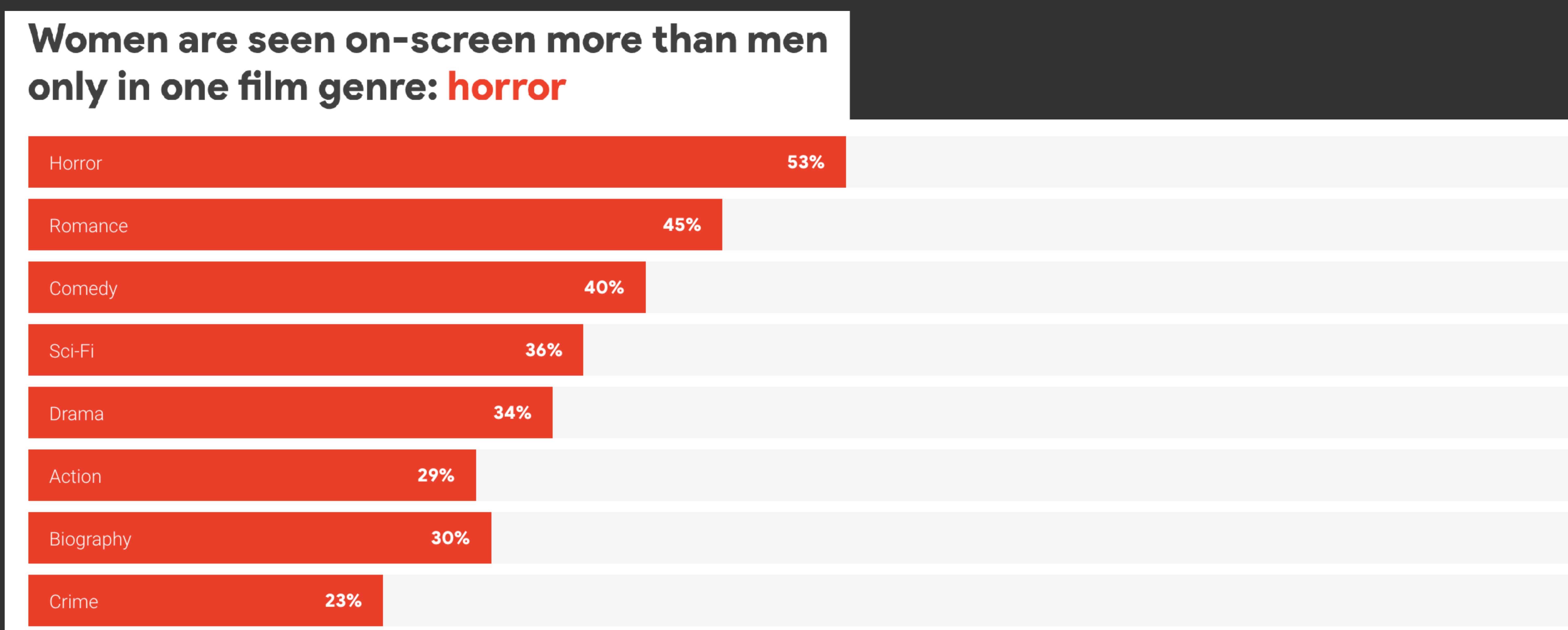


Image credit: https://www.google.com/intl/en/about/main/gender-equality-films/

American TV news analysis (first 100 hrs)

Fareed Zakaria GPS

17% female

CNN Newsroom

43%

Situation Room

32%

CNN Newsroom with Poppy Harlow

40%

The Lead with Jake Tapper

32%

America News Headquarters

35%

The Five

40%

The Real Story With Gretchen Carlson

45%

Shepard Smith Reporting

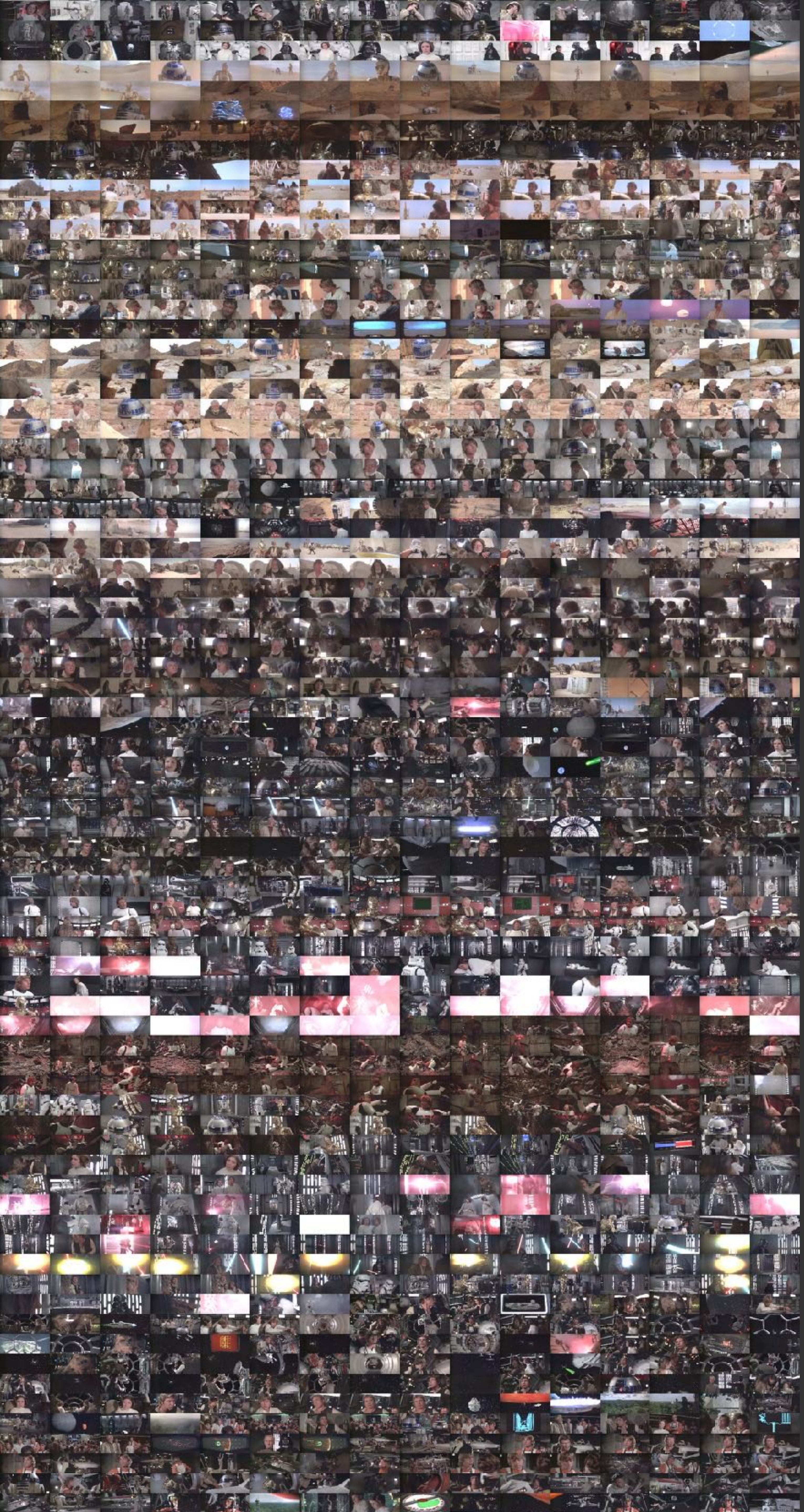
27%

On the Record With Brit Hume

28%

Cinematography analysis

Collaboration with Alex Hall, Maneesh Agrawala (Stanford)



What is the average length of shot in a movie?

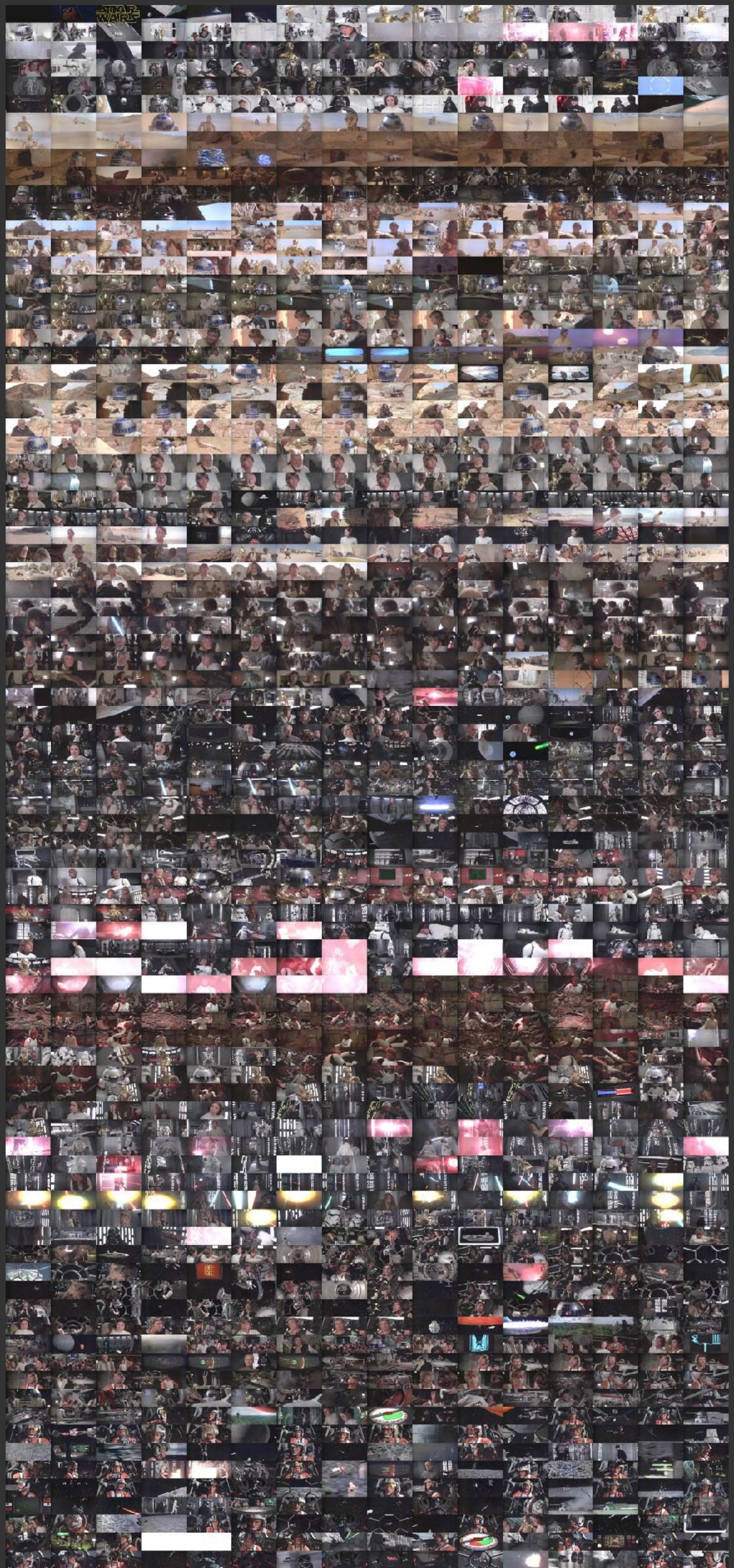
Does the director favor close ups or wide shots? How much camera motion is used?

