

# Learning for Better Video Processing Systems

**FastPath 2021**

**Amrita Mazumdar / Vignette AI & University of Washington**

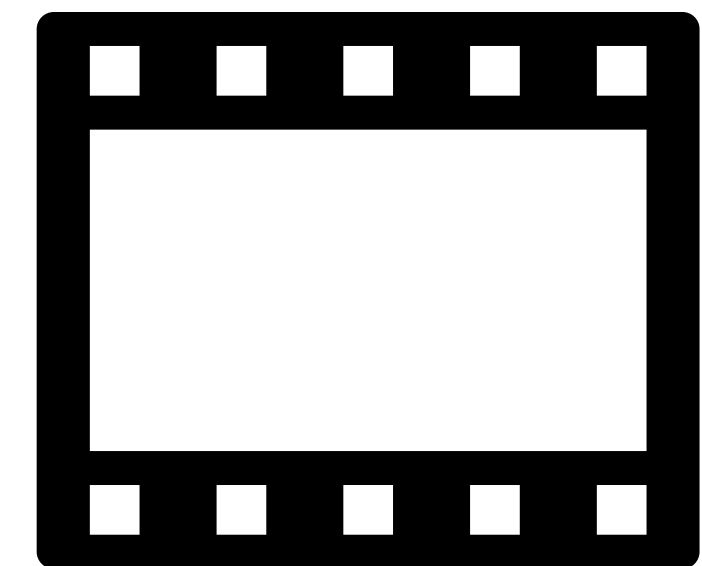
*In collaboration with: Maureen Daum, Brandon Haynes, Dong He, Magda Balazinska, Luis Ceze, Alvin Cheung, Mark Oskin*



# **Video is an increasingly popular source of data but presents challenges for streaming and ML processing pipelines.**

Twitch streamed 75 million hours of video / month in 2020

Video communications consume 82% of internet traffic (Cisco 2019)

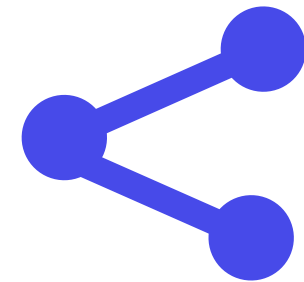


# Cloud services use machine learning to process and understand video content.

Read video from storage and decompress



machine learning



features and parameters

saliency

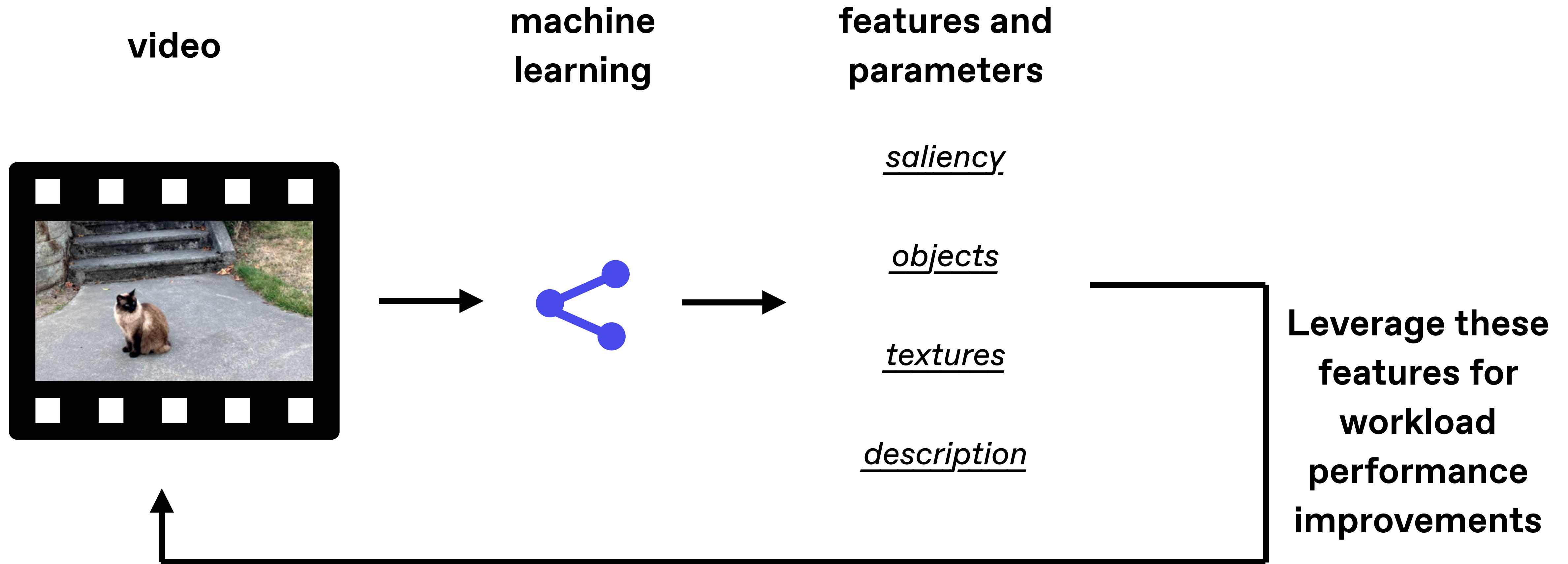
objects

textures

description

Decoding visual media takes 20x longer than accelerated DNN processing (Kang et al., VLDB 2021)

# This talk: using learned features to improve performance



# **This talk: using learned features to improve performance**

How can we use learned features to **reduce video streaming bandwidth** while maintaining quality?

*Vignette (Mazumdar et al., SoCC 2019)*

How can we use learned features to **reduce decode overhead for video analytics queries**?

*TASM (Daum et al., ICDE 2021)*



# Video streaming systems trade off between visual quality and network bandwidth available.

fine details (noise,  
high frequencies)

