

Computer Vision Applications

COMP 388-002/488-002 Computer Science Topics

Daniel Moreira
Fall 2022



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Sensitive Video Analysis

COMP 388-002/488-002 Computer Science Topics

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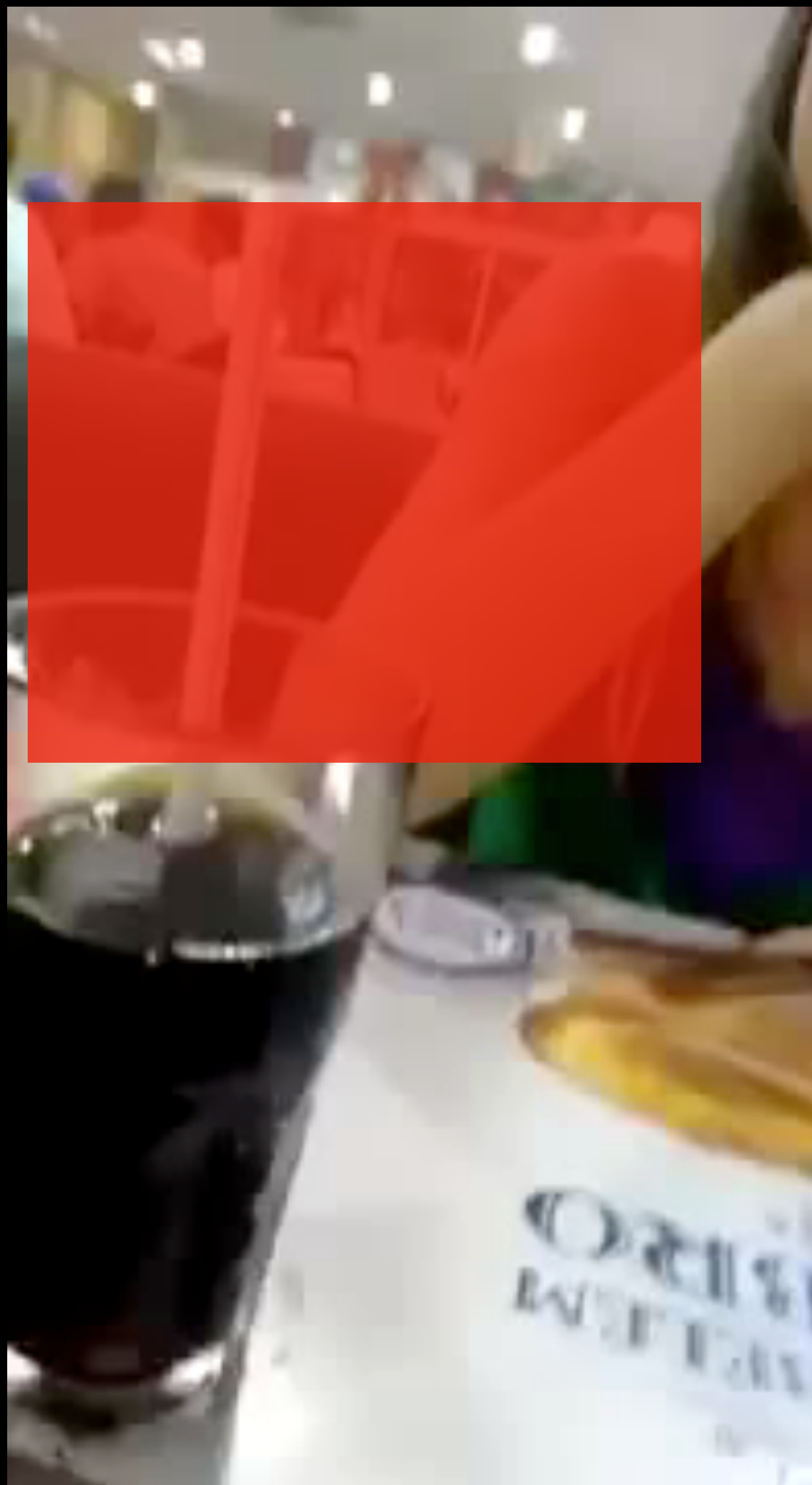
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Sensitive Video

“Motion pictures whose content may inflict harm (*e.g.*, trauma, shock, or fear) to particular audiences (*e.g.*, children or unwary spectators), due to the inappropriateness of content.”



Justin Bieber getting his ass kicked!!



A photograph of two women in an office setting. A woman with long dark hair, wearing a bright pink short-sleeved button-down shirt, stands behind a desk. Her hands are on her hips. Seated at the desk is another woman with dark hair, wearing a blue short-sleeved top. She is looking at a laptop screen. The background features a window with horizontal blinds and a wooden cabinet with a potted plant on top.

Why do we care?