What are the main color palettes in the film?

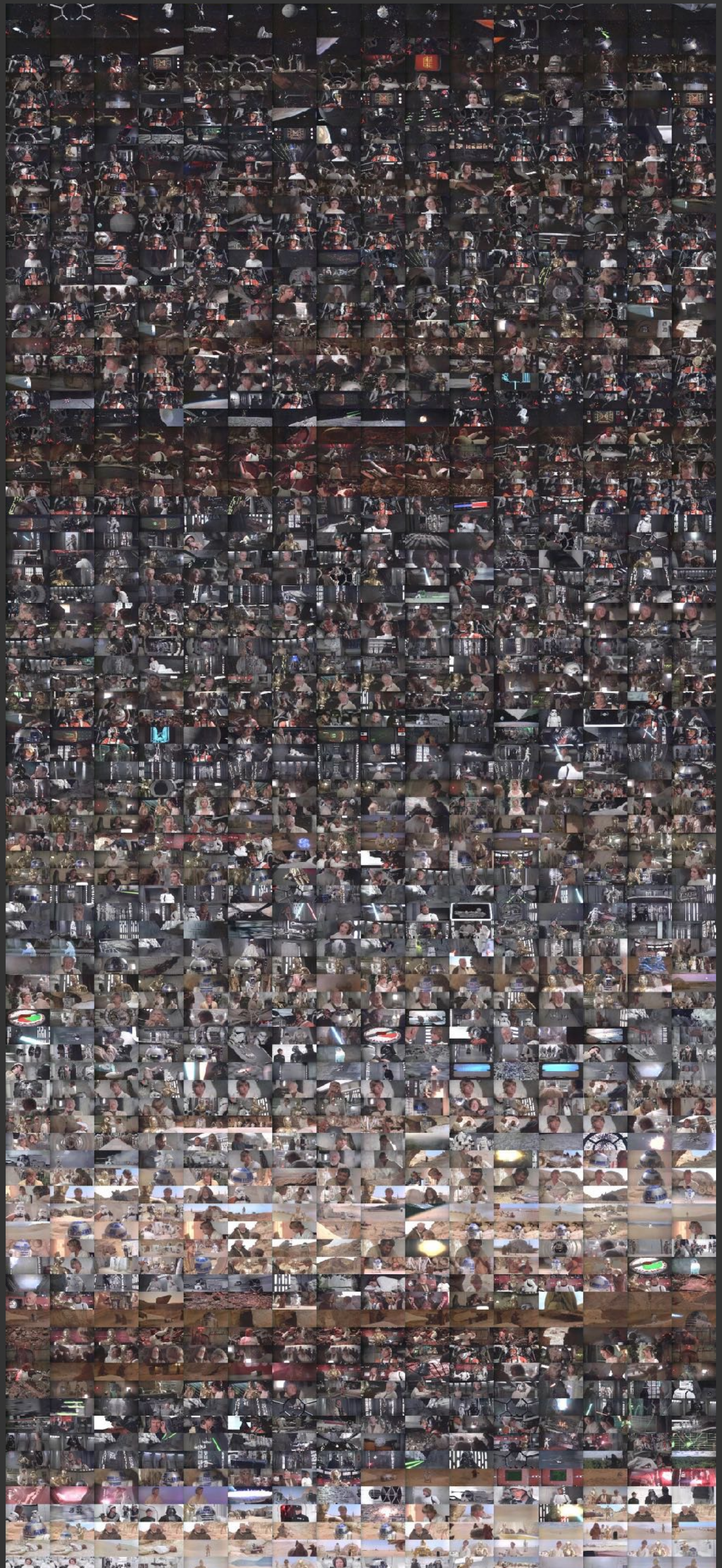
How do these traits vary across films or time?

"Star Wars Episode IV: a New Hope"
Segmented into shot boundaries based on image histograms