fast motion

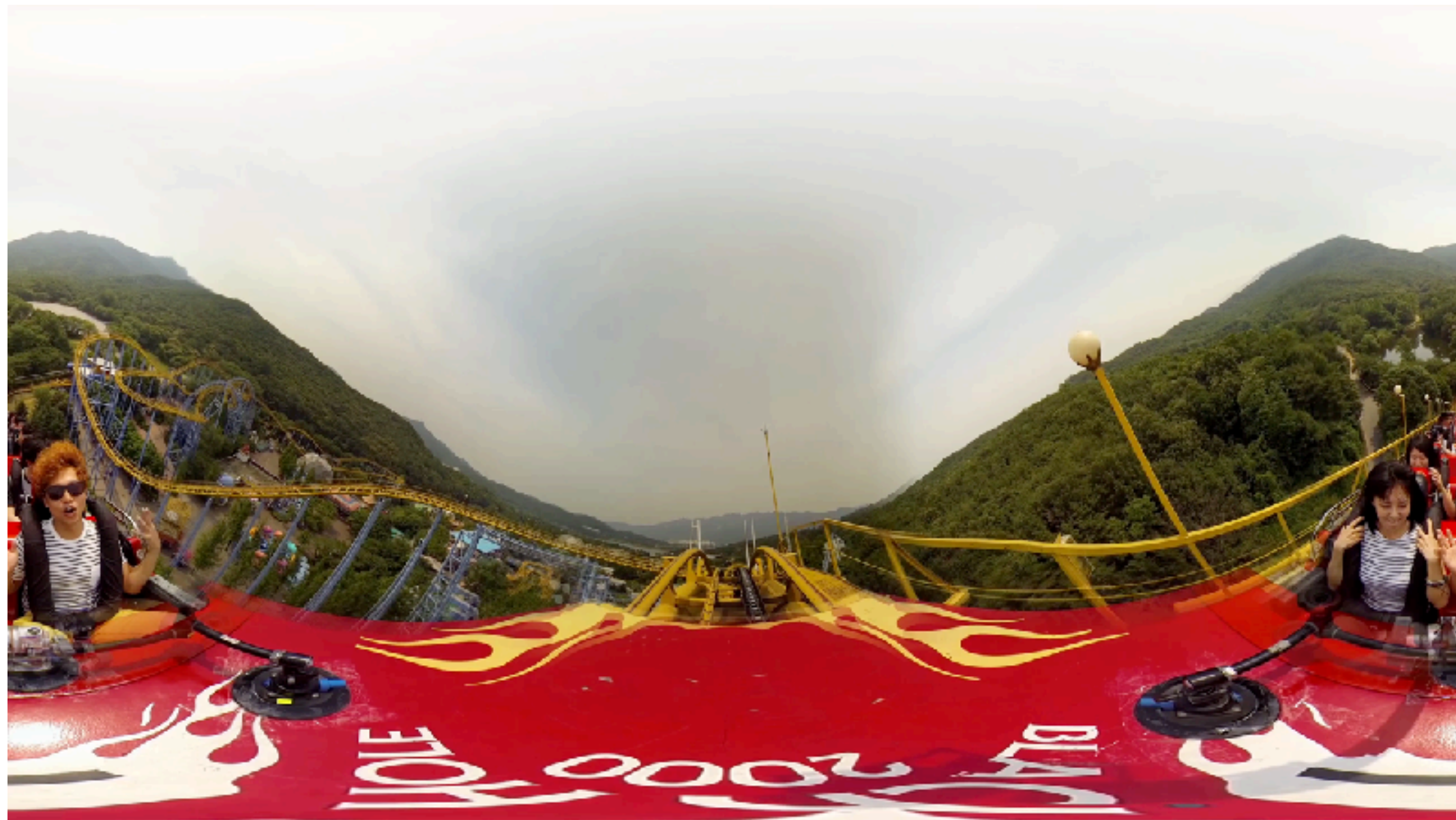


color perception

Baseline codec (HEVC) @ 20 Mbps  
4 hours video playback

Source: Netflix Public Dataset

# Saliency is a powerful perceptual cue for compressed video workloads.



4K 360° video  
300 MB



AI-generated saliency map  
only 15% of pixels are important

Source: Lo et al., MMSys 2017



# Leveraging perceptual cues at scale presents design challenges.

Requires custom, outdated codecs

No integration with storage manager

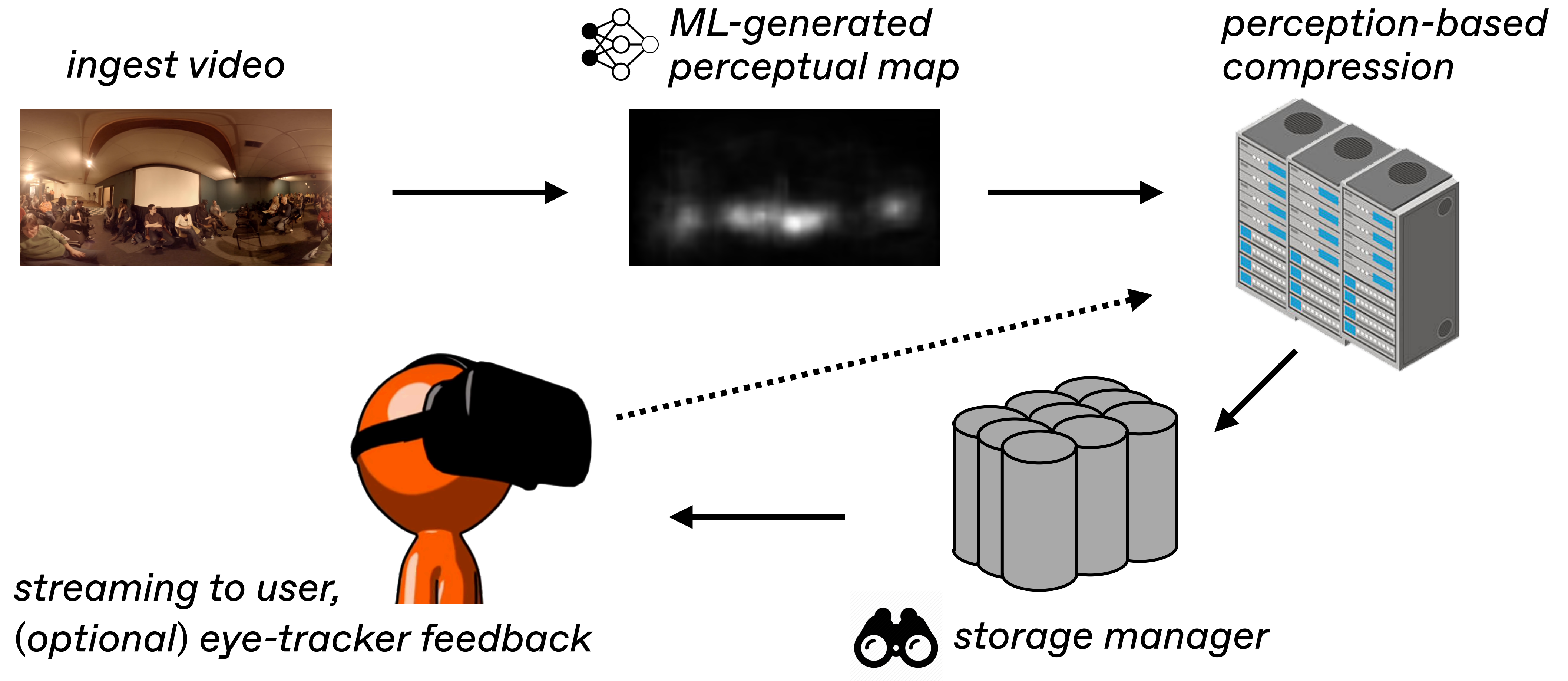
No interface for applications

## Goals:

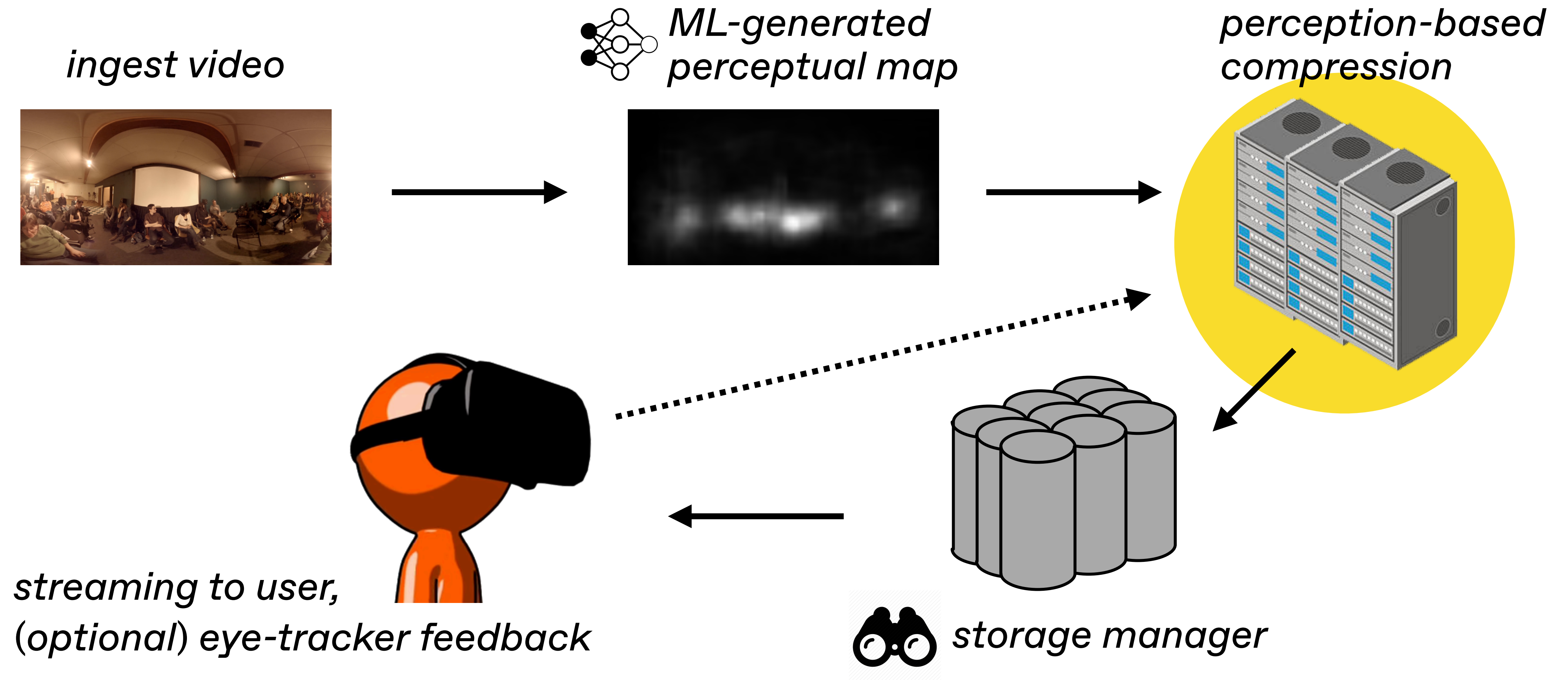
- ✓ Modern codecs
- ✓ API for storage
- ✓ Application portable