Challenges

Big Data



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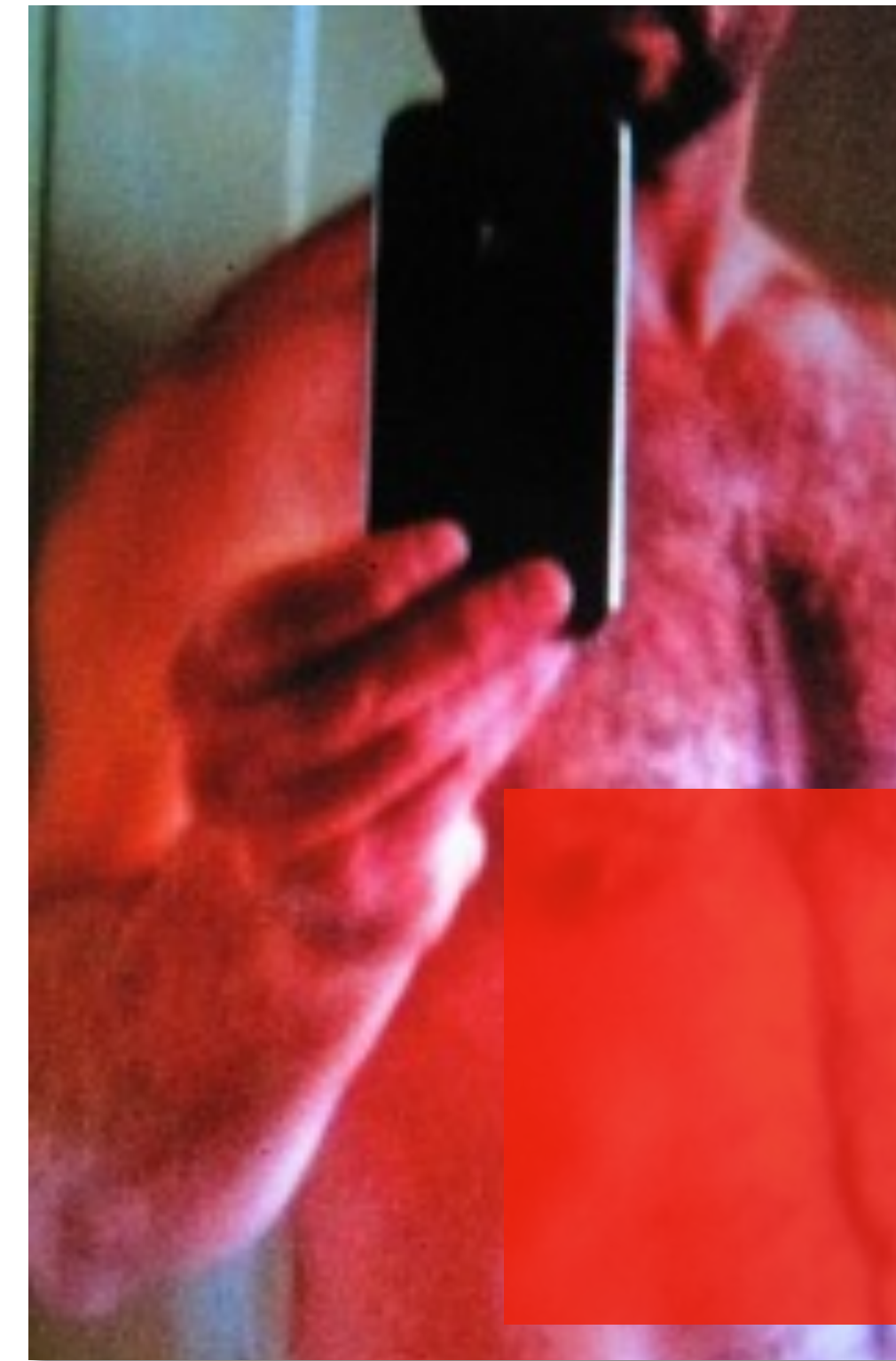
Challenges