Star Wars Ep IV: Sorted by time

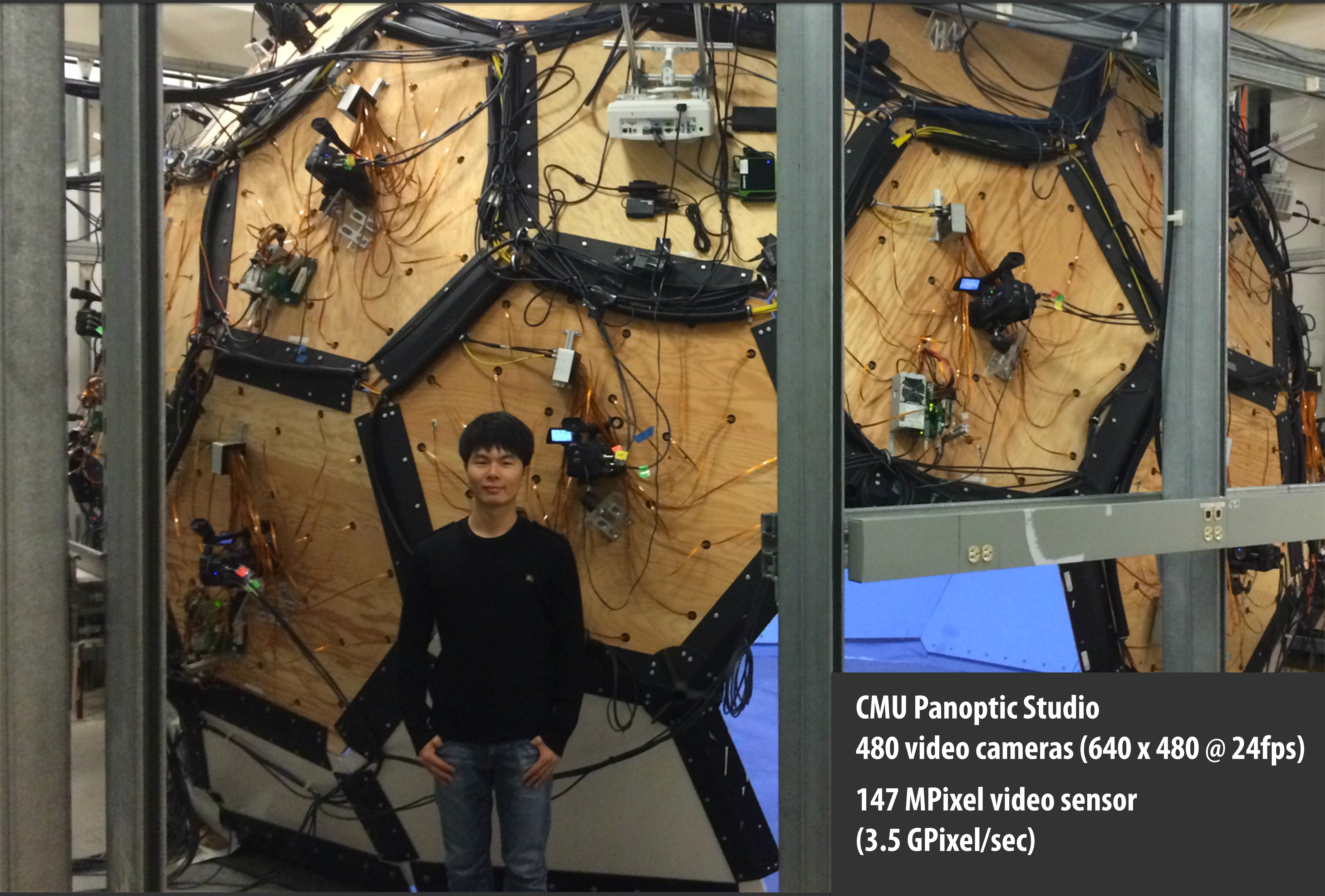


Sorted by color



Sensing human social interactions

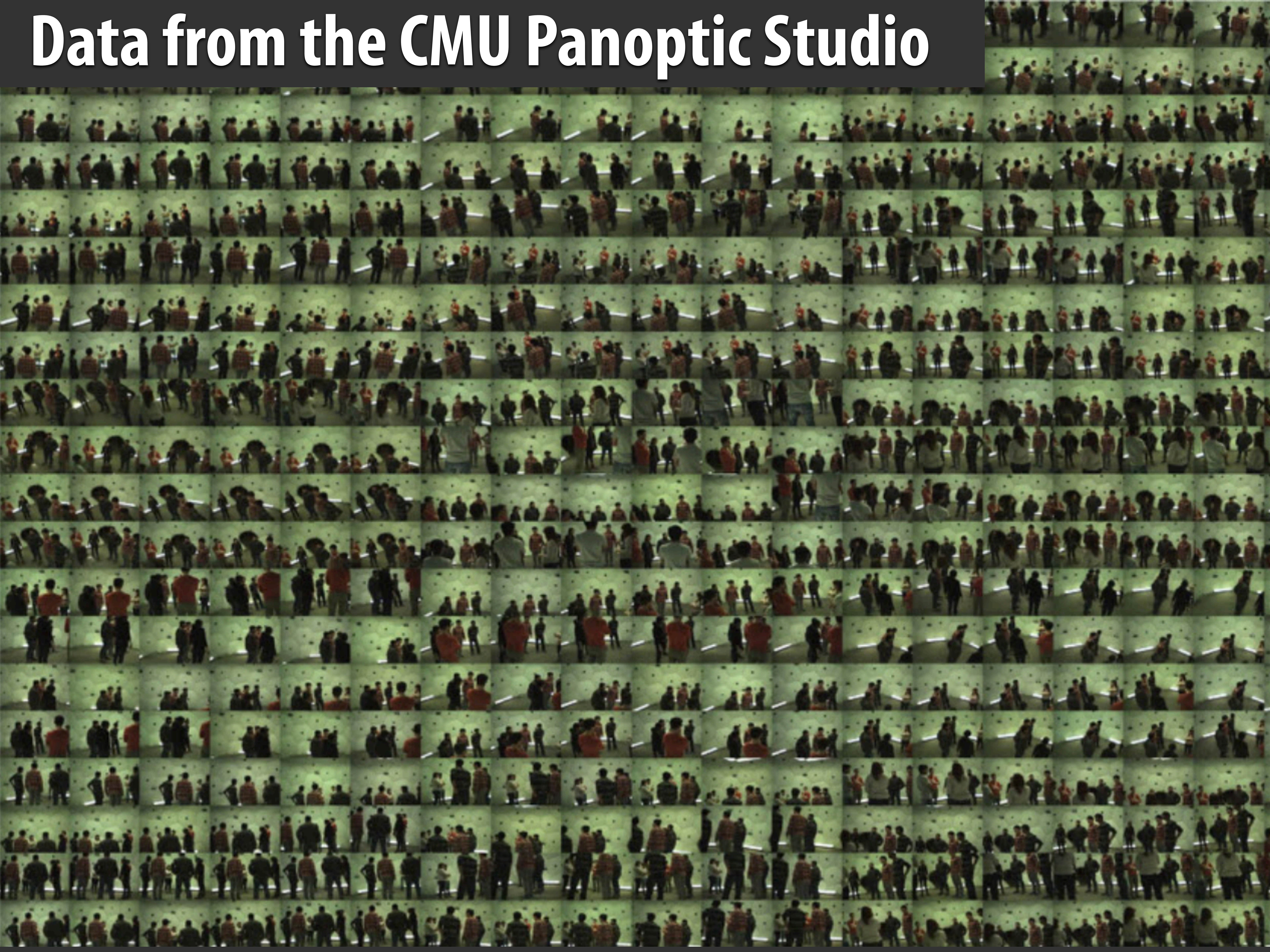
[Joo 2015]



CMU Panoptic Studio
480 video cameras (640 x 480 @ 24fps)

147 MPixel video sensor
(3.5 GPixel/sec)

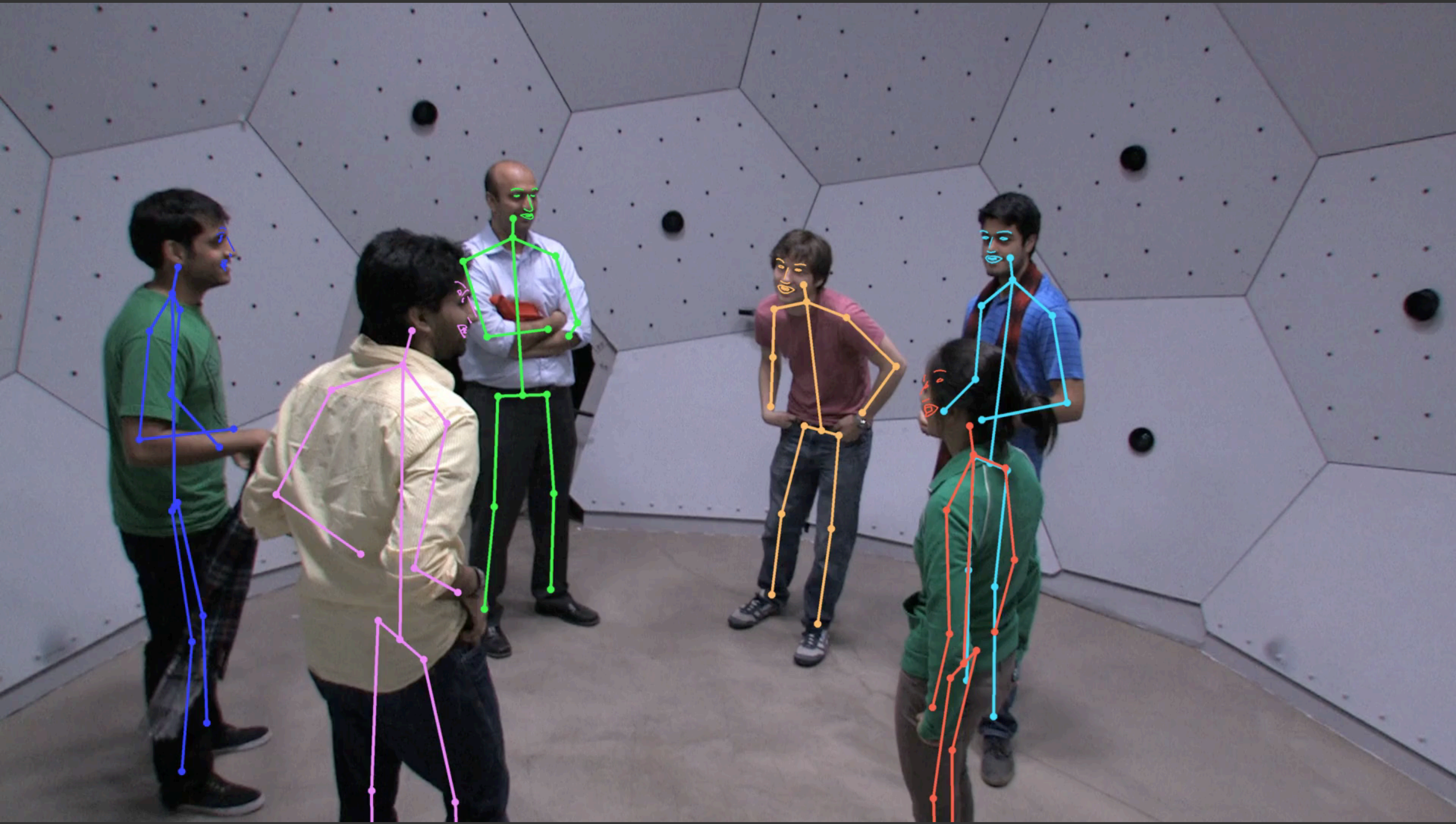
Data from the CMU Panoptic Studio



Capturing human social interactions

40-second sequence

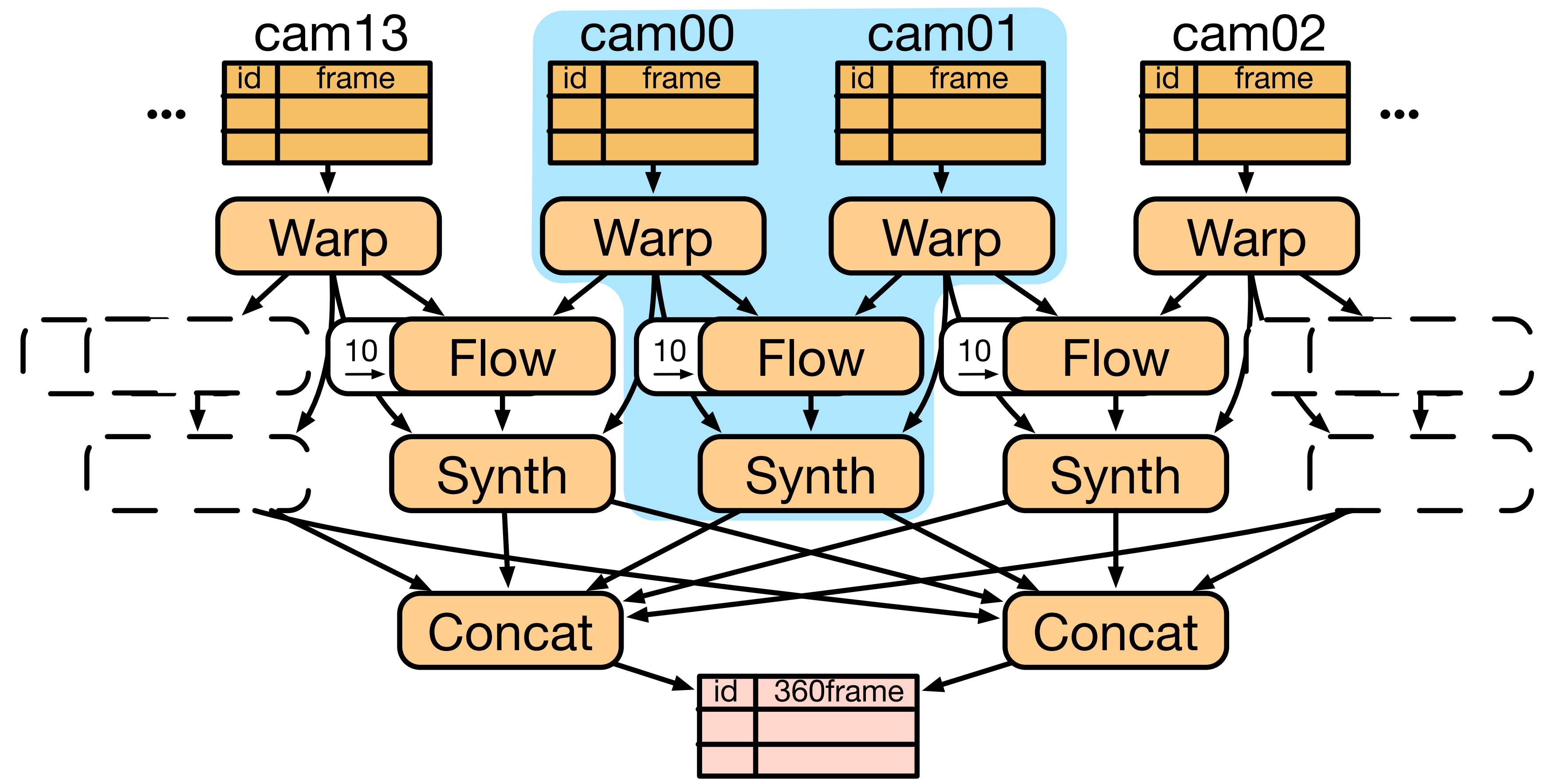
3D pose reconstruction time: hand-coded solution — 7 hours on 4-Titan Xp's [Cao 2016]