# Vignette is a perception-aware video compression and storage system.



# Vignette is a perception-aware video compression and storage system.



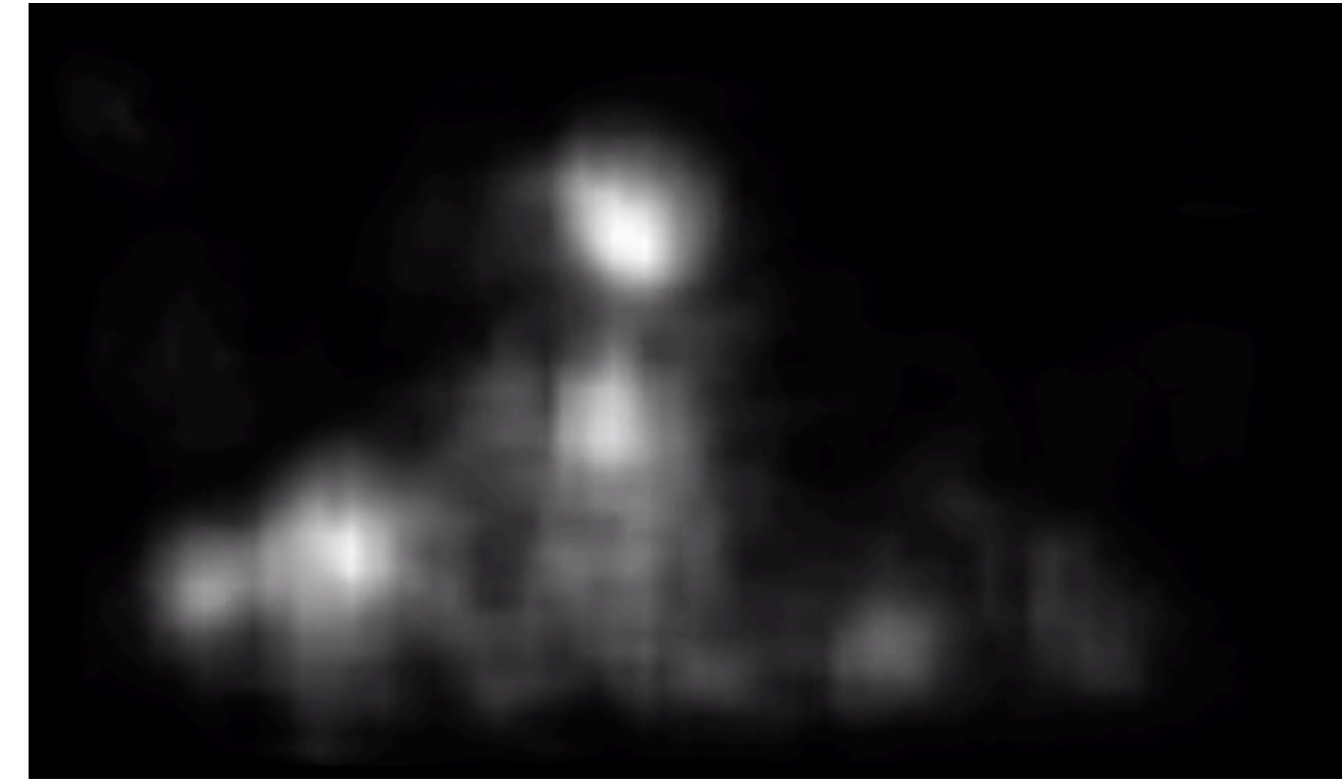


# Vignette Compression uses tiles to convert saliency maps to video encoder parameters.

Automatically generate a saliency map

Split the video segment into tiles

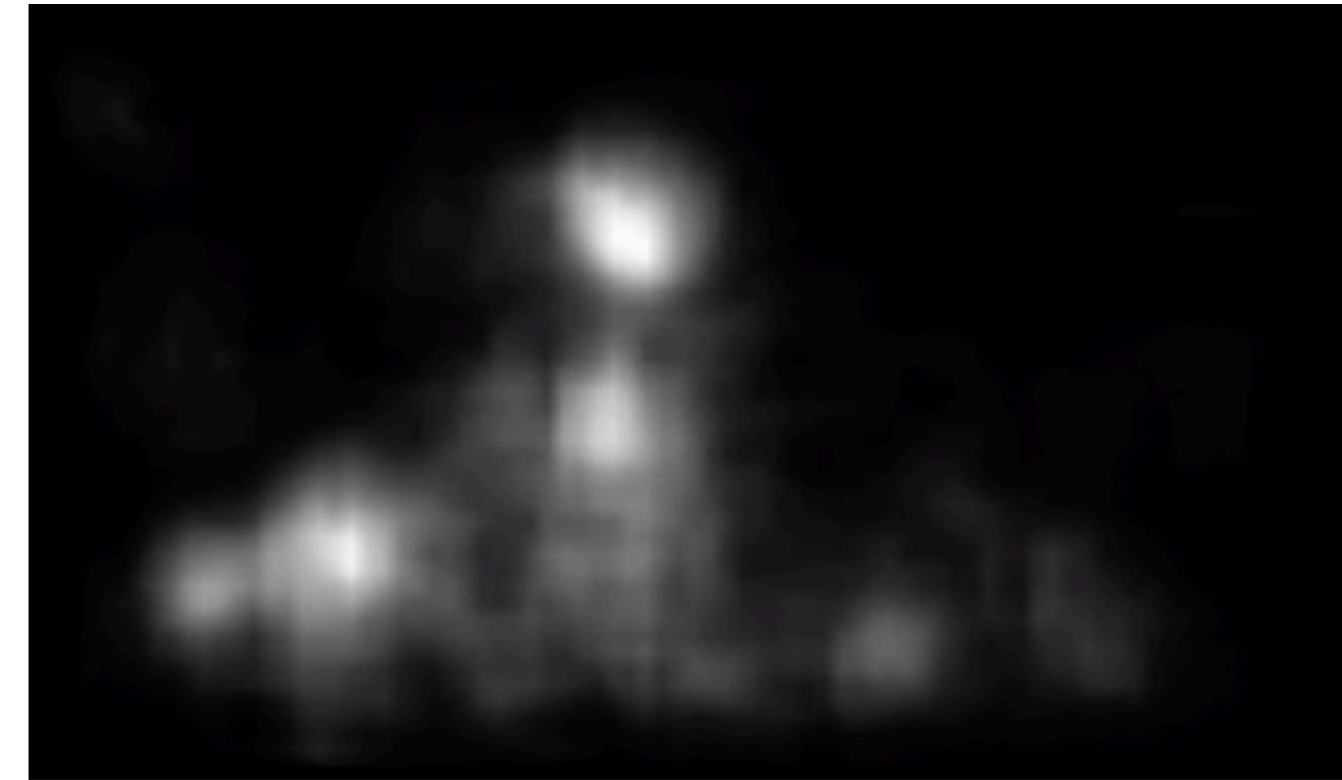
Map saliency values to tiles



Source: Wong 2000

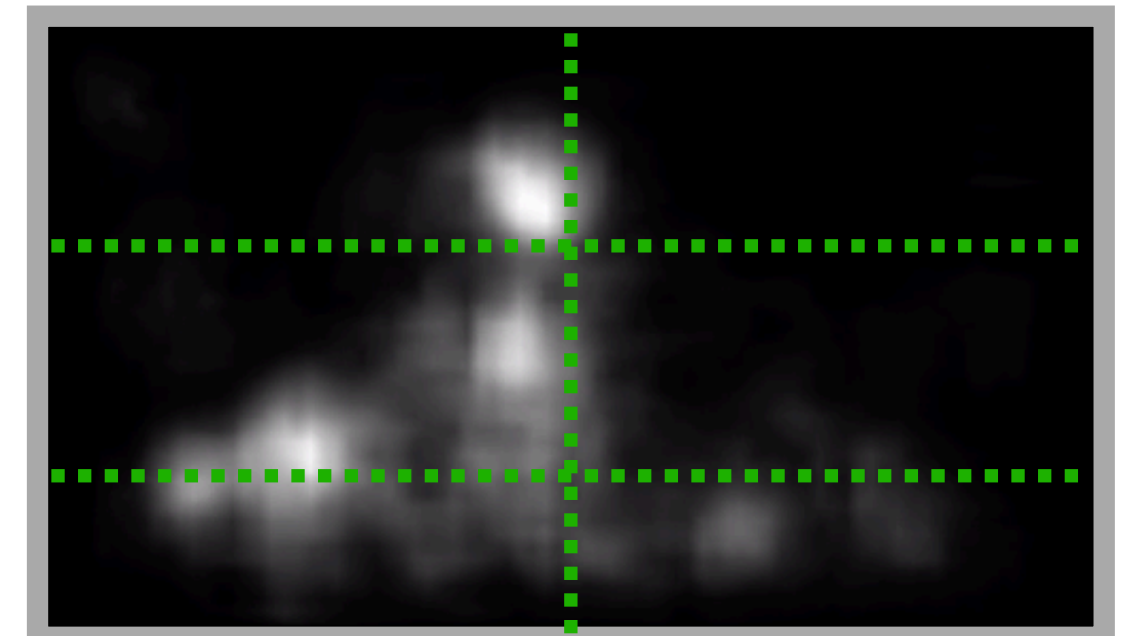
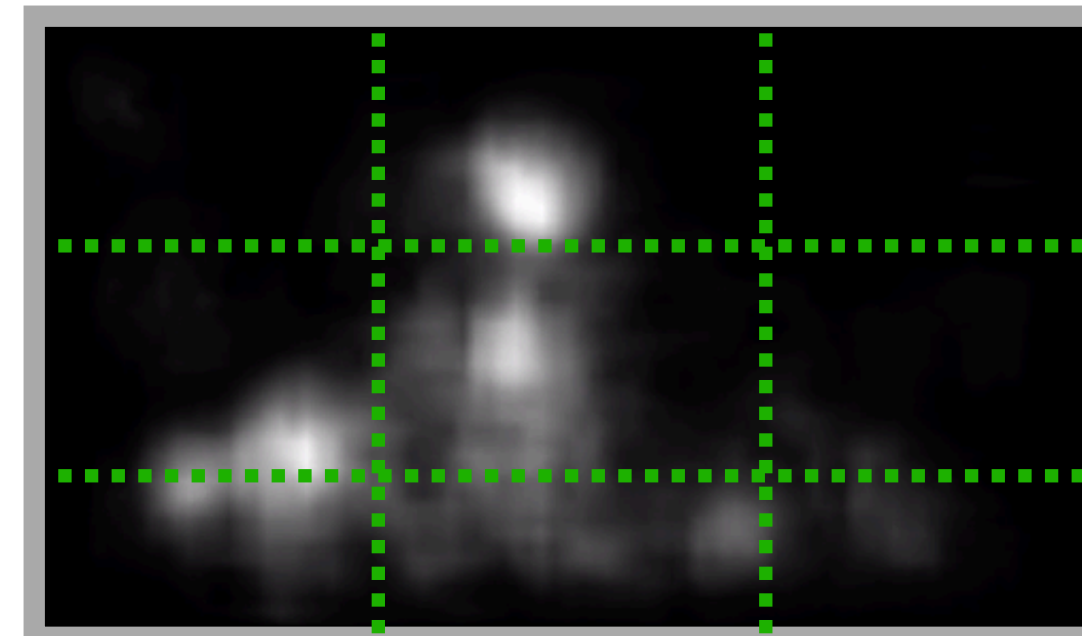
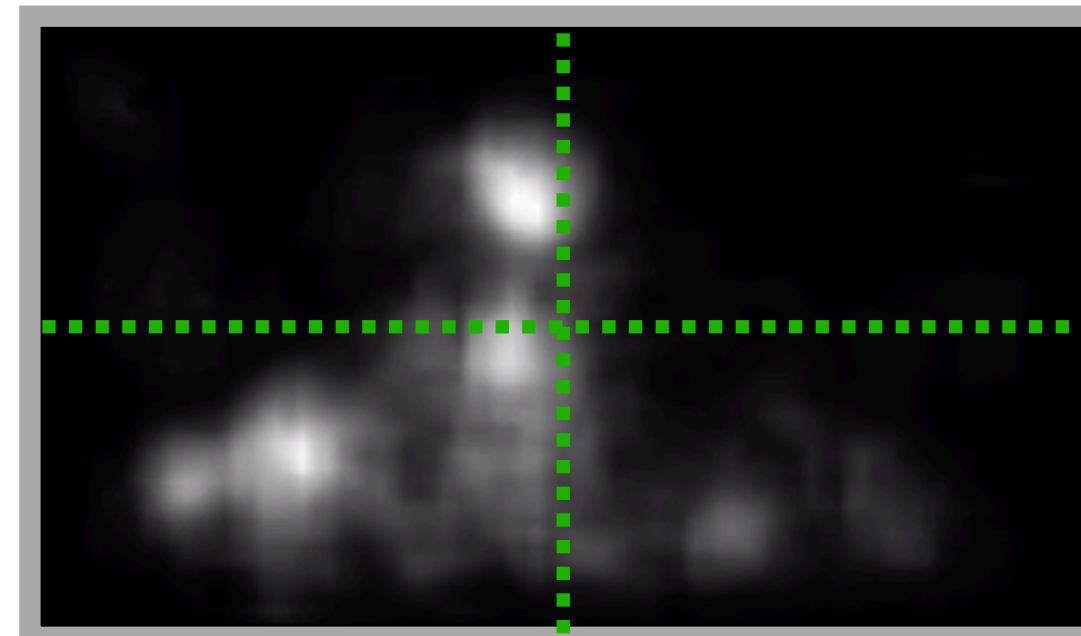
# Vignette Compression uses tiles to convert saliency maps to video encoder parameters.

Automatically generate a saliency map



Split the video segment into tiles

Map saliency values to tiles



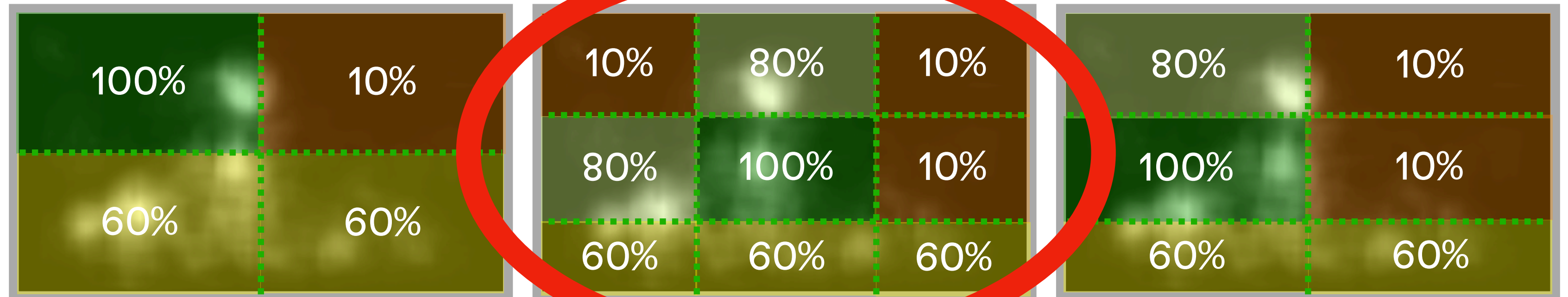


# Vignette Compression uses tiles to convert saliency maps to video encoder parameters.

Automatically generate a saliency map

Split the video segment into tiles

Map saliency values to tiles



**pick best quality,  
lowest overhead**

Source: Wong 2000



# Vignette Results

Participants either preferred Vignette or perceived no difference for 75% smaller videos.