Subjectivity



Challenges

Pervasiveness



Challenges

Urgency



Tasks

Part I: Sensitive Video Classification

Part II: Sensitive Video Detection

Tasks

Part I: Sensitive Video Classification

Part II: Sensitive Video Detection

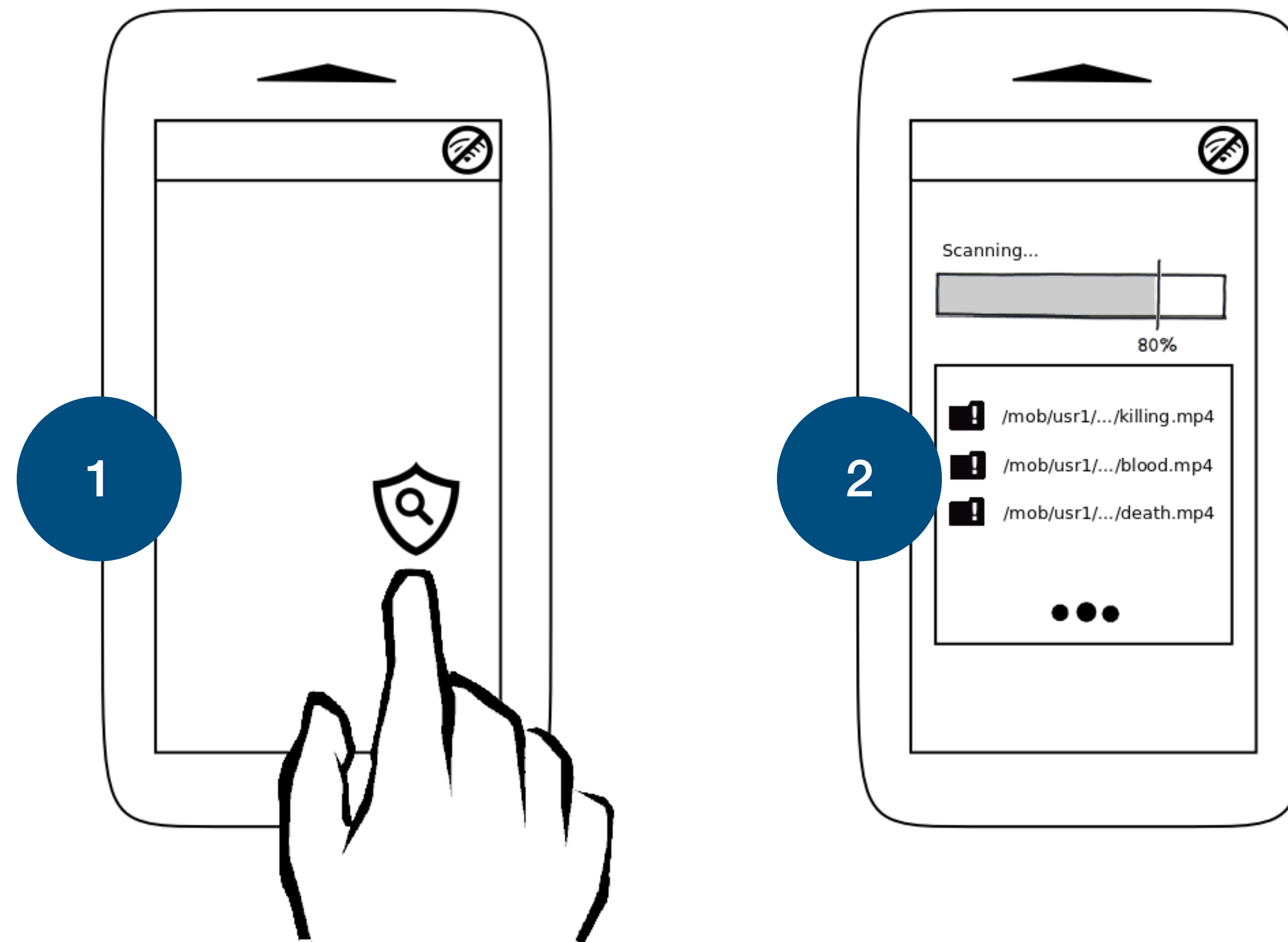
Sensitive Video Classification



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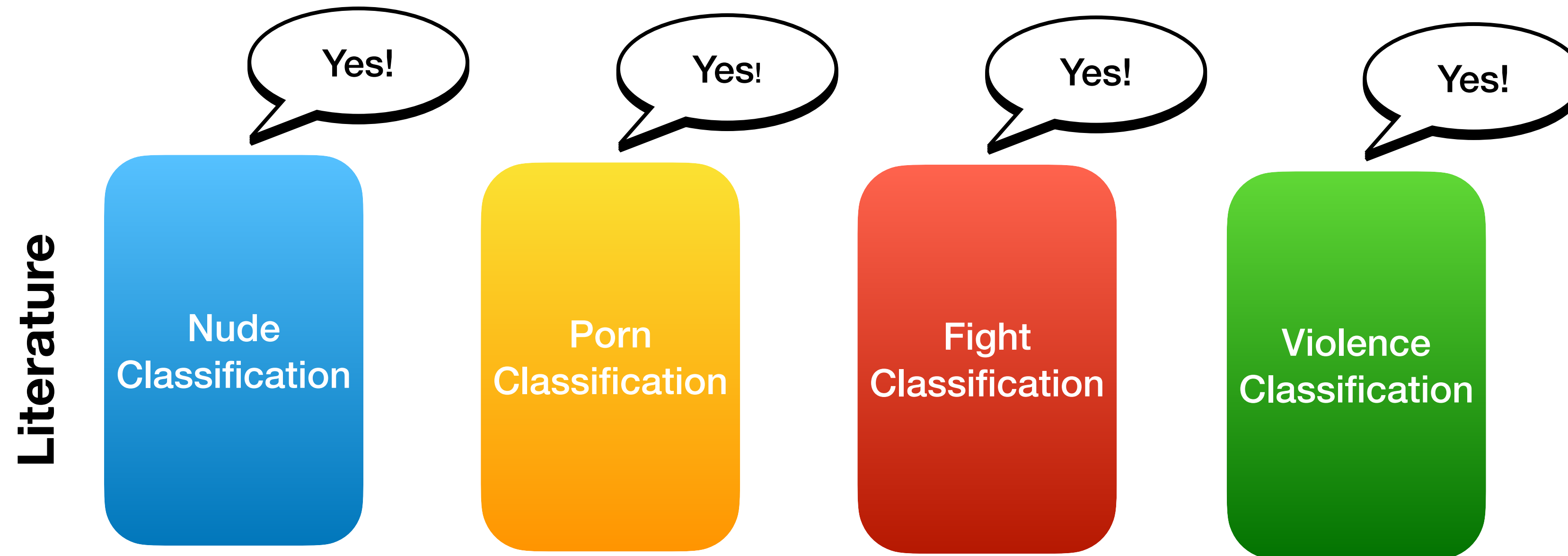
Task

Can a computer decide if a video is either sensitive or non-sensitive?

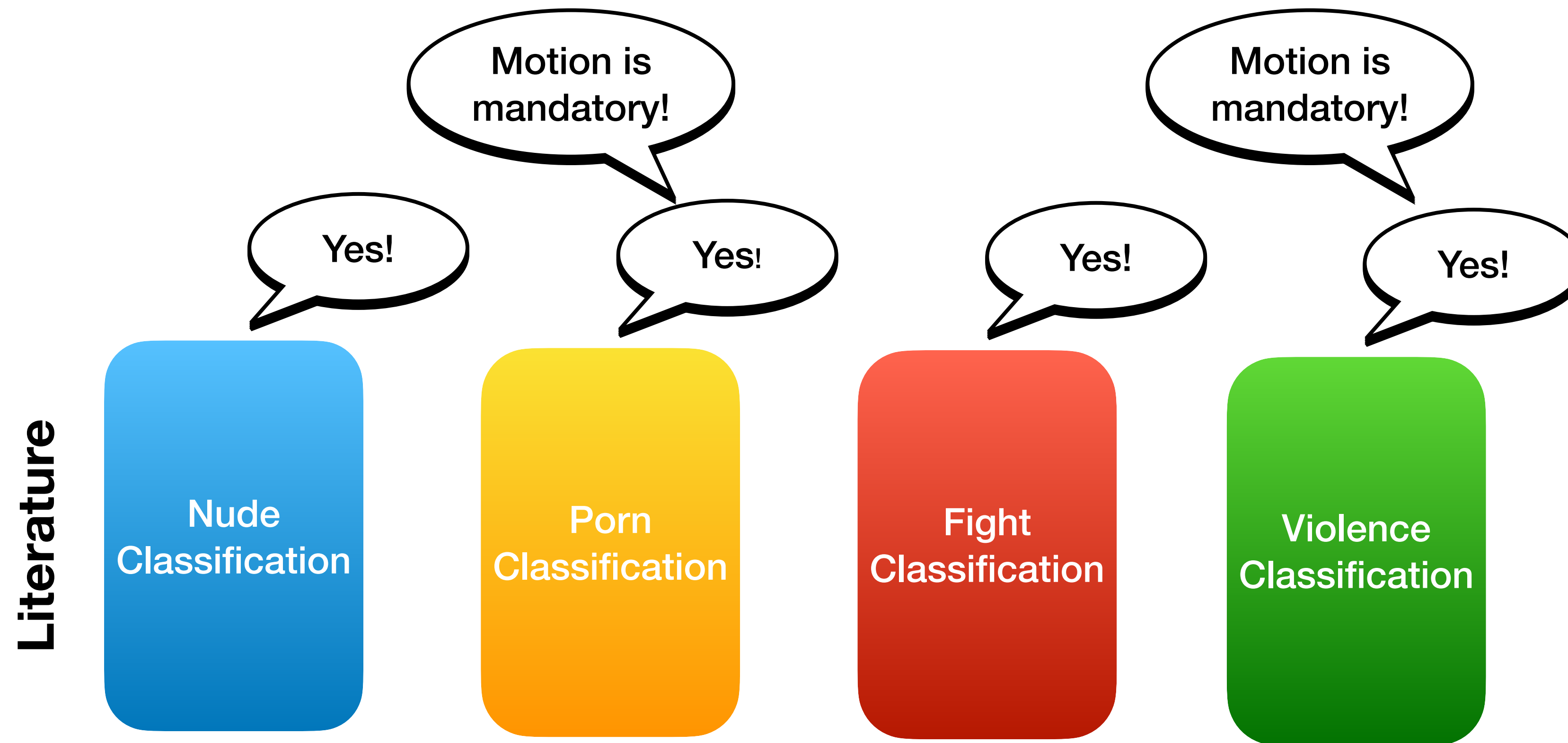


State of the Art

Can a computer decide if a video is either sensitive or non-sensitive?