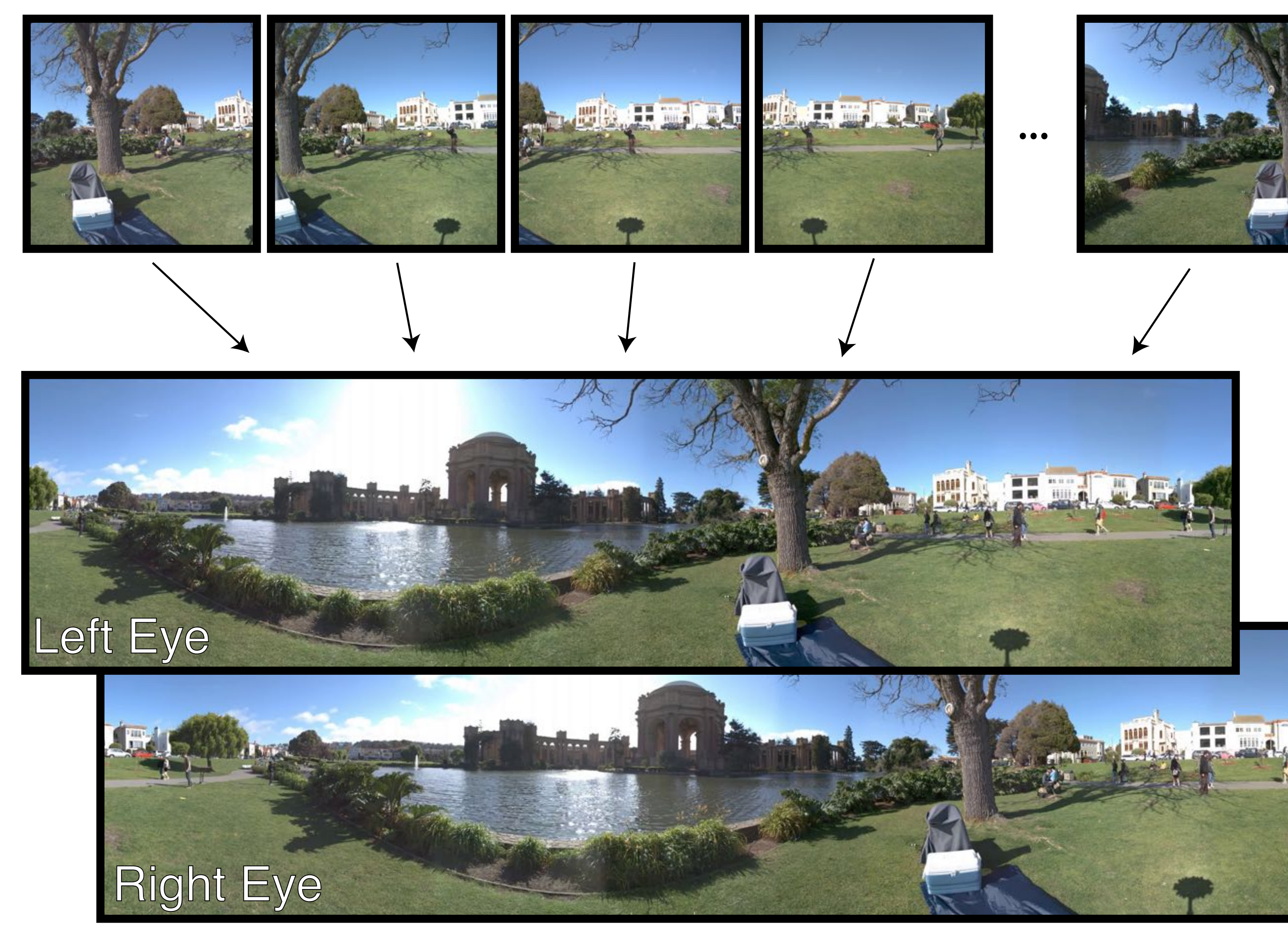
[Courtesy Yaser Sheikh, Tomas Simon, Hanbyul Joo] [Joo et al. 2015]

Facebook Surround 360 VR video

14 2K x 2K cameras



2048 x 2048 PointGrey Camera @ 30 FPS



Surround 360 Open Edition

14 cameras

8K x 8K stereo panorama output =

12.5 secs per frame on 32-core CPU

Workload

- 100's to 1000's of videos, different video lengths
- Sparse frame sampling: evaluate a kernel on every (Nth) frame, or on a specific list of frames (every frame with people)
  - DNN inference (detection, facial landmarks, segmentation, etc.)
- Operations that require a window of multiple frames in sequence
  - Optical flow, hyperlapse sliding windows, etc…
- Operations with temporal dependencies (frame-to-frame state)
  - Object tracking
- Operations that combine multiple video streams

Scanner: design goals / principles

Design principle 1: keep it simple

- Enable non-expert programmers (computer vision researchers, visual data analysts) to rapidly develop and deploy video analysis applications at cloud scale

Design principle 2: be near speed-of-light efficient

- "Near-HW-peak single-node perf", then scale out
- Utilize heterogenous hardware: ASICs for video encode/decode, run kernels on multi-core CPUs, GPUs, future DNN accelerators

What do I mean by scale? axes of scaling

Scale to arbitrarily large video datasets:

- A modest number of long videos (hundreds of feature films)
- Many short videos (1M youtube videos)

Scale to large numbers of compute resources:

- Efficiently utilize a single large parallel machine (grad student workstation)
- Efficiently utilize many machines (100's GPUs or 1000's CPUs in the cloud)

Scale to real-time processing:

- Processing (and joining results of) multiple video streams

Current non-goal of Scanner: scaling to very large single images (satellite images, maps, etc.)

Basic Scanner workflow

I have a list of videos in a filesystem…

```
myvideos/vid00.mp4
myvideos/vid01.mp4
myvideos/vid02.mp4
…
myvideos/vid99.mp4
```

And I have a library of parallel pixel processing kernels for CPUs and GPUs:

- Image crop/rescale (Halide)
- Depth from disparity (Halide)
- Optical flow (OpenCV)
- Eigen (C)
- Video Tracker (CUDA)

Caffe DNN Eval
NVIDIA cuDNN

- Human Pose estimation [Cao16]
- Object detector [Redmon16]
- Face detection network [Hu17]
- …
- Depth/normal estimator [Bansal17]

Represent videos as relations (tables)

```
myvideos/vid00.mp4
myvideos/vid01.mp4
myvideos/vid02.mp4
…
myvideos/vid99.mp4
```

Ingest into Scanner…

```
videos = ['vid_00.mp4',...,'vid_99.mp4']
db = scanner.Database();
video_tables = db.ingest_videos(videos)
```

table: vid00.mp4

frame_id	frame

table: vid01.mp4

frame_id	frame

table: vid02.mp4

frame_id	frame

…

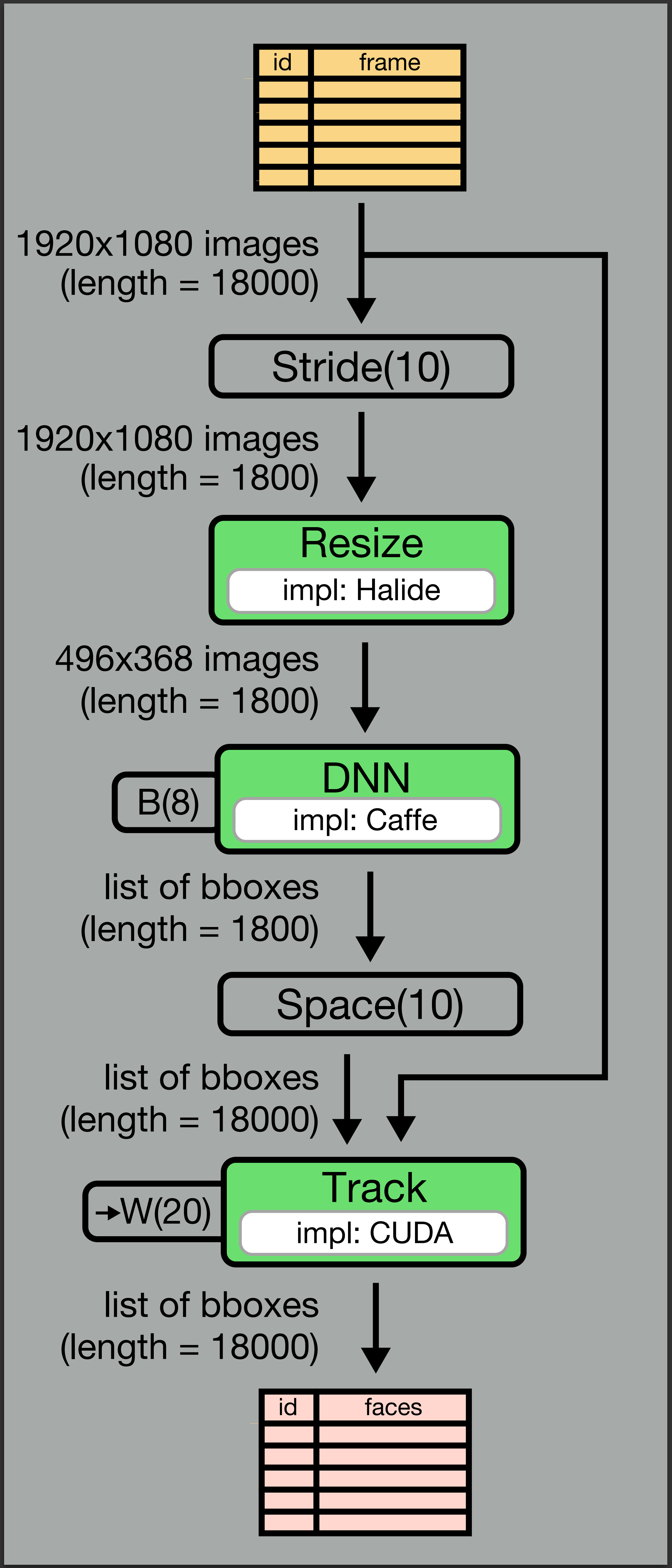
table: vid99.mp4

frame_id	frame

Computation as dataflow graph

```
videos = ['vid_00.mp4',...,'vid_99.mp4']
db = scanner.Database();
video_tables = db.ingest_videos(videos)
```

```
frame = db.ops.FrameInput()

sparse_frames = frame.stride(10)

resized = db.ops.Resize(
    frame  = sparse_frames,
    width  = 496, height = 398)

detections = db.ops.DNN(
    frame = resized,
    model = ‘face_dnn.prototxt’,
    batch = 8)

frame_detections = detections.space(10)

faces = db.ops.Track(
    frame      = frame,
    detections = frame_detections,
    warmup     = 20)

output = db.ops.Output(columns=[faces])
```