Baseline HEVC @ 20 Mbps  
4 hours video playback

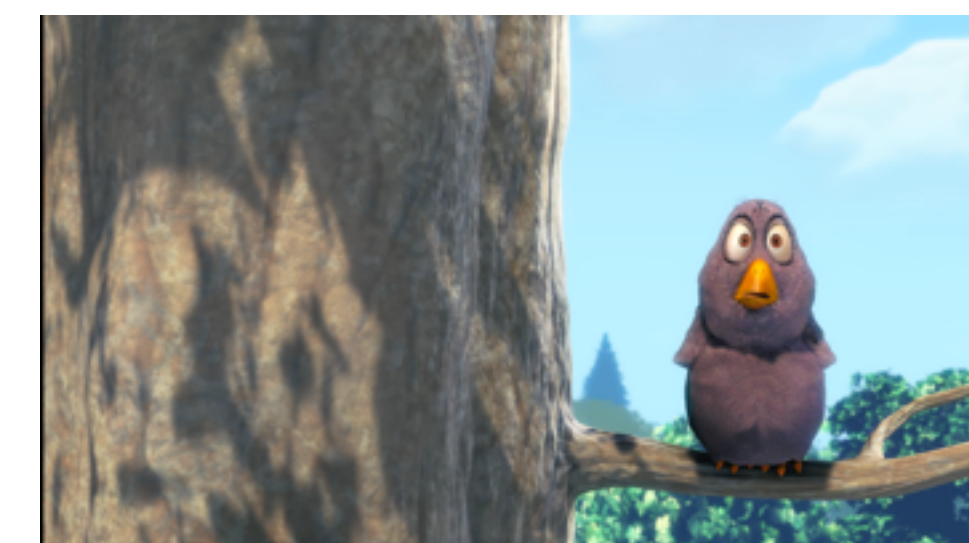
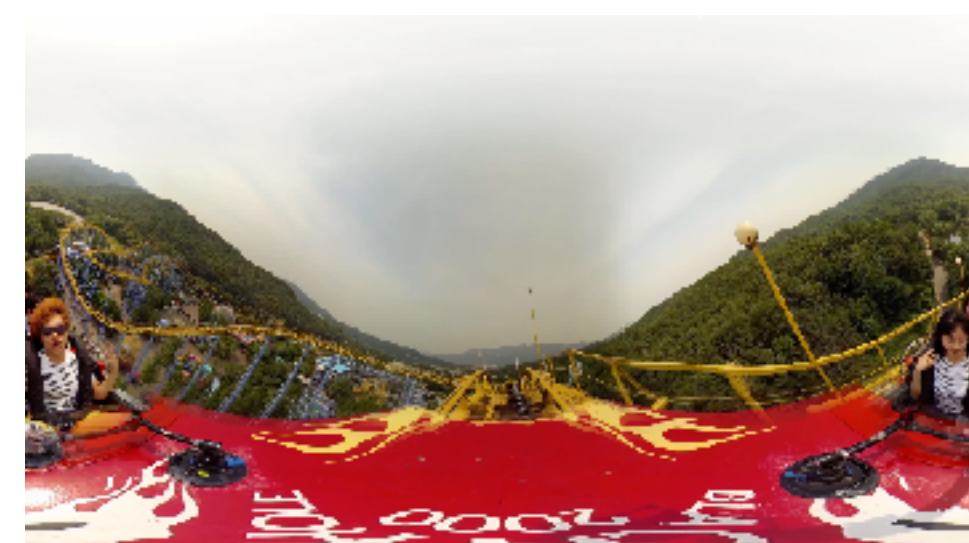
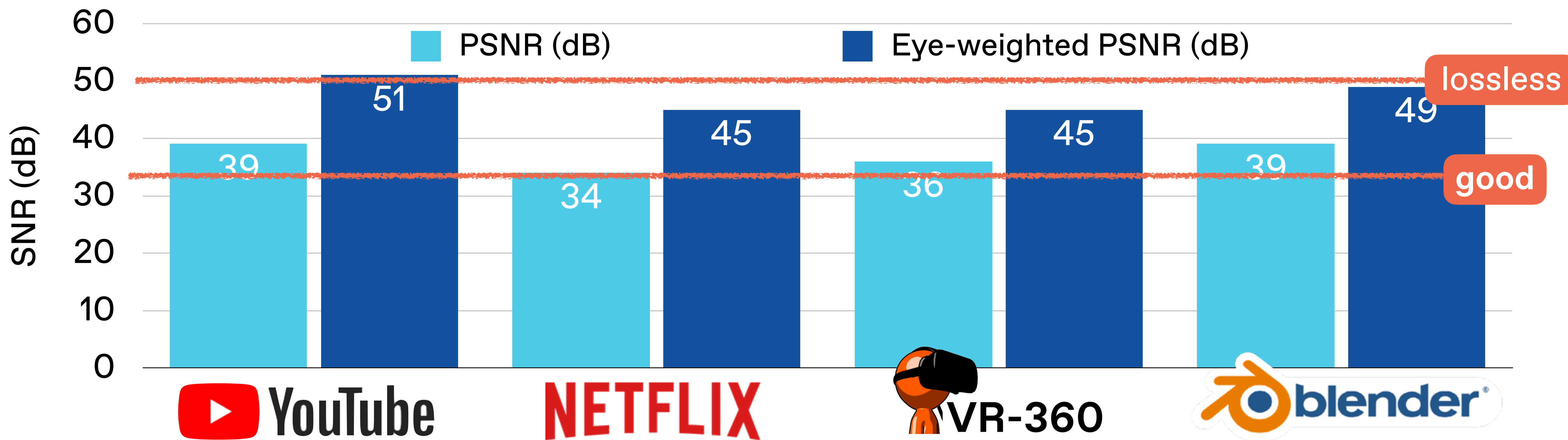


Vignette @ 1 Mbps  
6.5 hours video playback

Full Study Results: [https://homes.cs.washington.edu/~amrita/vignette\\_socc19.html](https://homes.cs.washington.edu/~amrita/vignette_socc19.html)



# Vignette videos reduce bitrate in non-salient regions, maintaining visual quality at lower storage sizes.



**Vignette is a video processing system for perceptual compression and storage.**

## **Vignette Compression**

codec-agnostic perceptual video compression

## **Vignette Storage**

storage manager for perceptually-compressed videos

**Reduces storage by up to 75% with little quality loss**



# **This talk: using learned features to improve performance**

How can we use learned features to **reduce video streaming bandwidth** while maintaining quality?

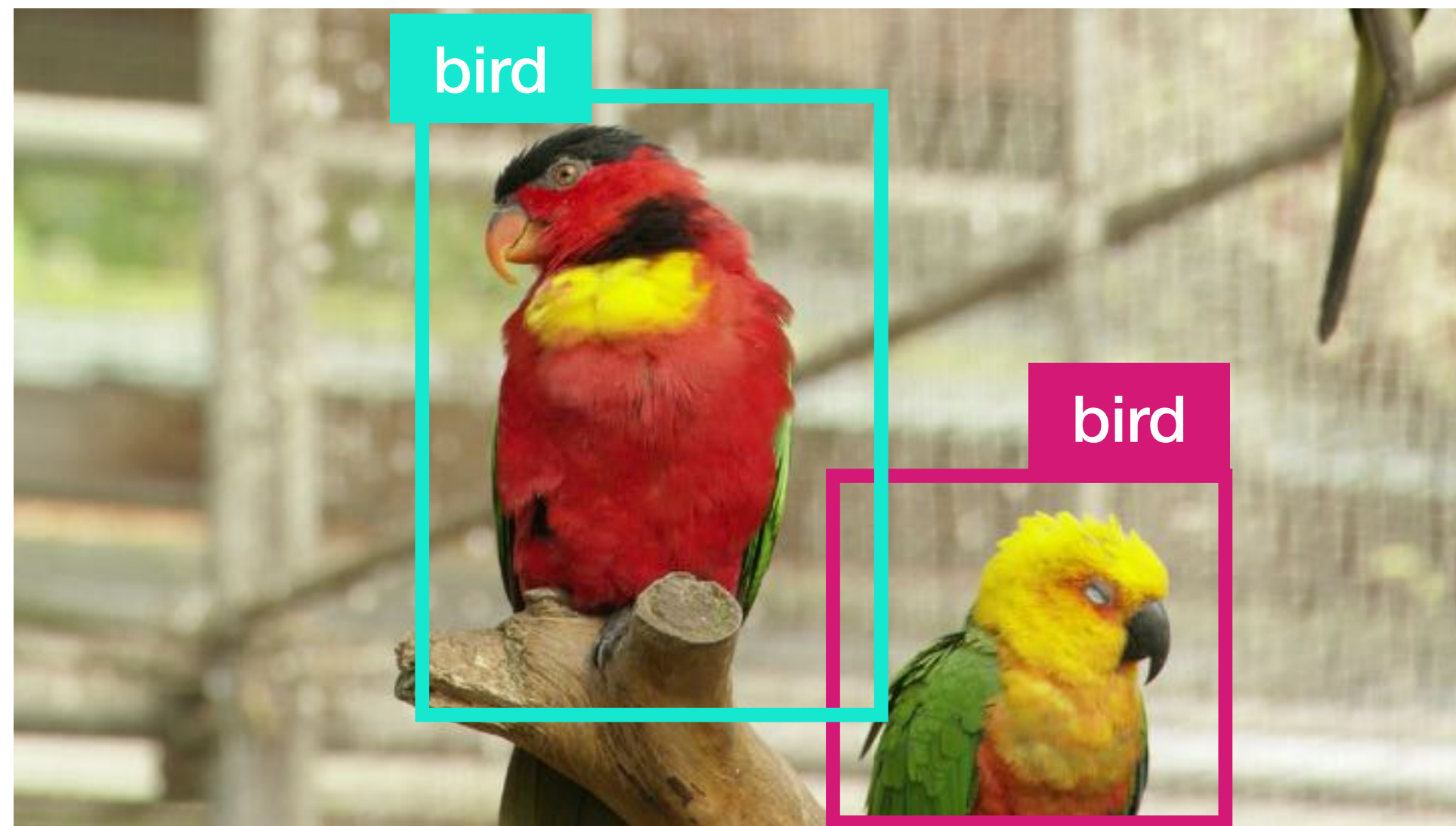
*Vignette (Mazumdar et al., SoCC 2019)*

How can we use learned features to **reduce decode overhead for video analytics queries**?

*TASM (Daum et al., ICDE 2021)*

# Analytics queries extract a subset of pixels in video

Select **bird** FROM **video**;

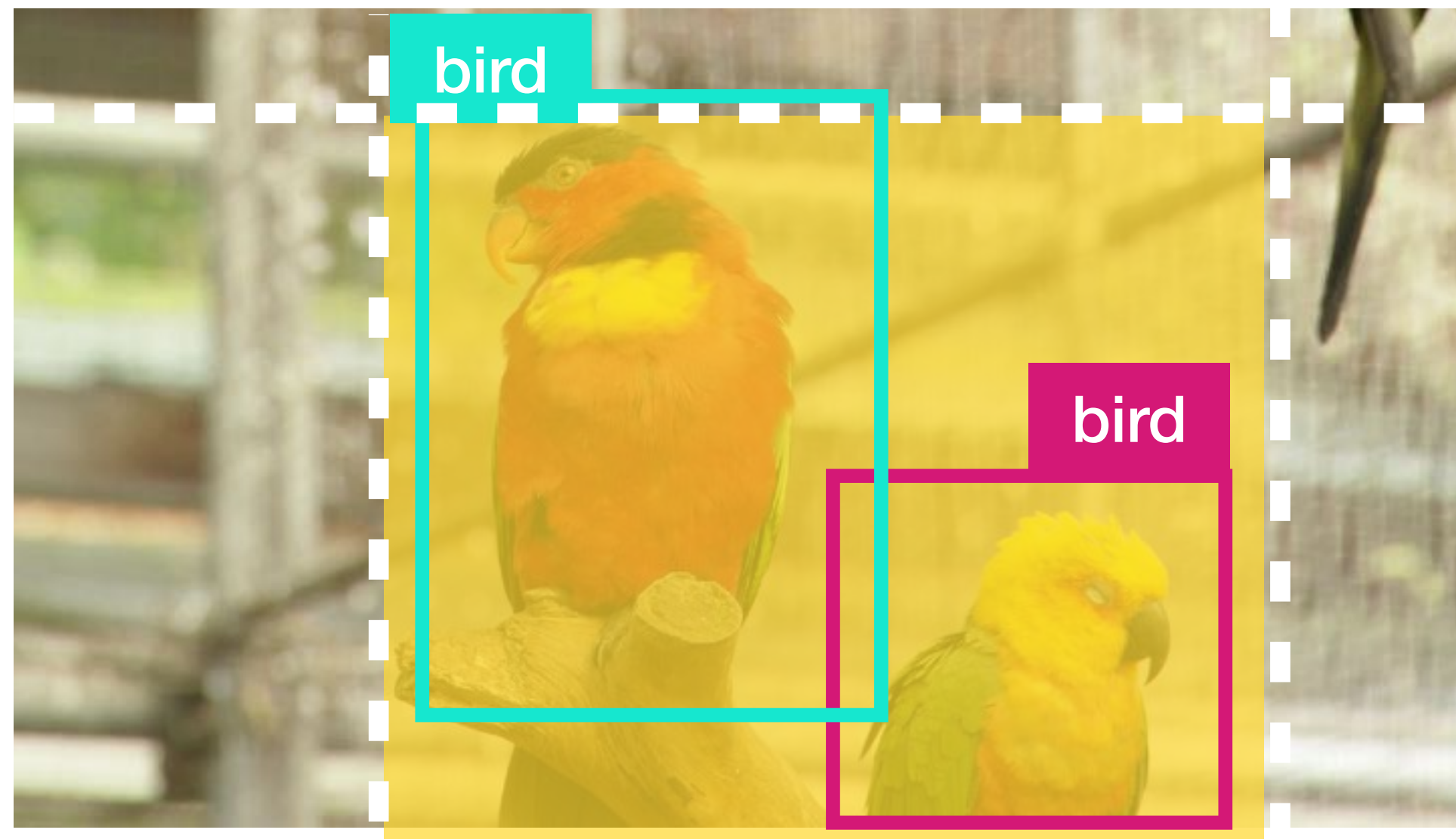


Typical workload:

- Identify objects in videos
- Extract pixels that correspond to objects of interest