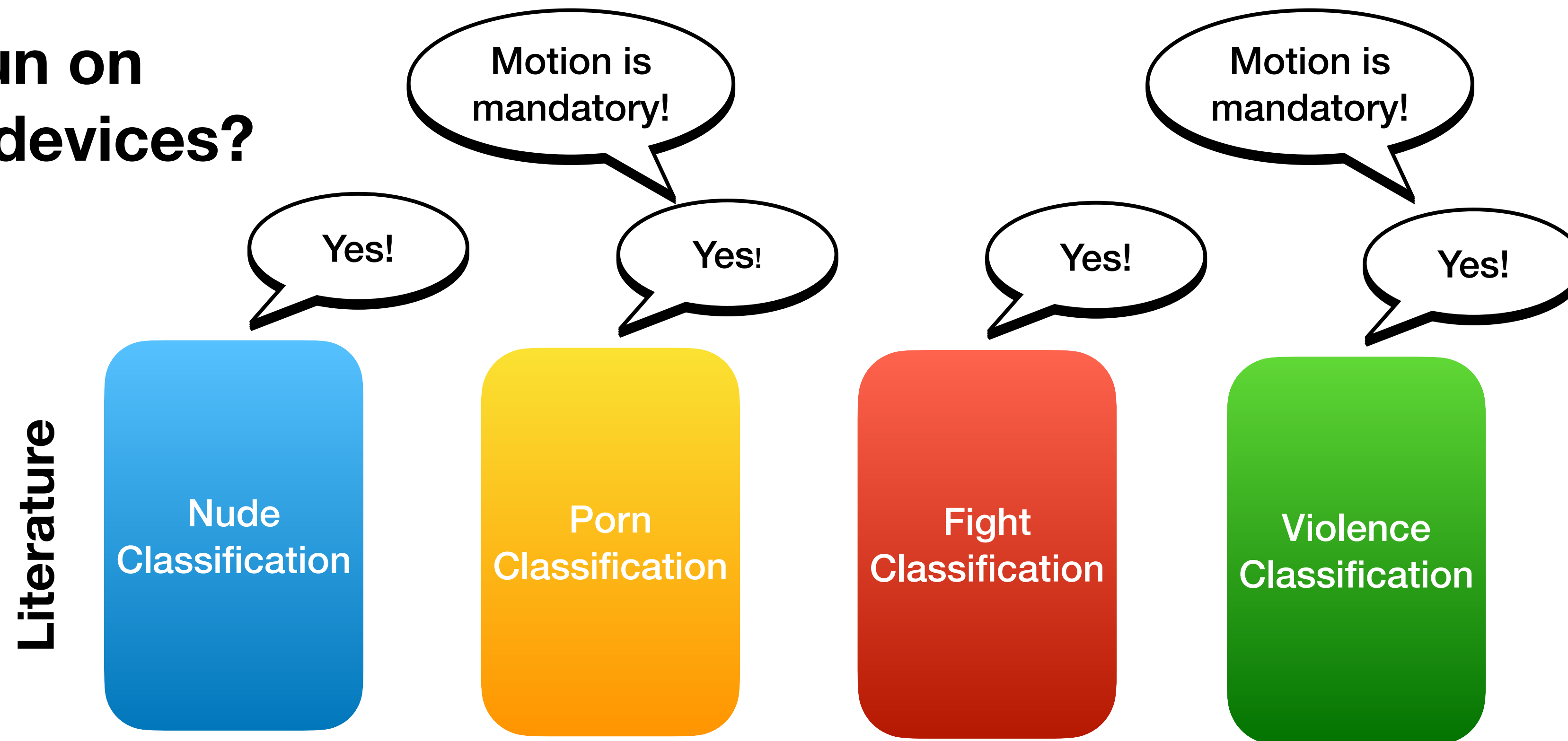


State of the Art



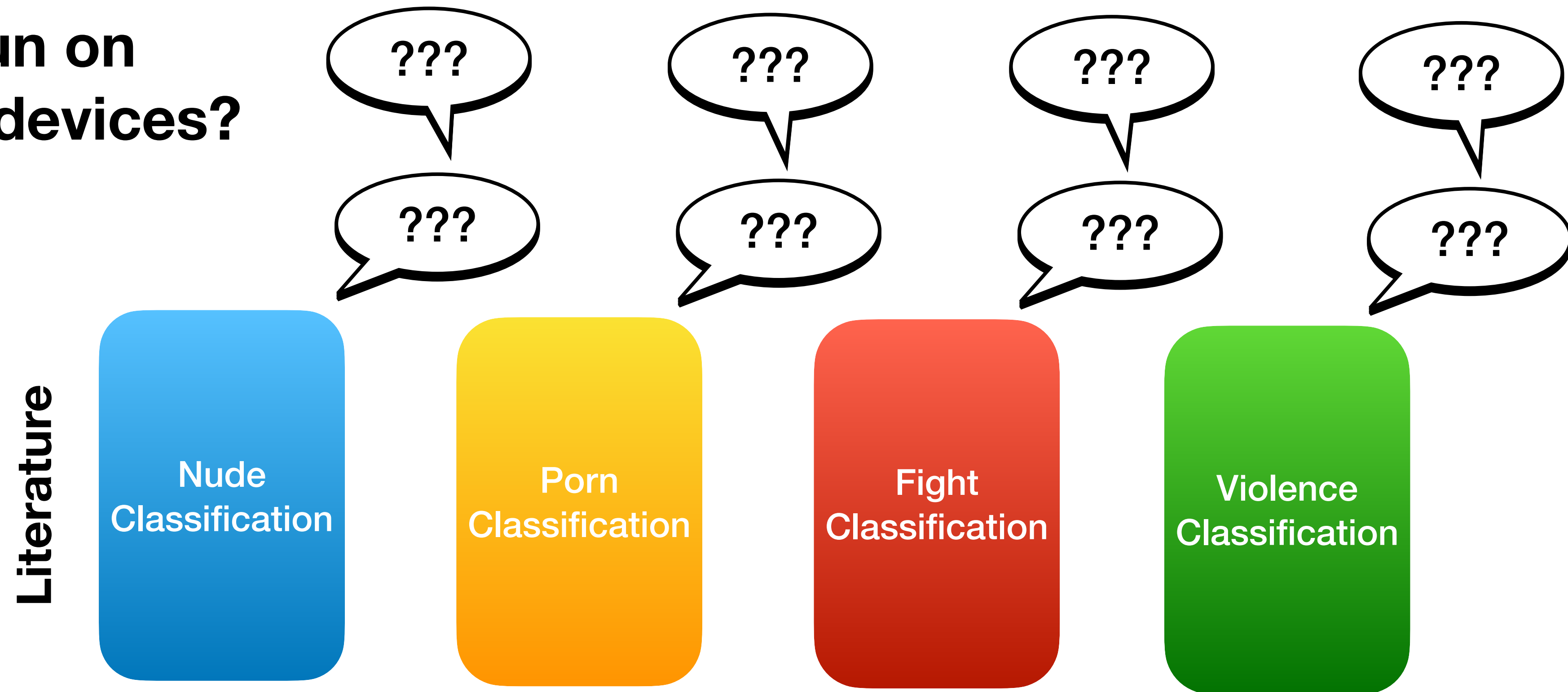
Sponsor's Challenge

Will it run on
mobile devices?



Sponsor's Challenge

Will it run on
mobile devices?



Sponsor's Challenge

**Will it run on
mobile devices?**

Effectiveness

Motion is mandatory.
Spatiotemporal description