* Similar to TensorFlow graph, or SVE processing graph

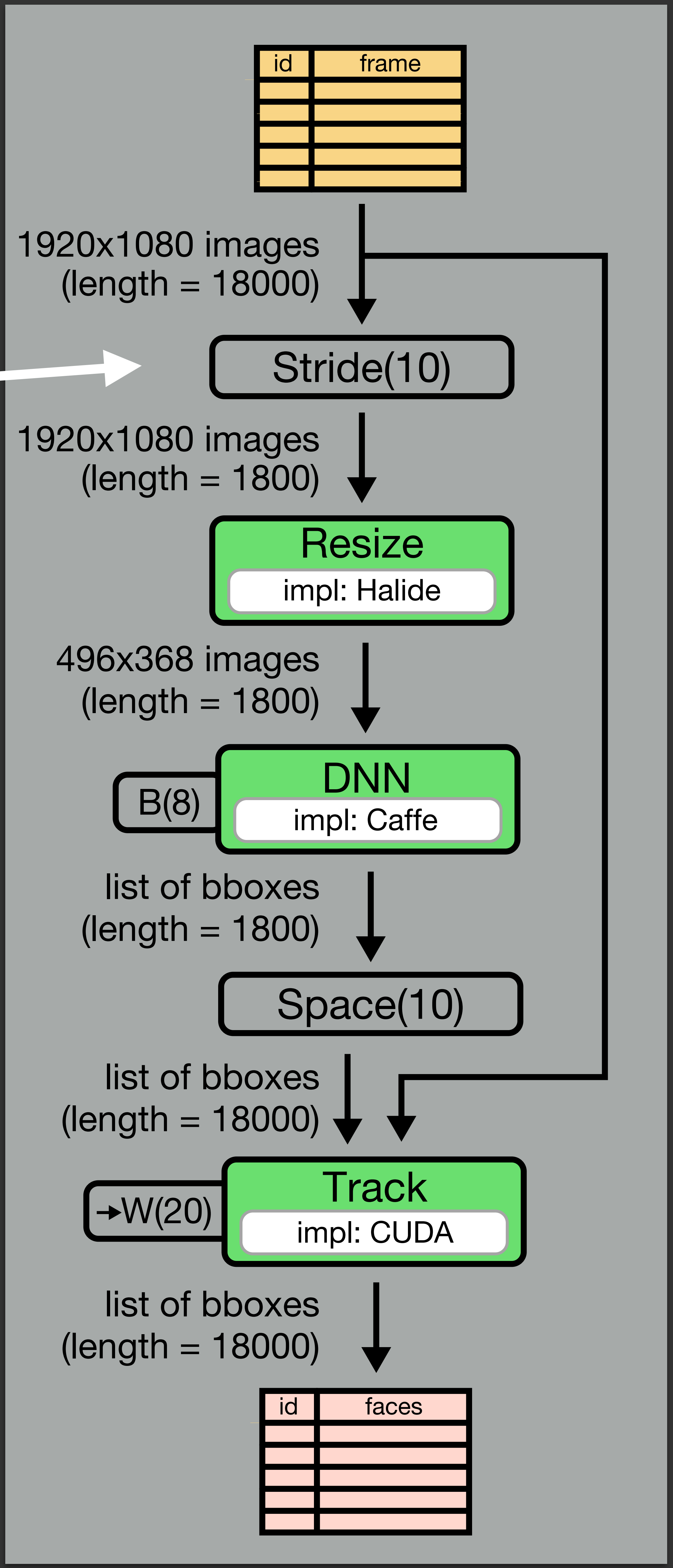
Scanner dataflow graph operations

Sequence sampling operations (stride, range, indexed gather)

Output sequence contains subset of elements of input sequence

e.g.
Run on every 5th frame
Run on a list of frames known to contain faces

Note: this is sampling, it is not data-dependent filtering



Scanner dataflow graph operations

Bounded stateful operations

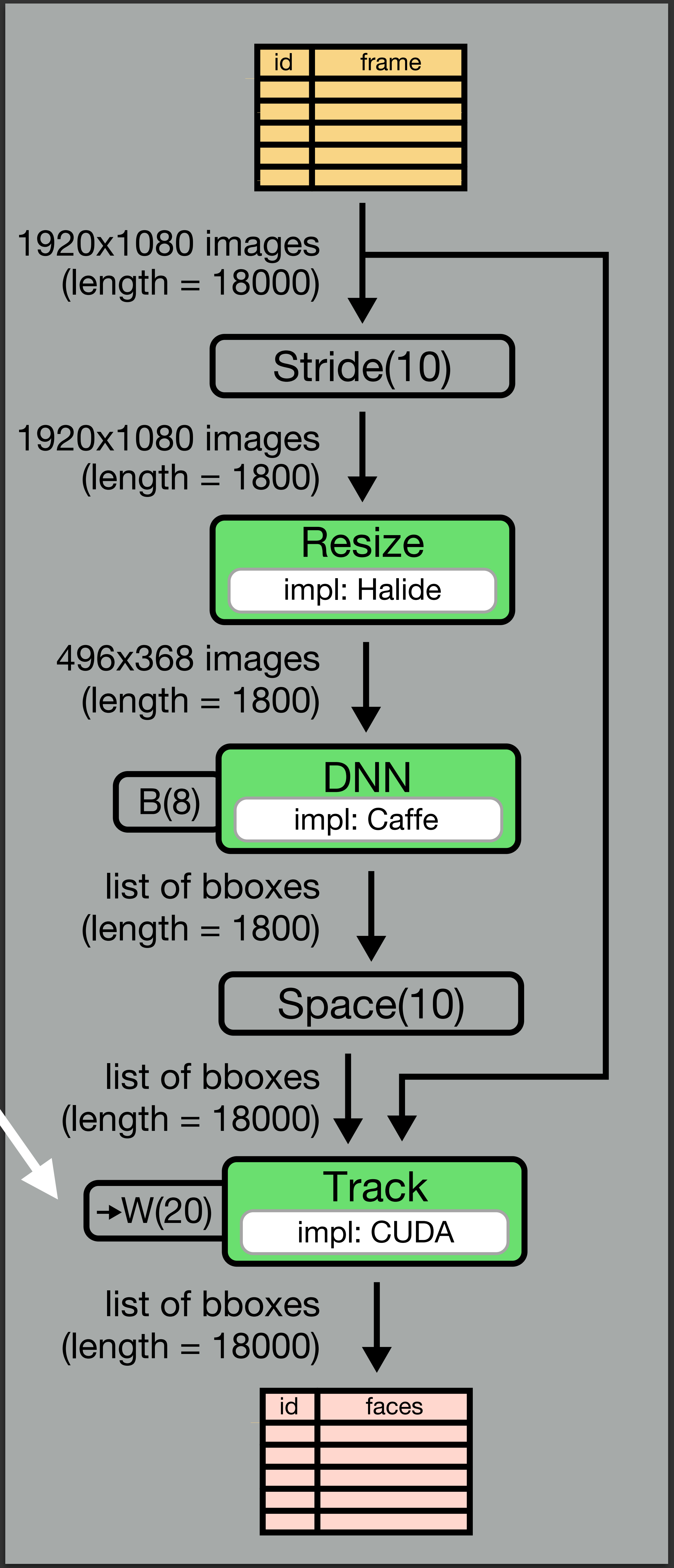
Each output element depends on results of processing prior output element

Runtime guarantees effects from at least W prior "warmup" elements will be visible

e.g.