# Tiled video can speed up processing

Select **bird** FROM **video**;



Tiles can enable *spatial random access* to video content

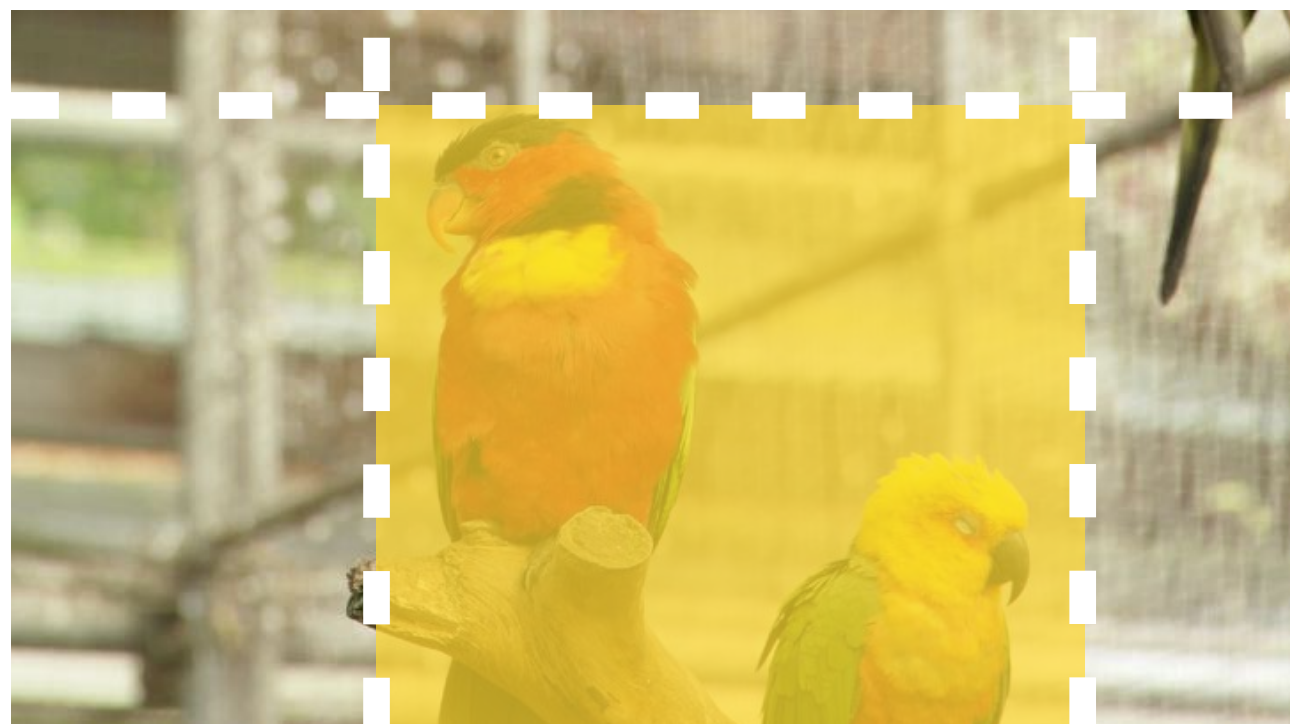
Knowing which tiles contain objects reduce video decode time and overall query processing time



# Tiled video can speed up processing

but some tile layouts are better than others for analytics

Select **bird** FROM **video**;



Tile boundaries on objects can impact query accuracy

Videos can have many moving objects within the frame

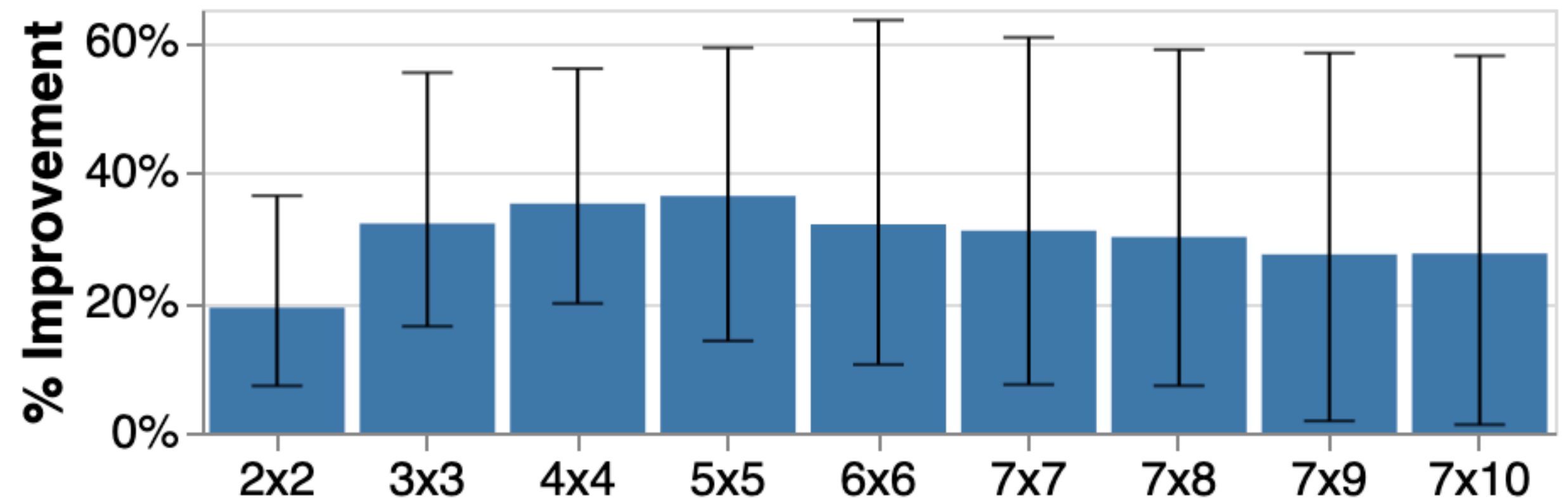
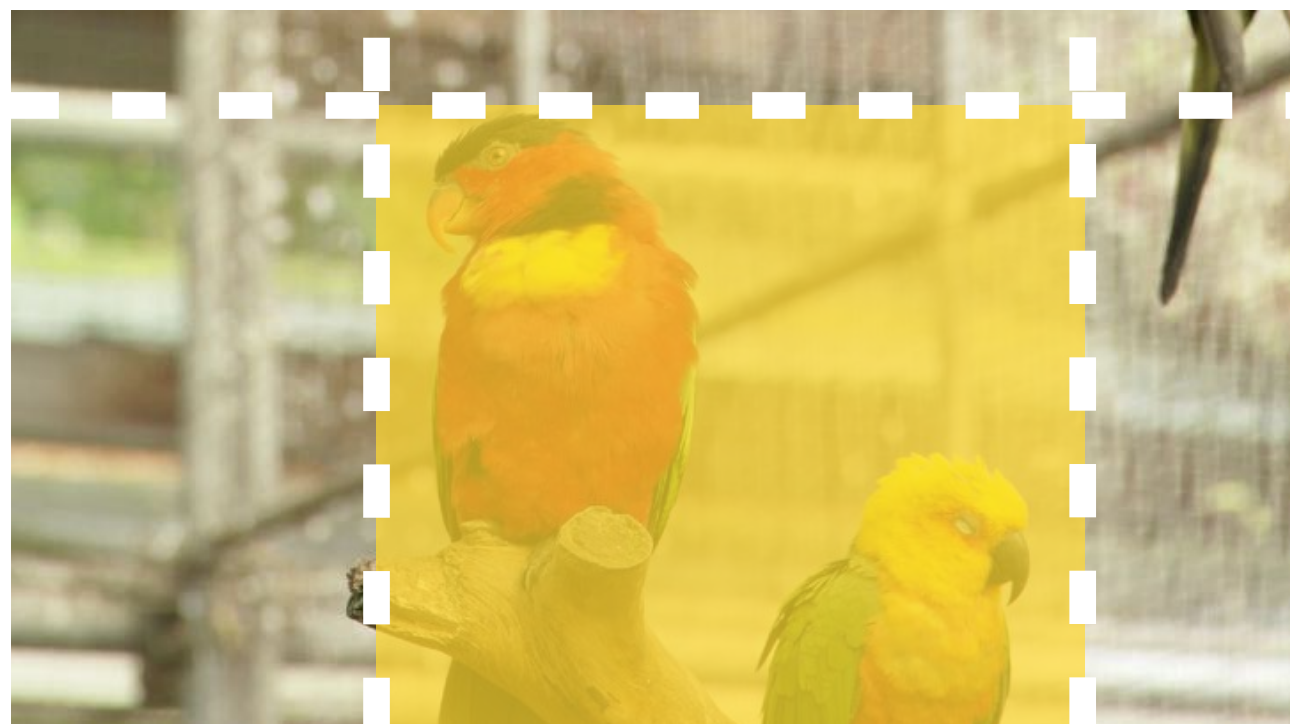
The optimal tile layout for a set of queries may not be known *a priori*



# Tiled video can speed up processing

but some tile layouts are better than others for analytics

Select **bird** FROM **video**;