takes time.

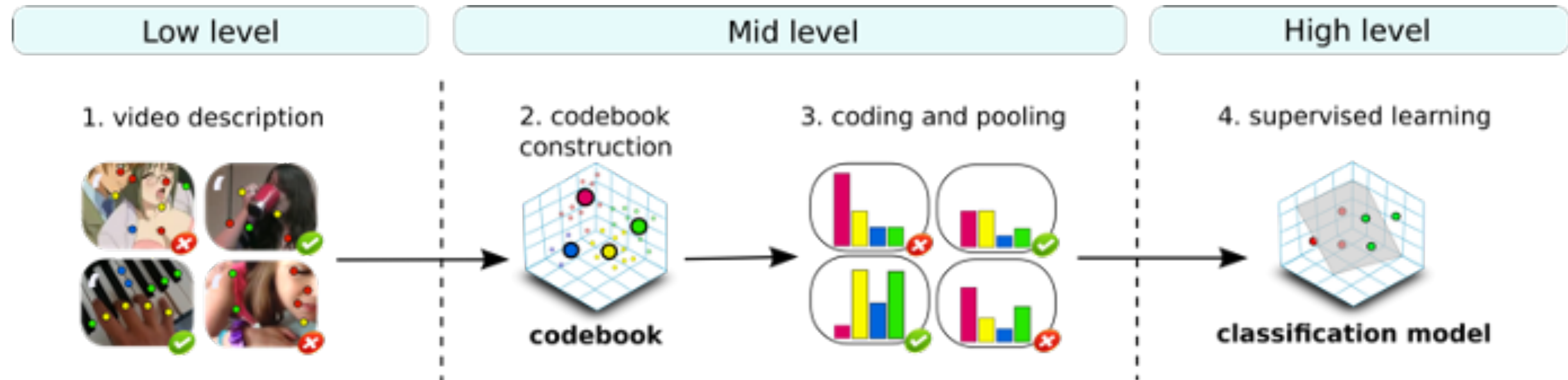
VS

Efficiency

Small runtime.
Low-memory footprint.

Proposed Solution

Based on Bags of Visual Words that (BoVW)



Proposed Solution

Based on Bags of Visual Words that (BoVW)



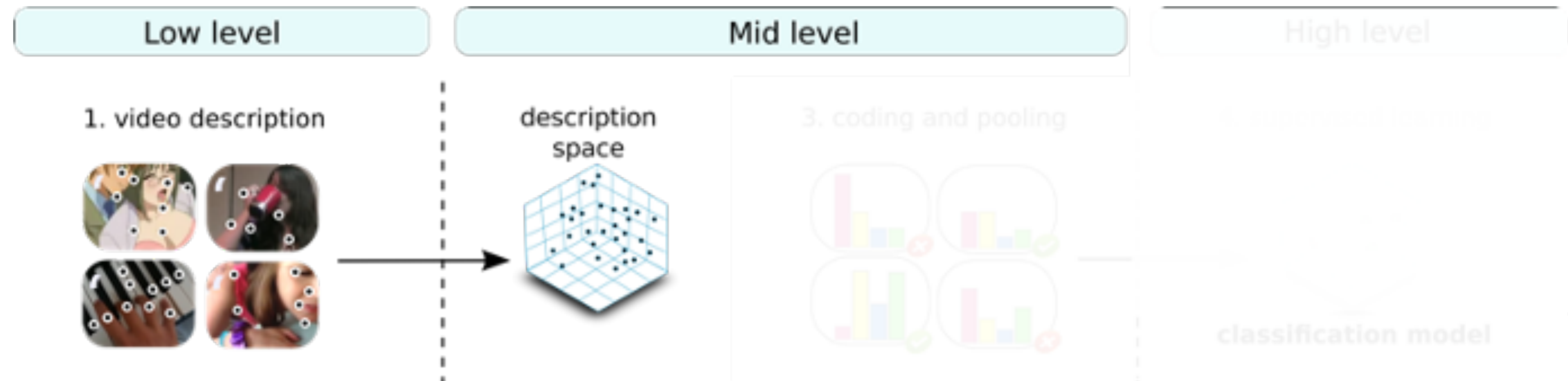
Proposed Solution

Based on Bags of Visual Words that (BoVW)