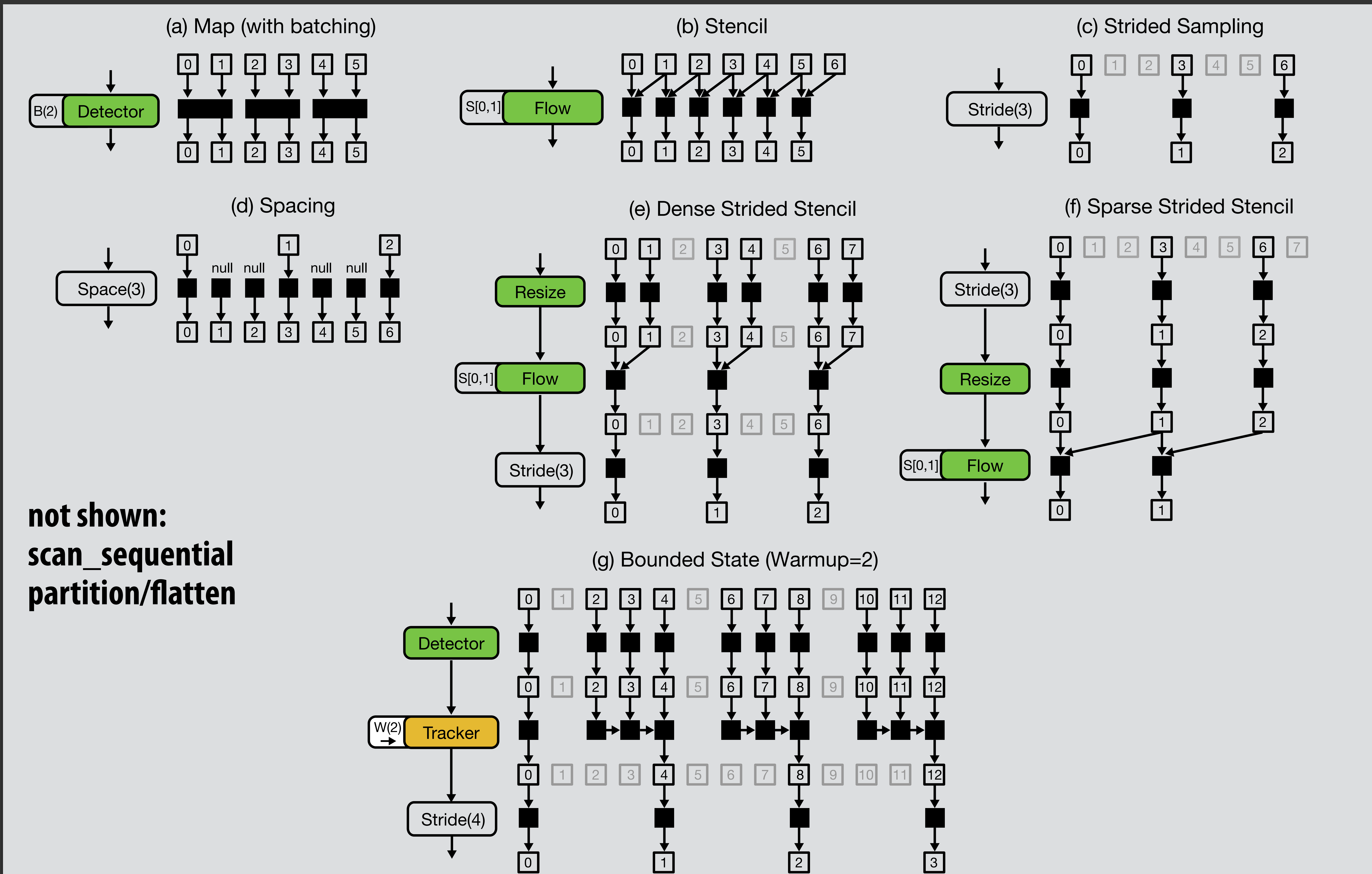
Object tracking

Minimizing temporal discontinuities while running in parallel



DAGs of data-parallel operations

map, stencil, stride, fold, bounded_fold, partition/flatten



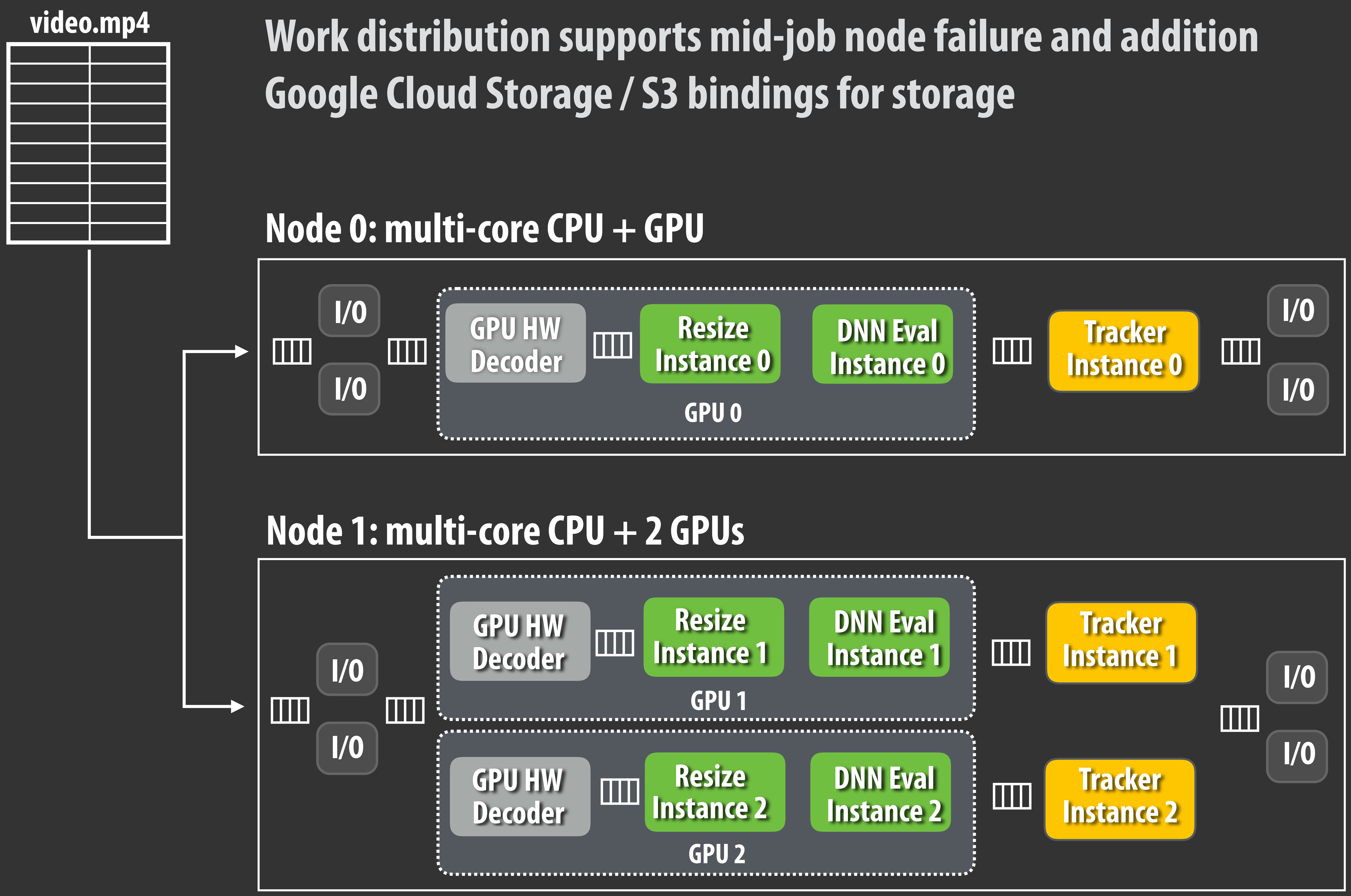
not shown:
scan_sequential
partition/flatten