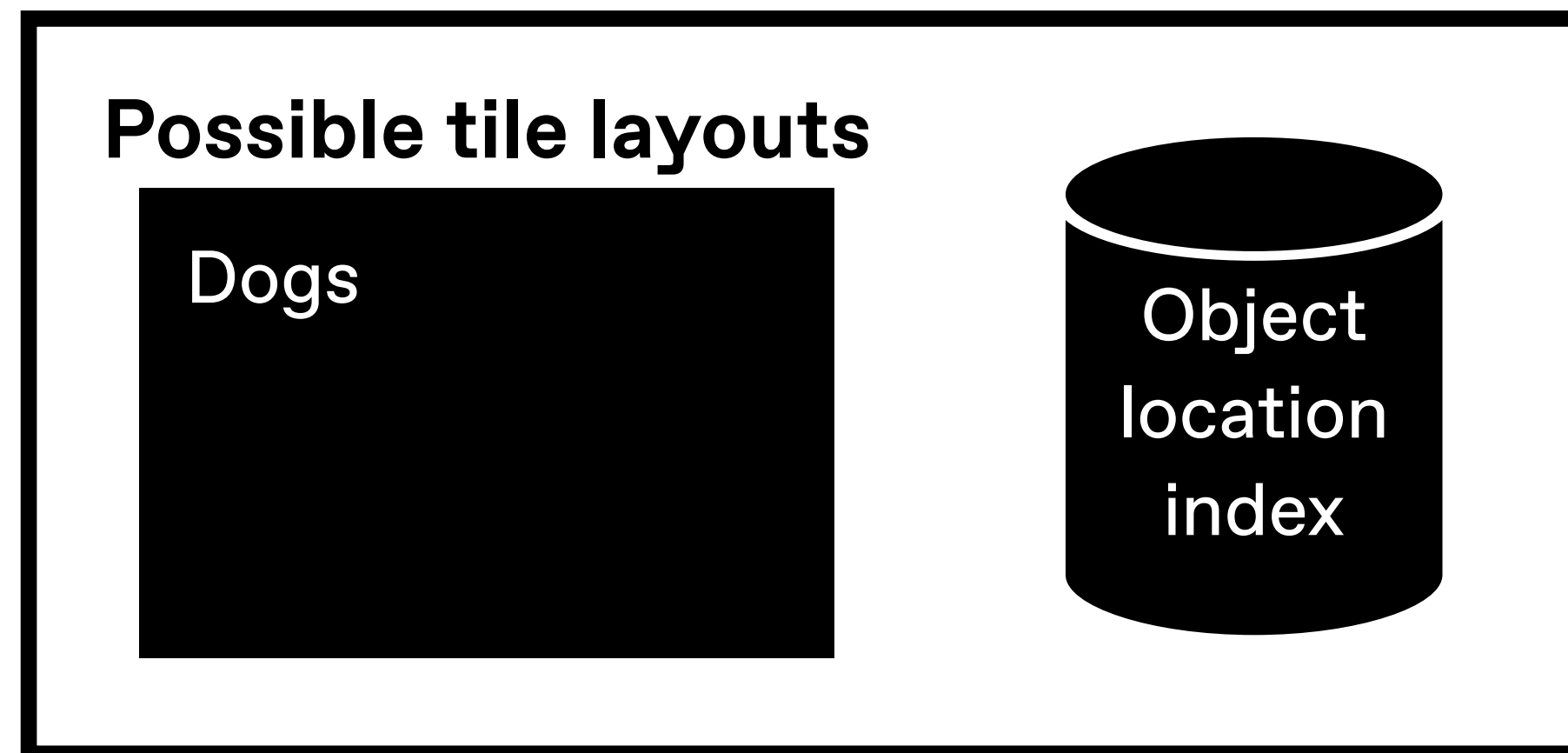


Even introducing uniform tiles can improve query performance

Overhead from too many tiles can outweigh benefits of subset selection

# TASM is a storage system for video analytics queries that optimizes tile layouts for performance.

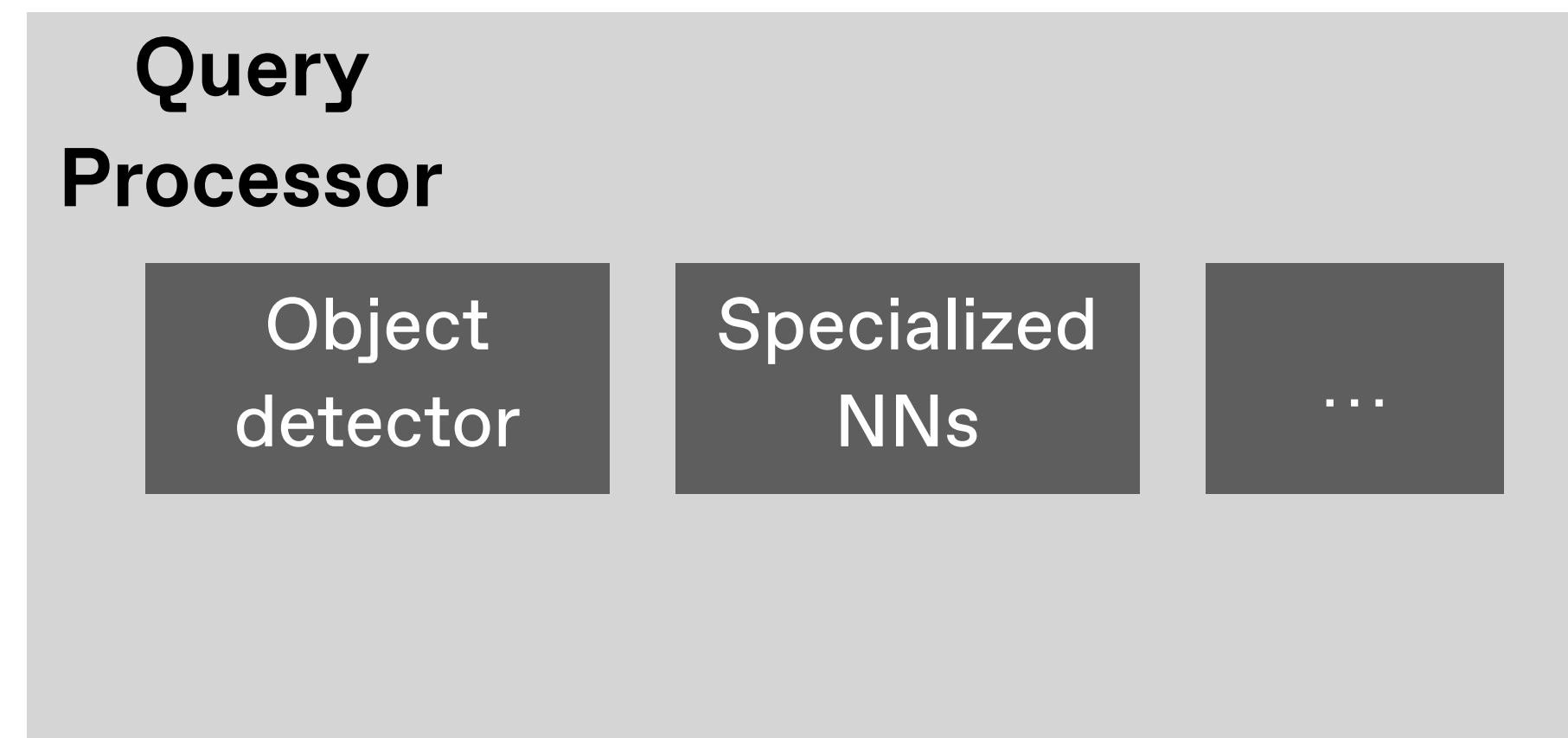
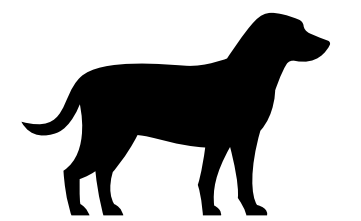
TASM



query ←

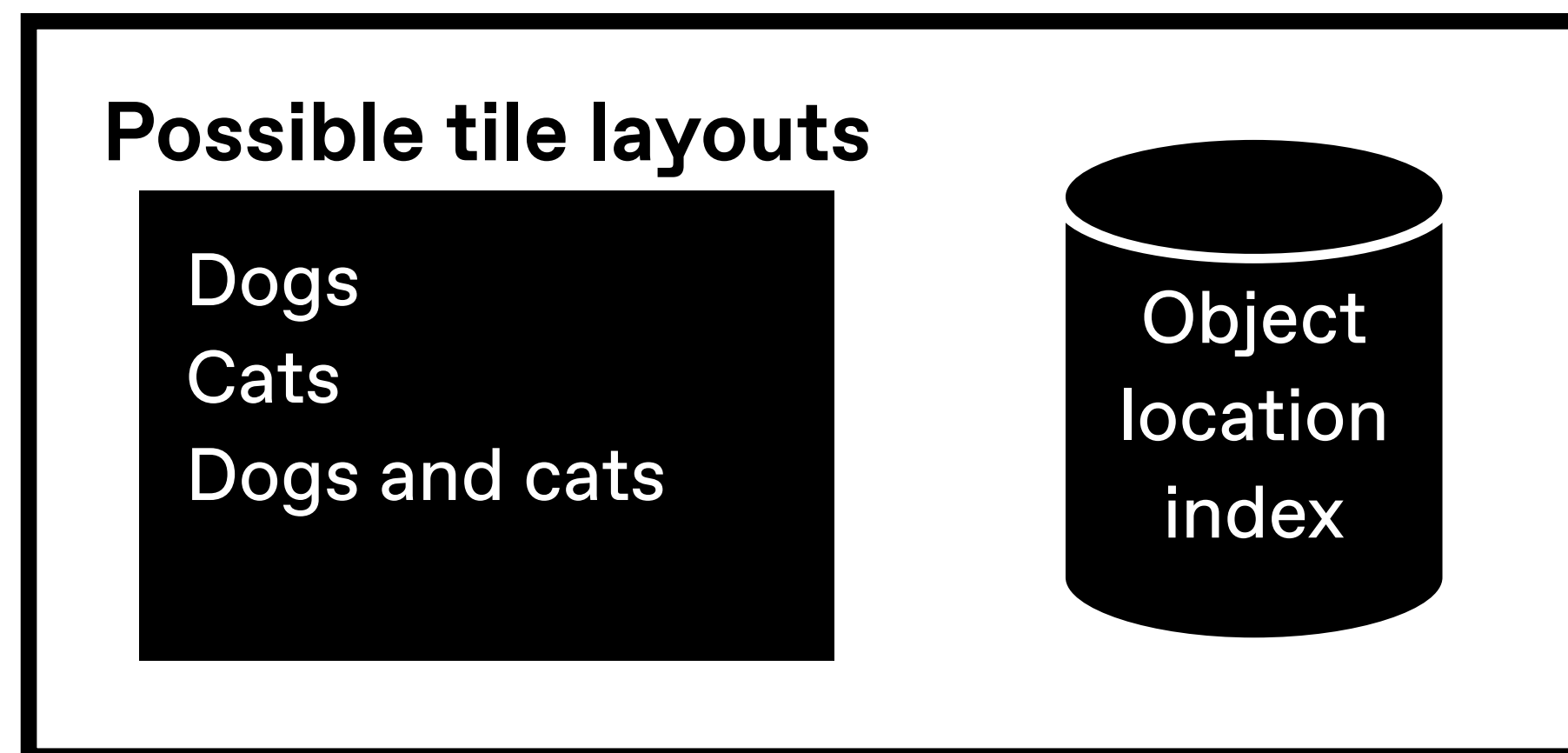
video →

```
SELECT dogs  
FROM video  
WHERE time < 60s;
```



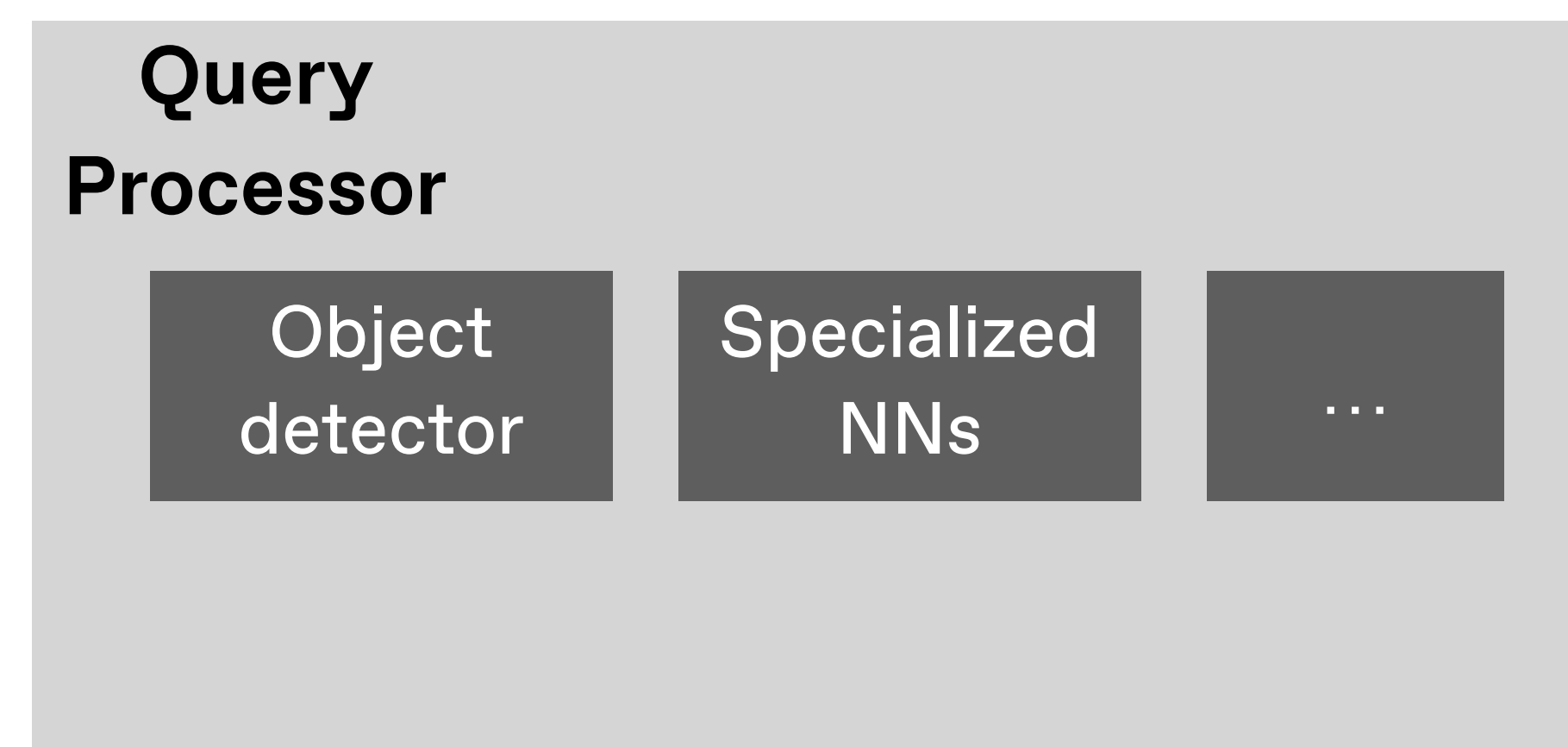
# TASM is a storage system for video analytics queries that optimizes tile layouts for performance.