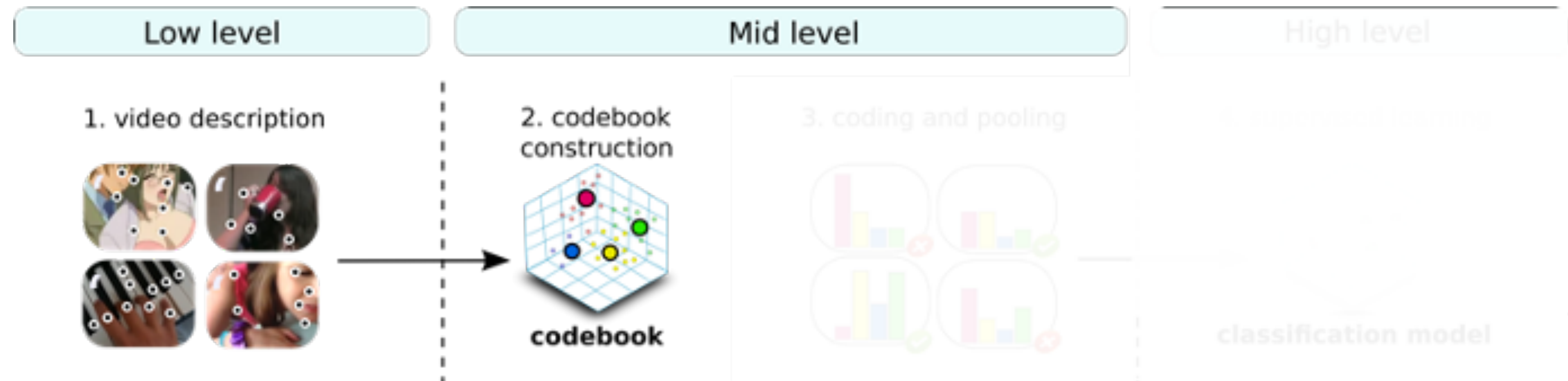
Proposed Solution

Based on Bags of Visual Words that (BoVW)



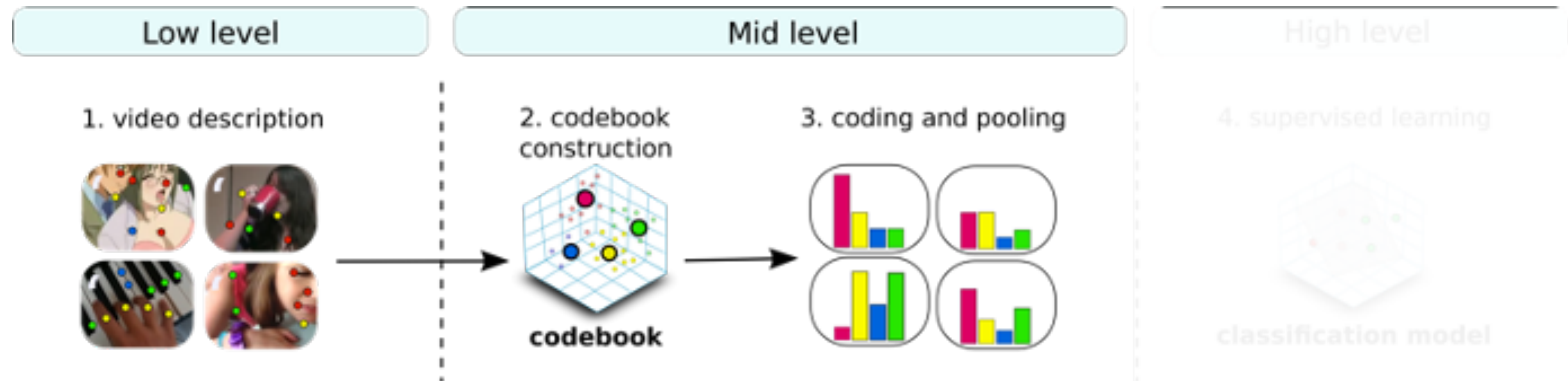
Proposed Solution

Based on Bags of Visual Words that (BoVW)



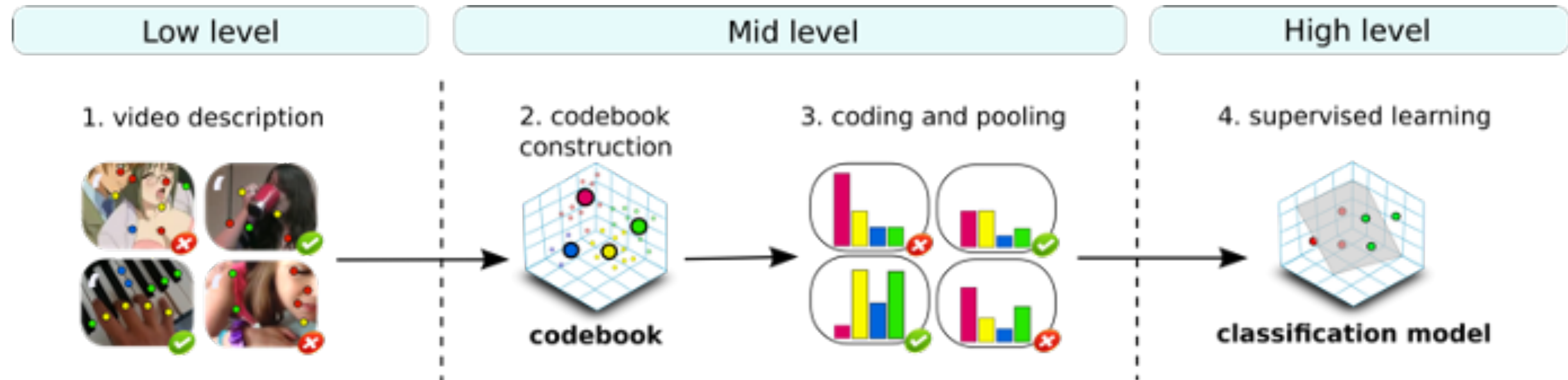
Proposed Solution

Based on Bags of Visual Words that (BoVW)