Scanner runtime

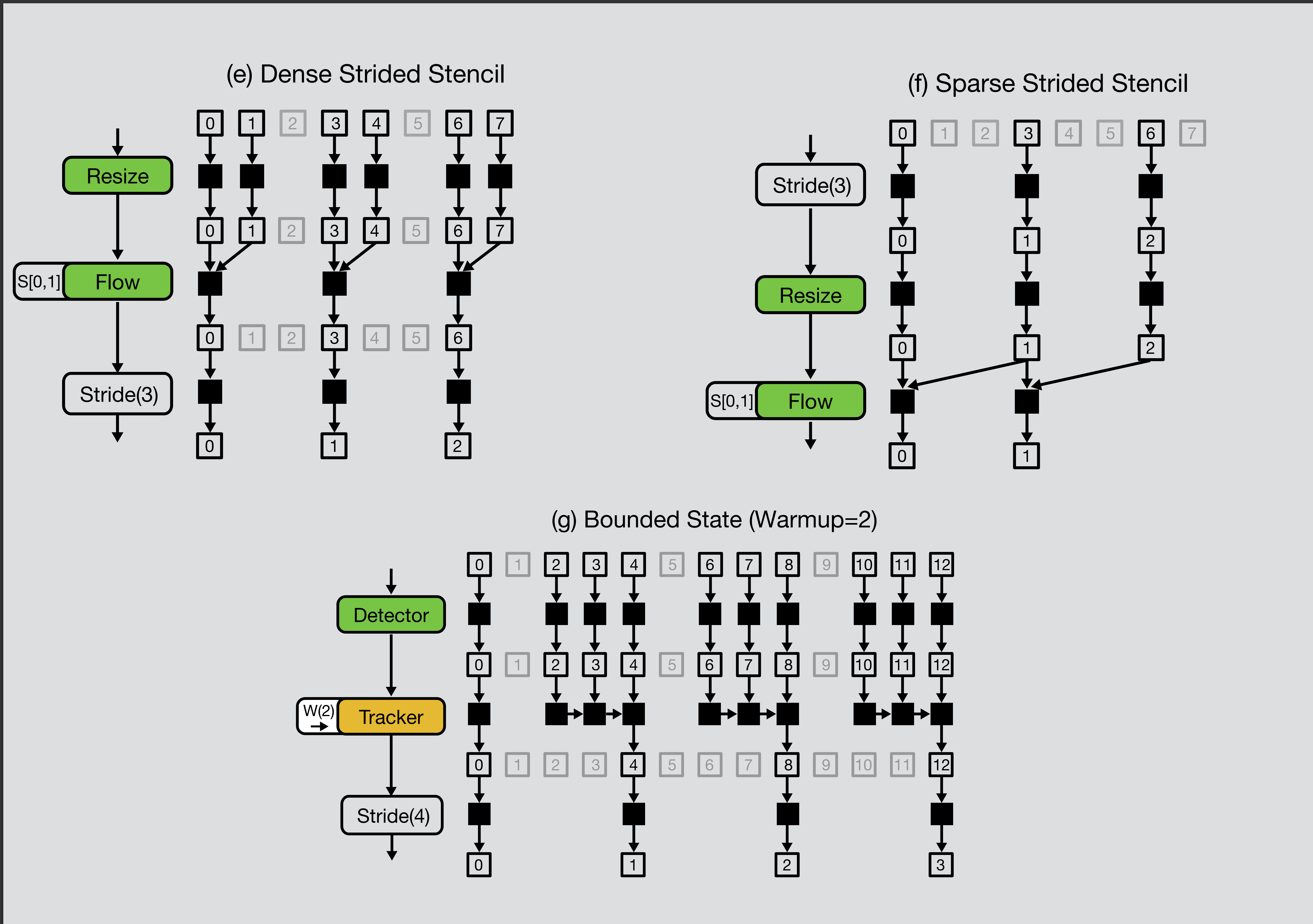
Parallel execution in Scanner

Work distribution supports mid-job node failure and addition

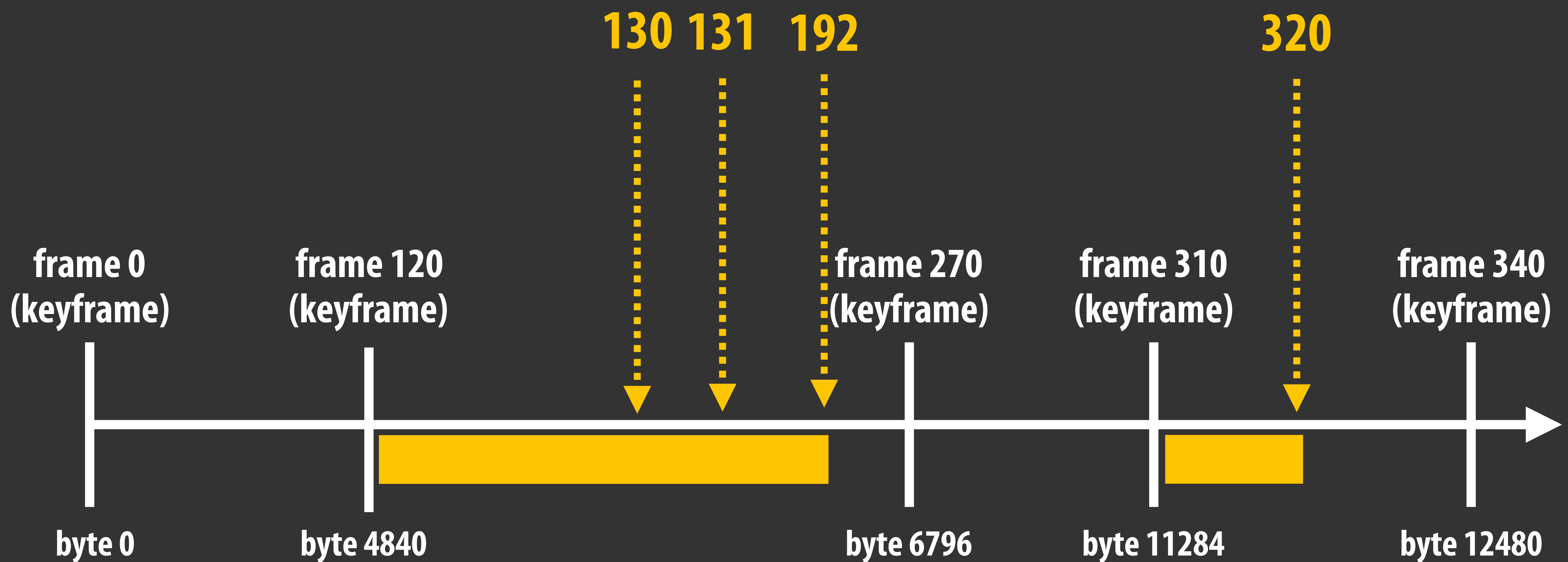
Google Cloud Storage / S3 bindings for storage



Per-element (sparse) dependency analysis



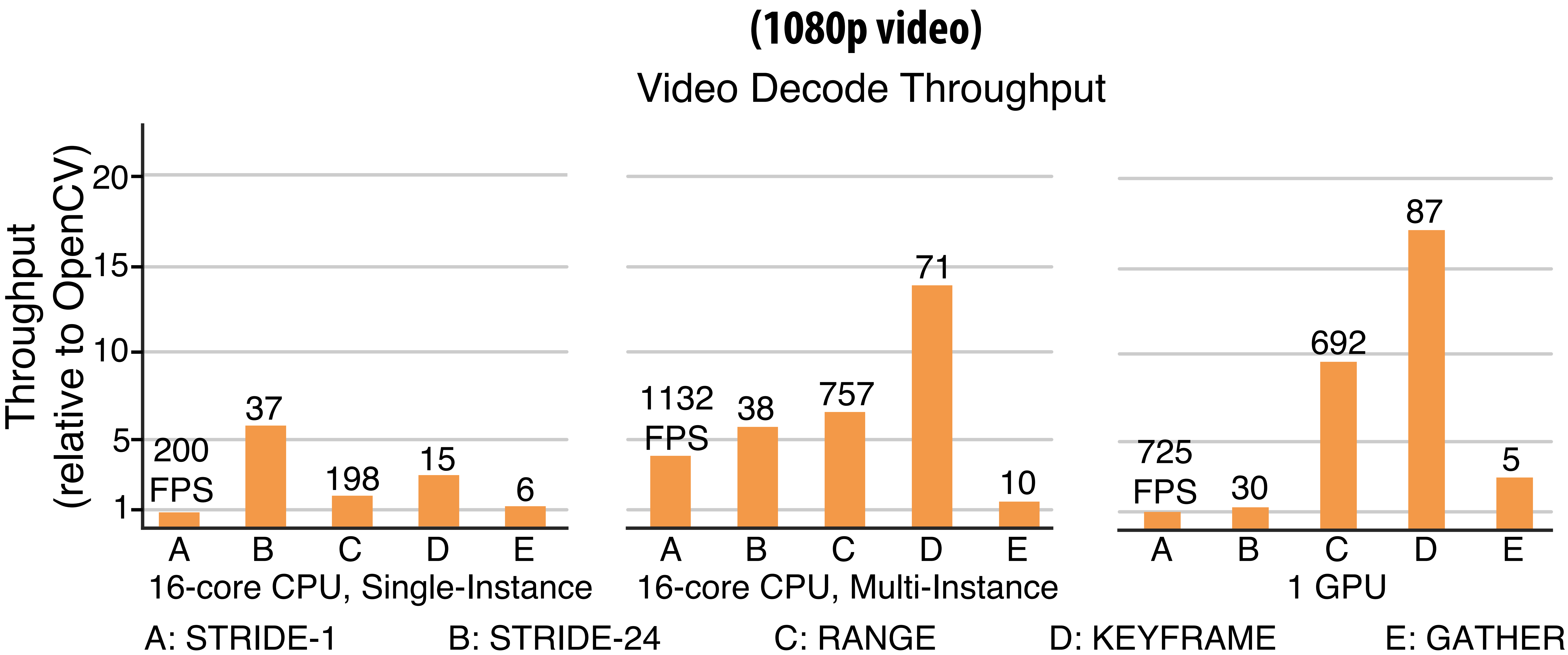
Accelerated parallel sparse frame decode using index of keyframe locations



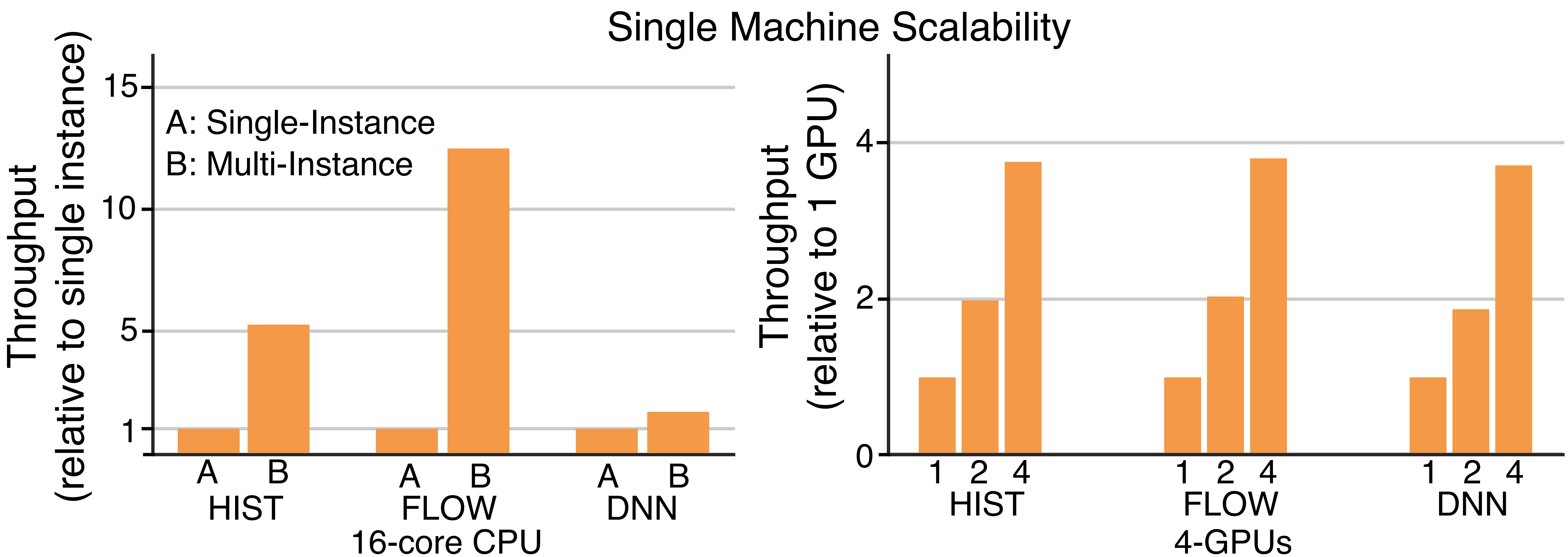
Scanner maintains index of keyframe locations to enable work-efficient parallel decode