TASM

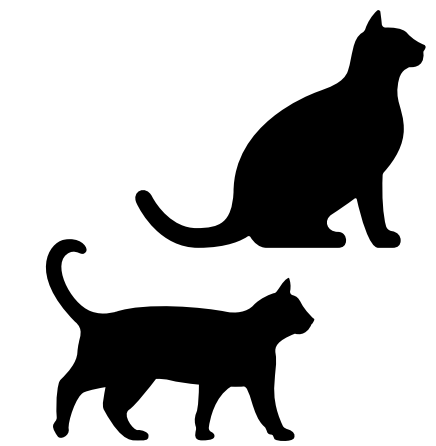
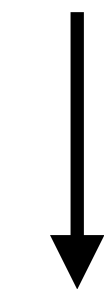


query ←

video →



```
SELECT cats  
FROM video  
WHERE time < 60s;
```

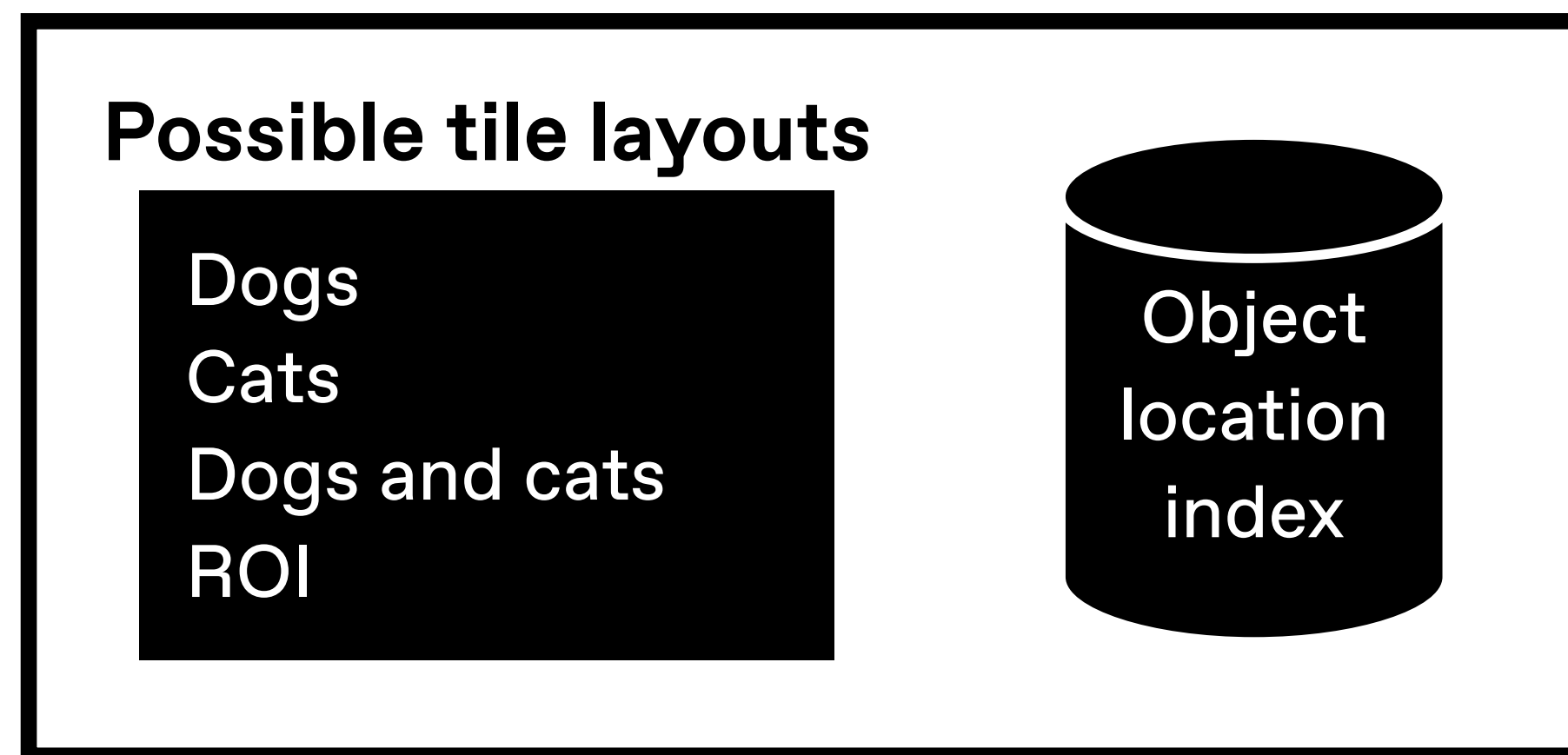




# TASM is a storage system for video analytics queries that optimizes tile layouts for performance.

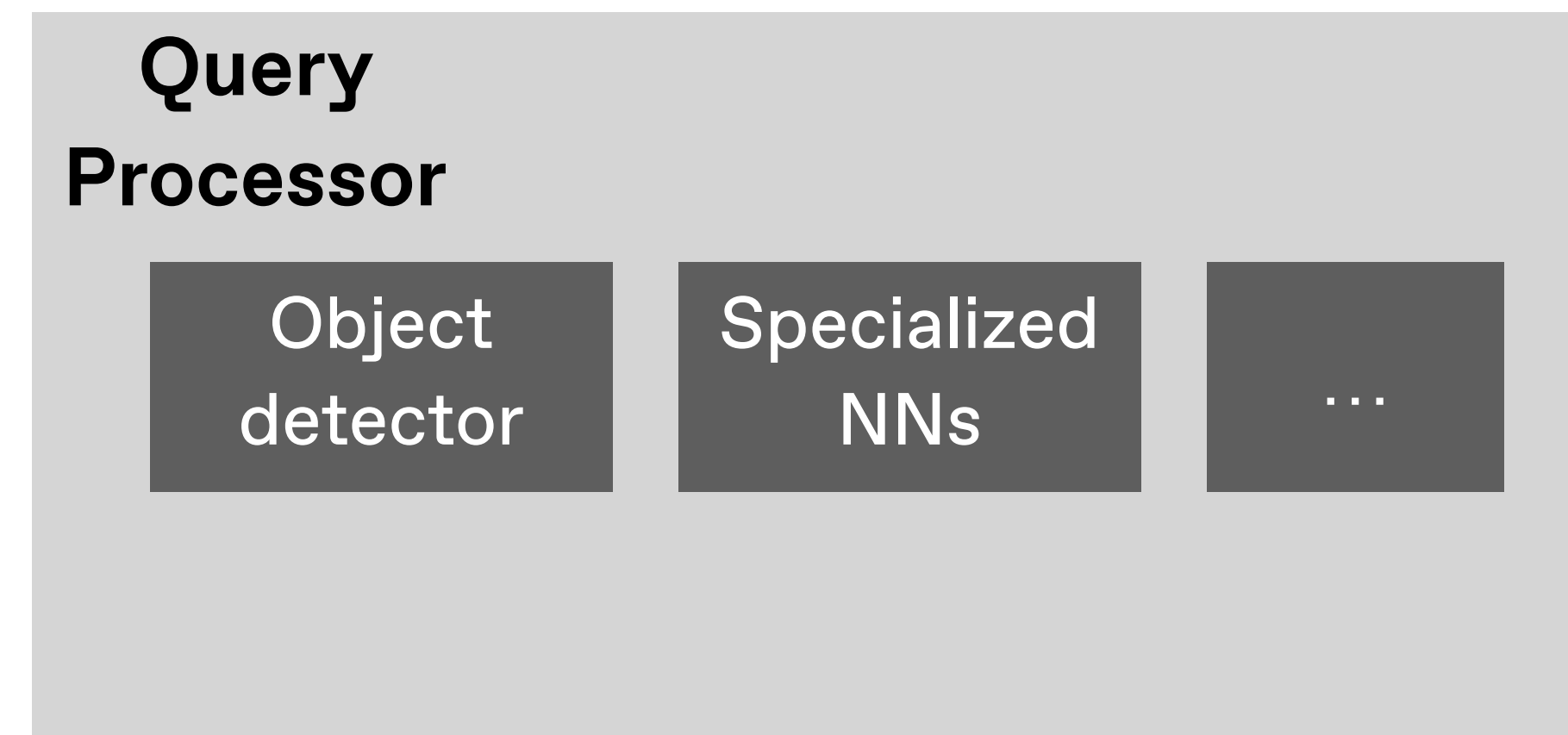
TASM incrementally re-tiles videos based on observed queries, and improves query performance by only decoding the necessary tiles for a query.