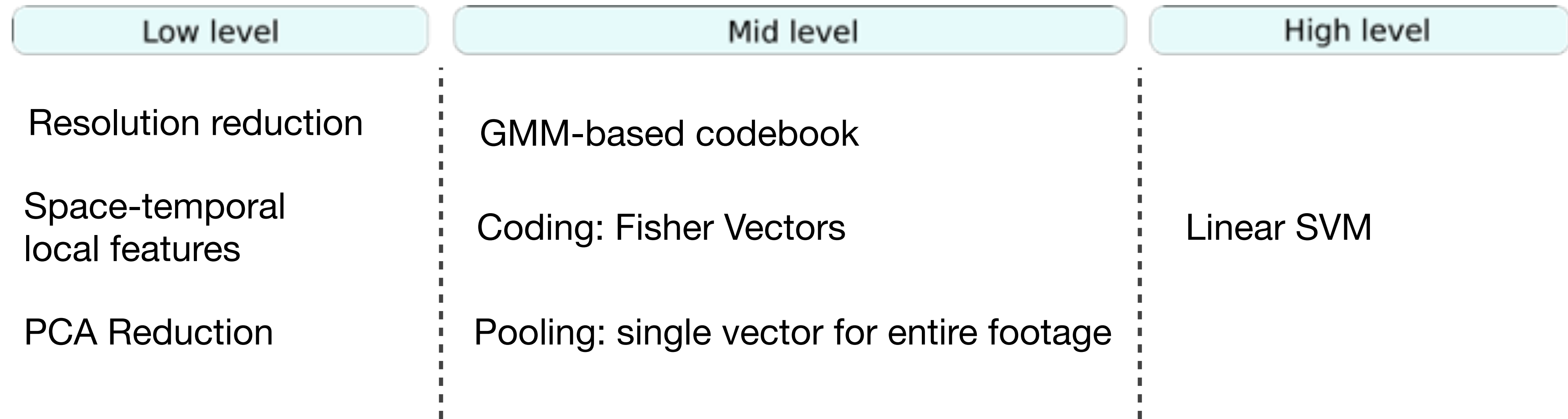
Proposed Solution

Based on Bags of Visual Words that (BoVW)



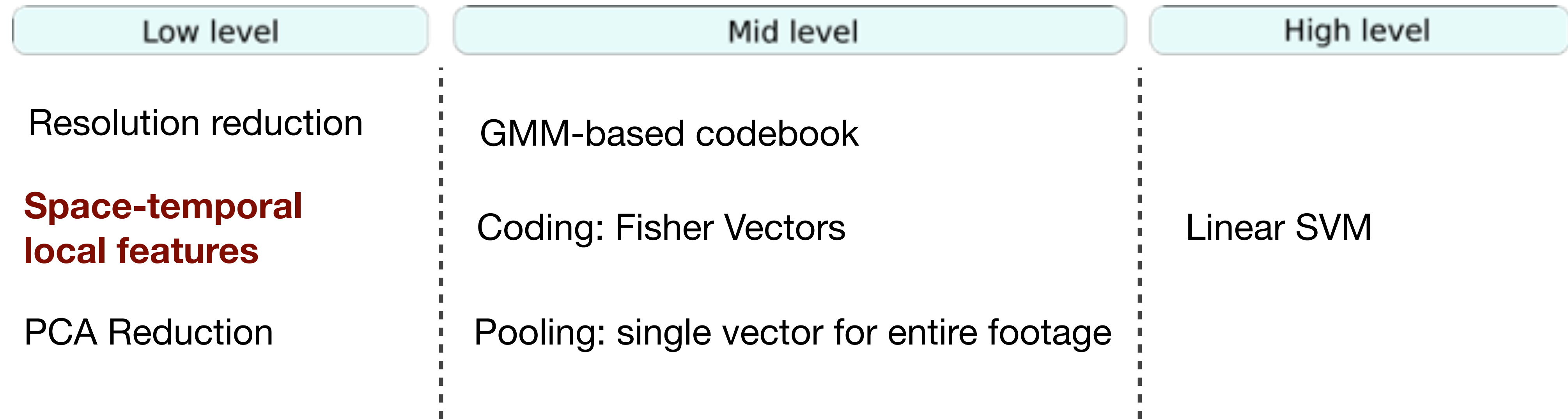
Proposed Solution

Based on Bags of Visual Words that (BoVW)



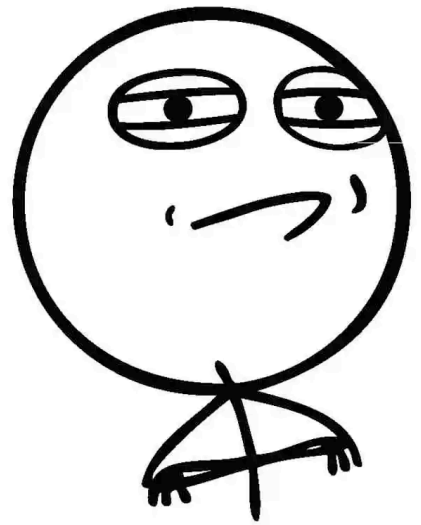
Proposed Solution

Based on Bags of Visual Words that (BoVW)



Temporal Robust Features (TRoF)

CHALLENGE ACCEPTED



Effectiveness

Motion is mandatory.
Spatiotemporal description
takes time.

VS

Efficiency

Small runtime.
Low-memory footprint.



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Temporal Robust Features (TRoF)

Inspiration on Speeded-Up Robust Features (SURF)

Hessian Matrix

Given an image pixel $I(x, y)$, a scale of interest σ ,
and Gaussian second order derivative functions $\frac{\delta^2}{\delta x^2}G(\sigma)$, $\frac{\delta^2}{\delta y^2}G(\sigma)$, and $\frac{\delta^2}{\delta xy}g(\sigma)$,
the Hessian matrix H is given by:

$$H(x, y, \sigma) = \begin{bmatrix} \frac{\delta^2}{\delta x^2}g(\sigma) * I(x, y) & \frac{\delta^2}{\delta xy}g(\sigma) * I(x, y) \\ \frac{\delta^2}{\delta xy}g(\sigma) * I(x, y) & \frac{\delta^2}{\delta y^2}g(\sigma) * I(x, y) \end{bmatrix}$$

RECAP



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Temporal Robust Features (TRoF)

Inspiration on Speeded-Up Robust Features (SURF)