Scanner performance

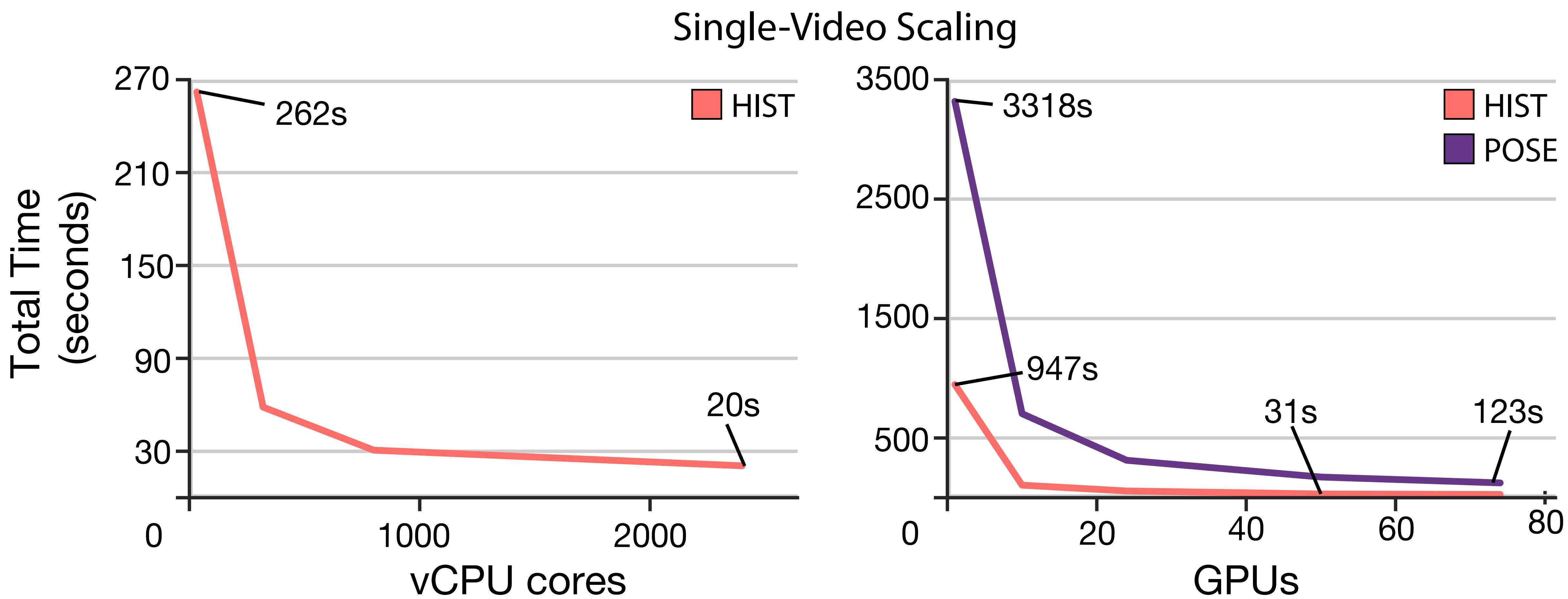
Efficient video decode under sparse access



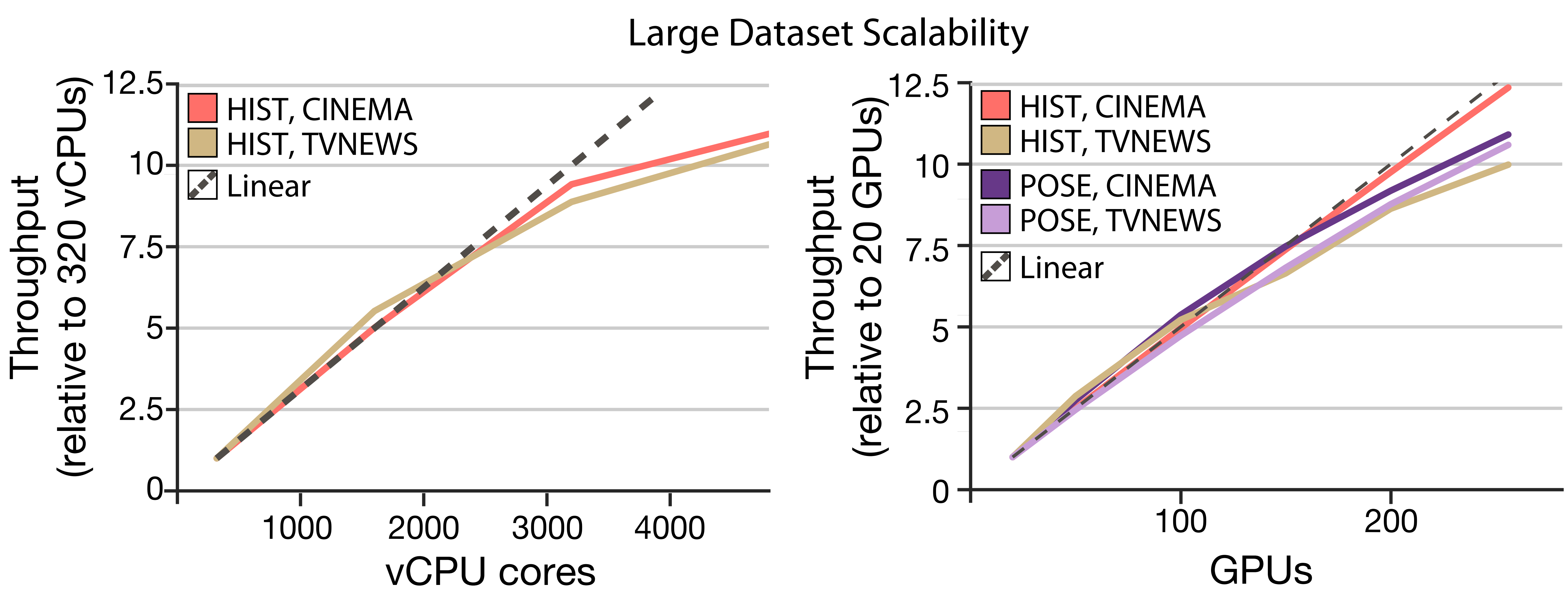
Scaling to bigger machines



Scalability to many cloud machines



Using many resources to process a 2.2 hour movie quickly (reduce latency of analysis)



Using many resources to process database of many videos

Facebook Surround 360 VR video generation

44-node computation DAG

8K x 8K stereo panorama output = 12.5 secs per frame on 32-core CPU

Joins multiple video streams

Bounded state operations (smoothing across parallel partitions)

15 minute sequence: (103 GB)

Single node Scanner (32-core CPU)

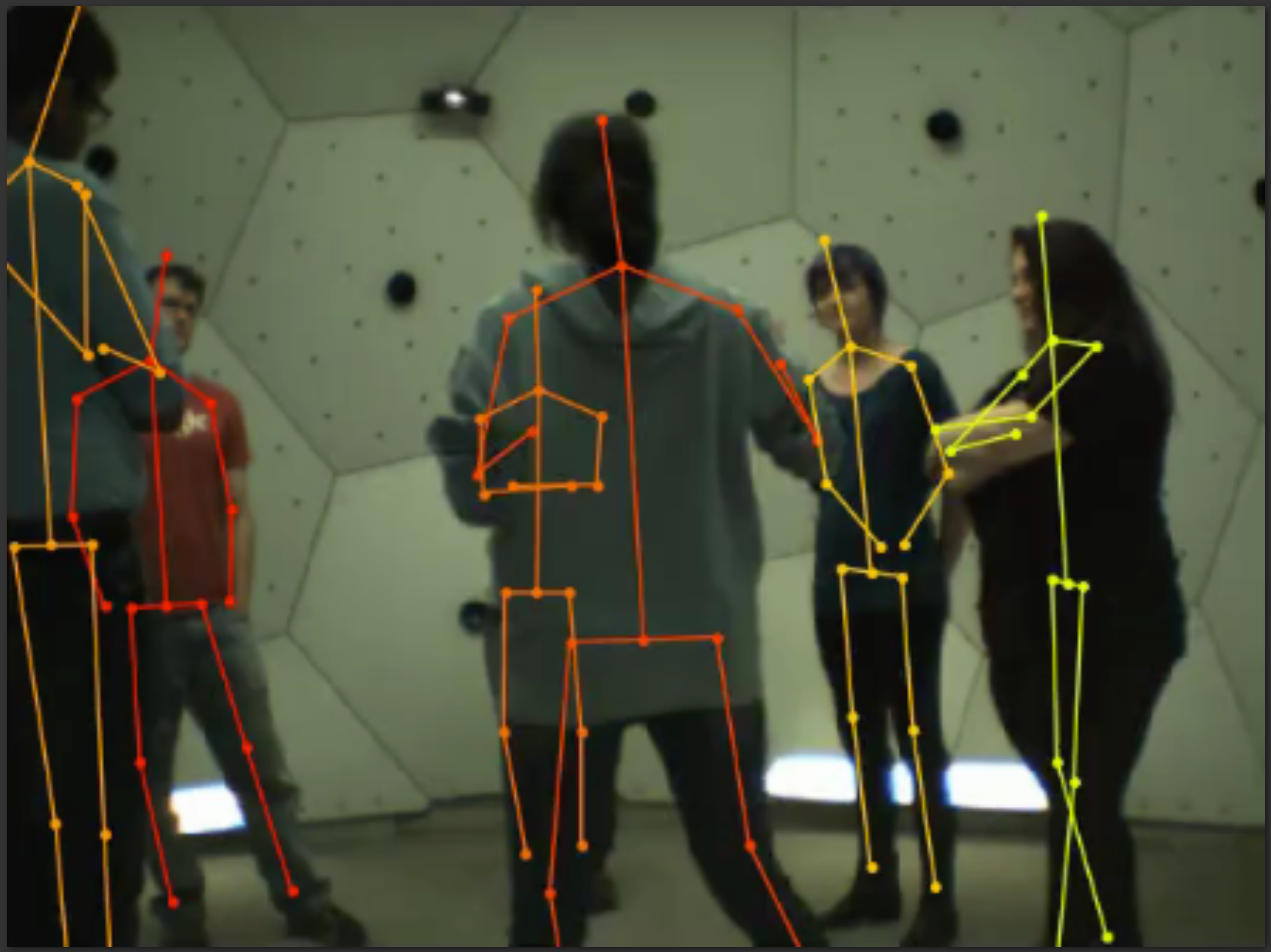
- 5 secs / frame

Multi-node on Google Compute Engine

- 64 x 32-core nodes (2048 cores)
- Approaching real-time

3D human pose reconstruction

Processing 40 seconds of video from CMU Panoptic studio



Grad student hand-tuned:	7 hrs	(1 node x 4 Titan Xp GPUs)
Scanner:	2.6 hrs	(1 node x 4 Titan Xp GPUs)
Scanner on GCE:	25 mins	(25 nodes x 4 K80 GPUs = 100 K80s)

Performance makes extended capture sessions possible

Today's summary

- Last time: algorithmic techniques for increasing efficiency of video processing

- Today: Cloud-scale infrastructure for processing large amounts of video at scale

- Good example of need for new infrastructure (to run at scale) AND new algorithms (to reduce the amount of work done)
  - The cost of per-frame processing remains way too high to mine large video collections in a brute force manner
  - Running three detectors: Faster R-CNN, Convolutional Pose Machines, TinyFaces on all 6M 720p frames on GCP ~ $3400
  - Currently resort to heavy use of subsampling frames