TASM



query ←

video →

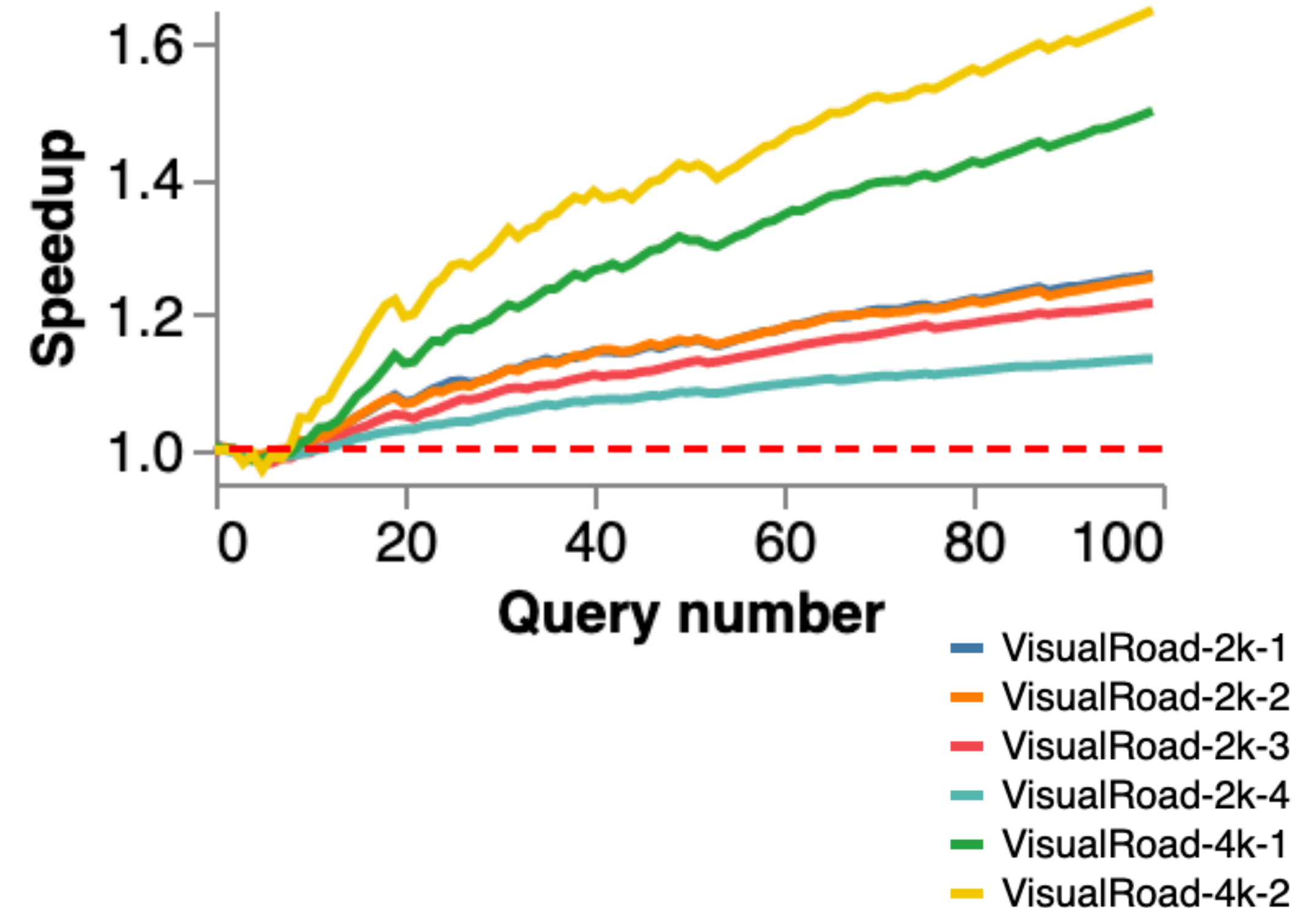


No query



# TASM reduces total workload runtime by processing only relevant regions of a frame.

- 60-second queries, randomly selected to be [cars, people]
- Comparing TASM with incremental regret-based tiling against untiled video
- TASM reduces total workload runtime by 12-39% across Visual Road benchmark



**TASM is a storage system for video analytics queries that optimizes tile layouts for better performance.**

**TASM enables spatial random access for video content**

**TASM incrementally tiles videos as new queries are observed**

**Subframe selection queries show average of 50% speedup (up to 94%)**



# **This talk: using learned features to improve performance**

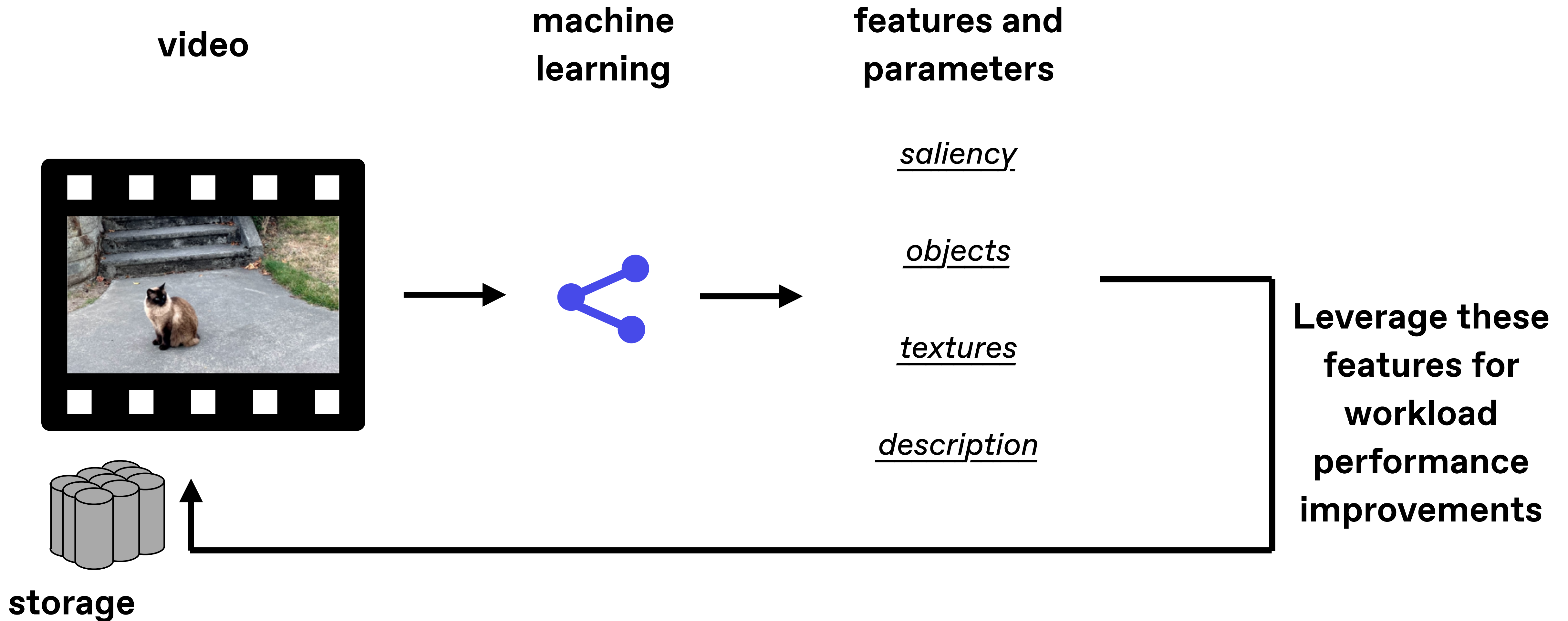
How can we use learned features to **reduce video streaming bandwidth** while maintaining quality?

*Vignette (Mazumdar et al., SoCC 2019)*

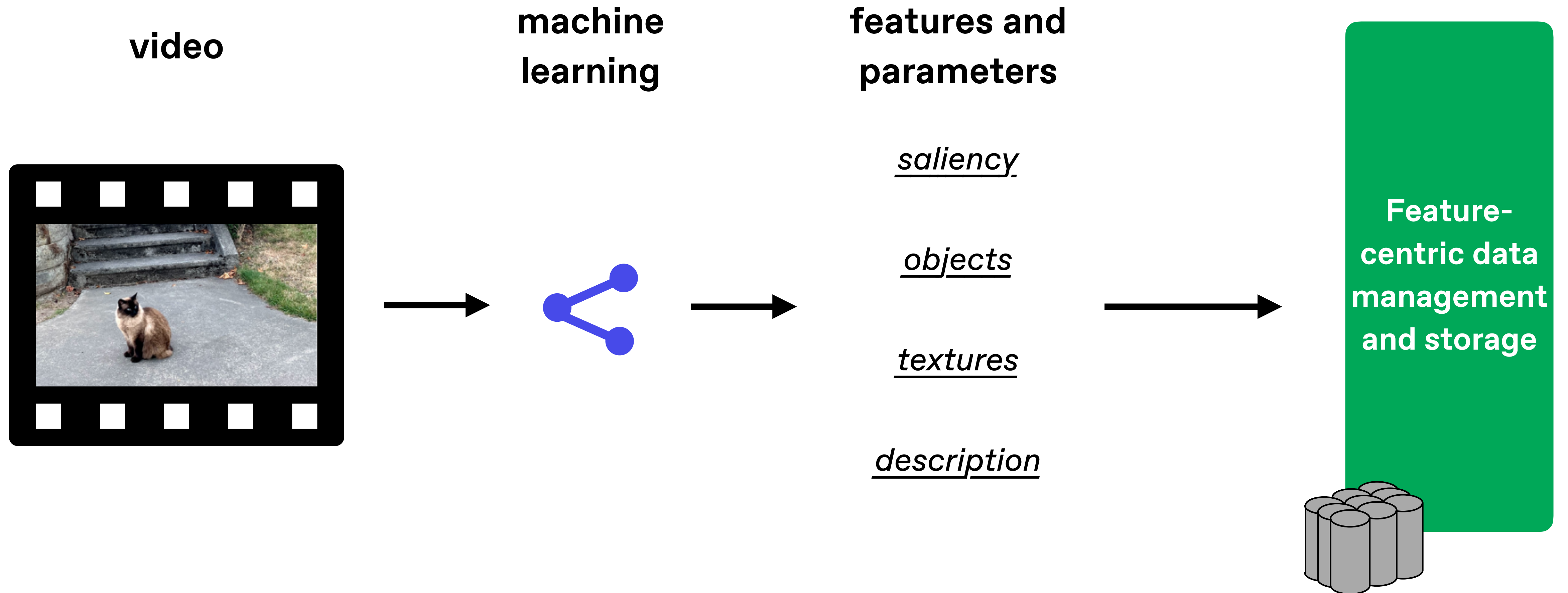
How can we use learned features to **reduce decode overhead for video analytics queries**?

*TASM (Daum et al., ICDE 2021)*

# This talk: using learned features to improve performance

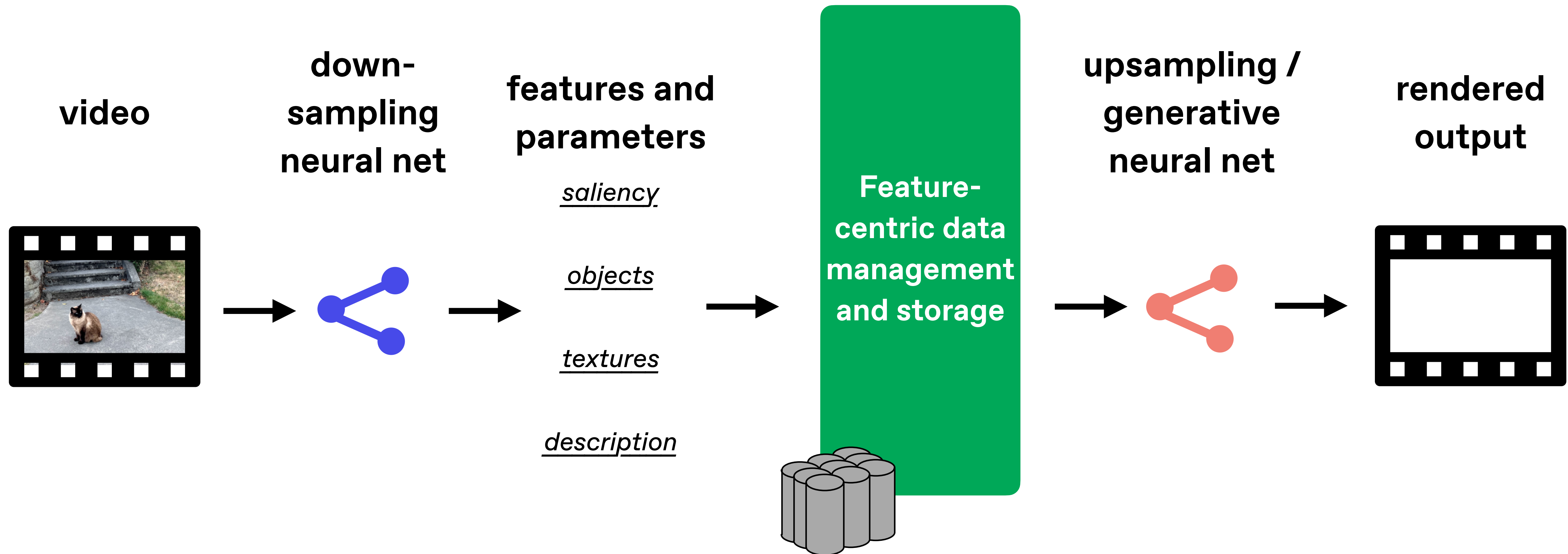


# This talk: using learned features to improve performance





# Opportunity: depending on learned features to replace video content



# Learning for Better Video Processing Systems

Thank you!

**Amrita Mazumdar / Vignette AI & University of Washington**

*In collaboration with: Maureen Daum, Brandon Haynes, Dong He, Magda Balazinska, Luis Ceze, Alvin Cheung, Mark Oskin*