Hessian Matrix

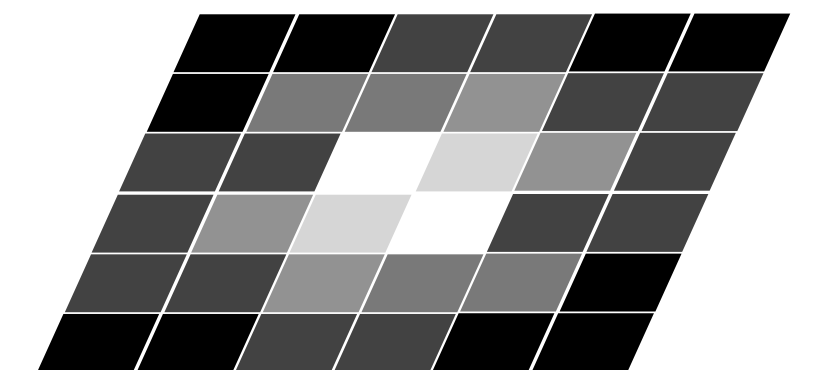
Given an image pixel $I(x, y)$, a scale of interest σ ,
and Gaussian second order derivative functions $\frac{\delta^2}{\delta x^2}G(\sigma)$, $\frac{\delta^2}{\delta y^2}G(\sigma)$, and $\frac{\delta^2}{\delta xy}g(\sigma)$,
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Property: blobs with scale σ
and centered at $I(x, y)$ will
lead to a large $\det(H)$.

Take the regions with large $\det(H)$
as candidate keypoints.

RECAP



Temporal Robust Features (TRoF)

Inspiration on Speeded-Up Robust Features (SURF)

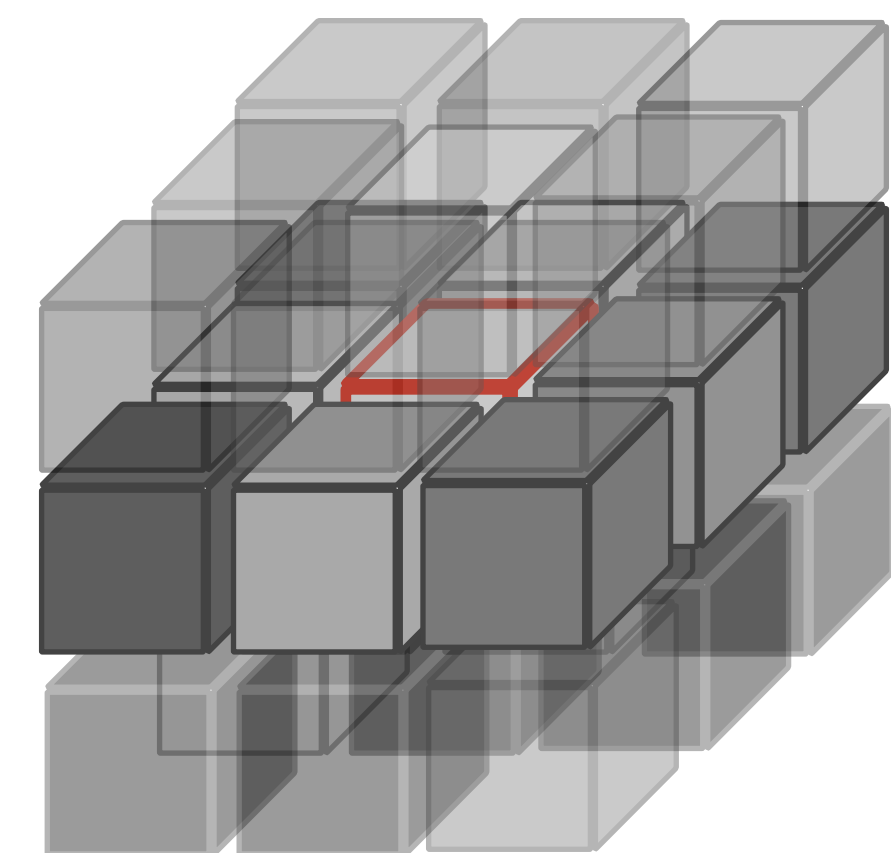
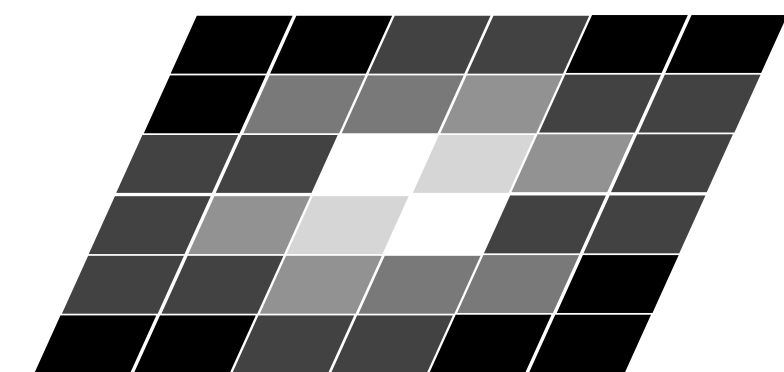
Statio-temporal Hessian Matrix

Given a **video voxel** $I(x, y, t)$, a scale of interest σ , and Gaussian second order derivative functions

$$\frac{\delta^2}{\delta x^2}G(\sigma), \frac{\delta^2}{\delta y^2}G(\sigma), \frac{\delta^2}{\delta t^2}G(\sigma), \frac{\delta^2}{\delta xy}g(\sigma), \frac{\delta^2}{\delta xt}g(\sigma), \text{ and } \frac{\delta^2}{\delta yt}g(\sigma),$$

the Hessian matrix H is given by:

$$H(x, y, t, \sigma) = \begin{bmatrix} \frac{\delta^2}{\delta x^2}g(\sigma) * I(x, y, t) & \frac{\delta^2}{\delta xy}g(\sigma) * I(x, y, t) & \frac{\delta^2}{\delta xt}g(\sigma) * I(x, y, t) \\ \frac{\delta^2}{\delta xy}g(\sigma) * I(x, y, t) & \frac{\delta^2}{\delta y^2}g(\sigma) * I(x, y, t) & \frac{\delta^2}{\delta yt}g(\sigma) * I(x, y, t) \\ \frac{\delta^2}{\delta xt}g(\sigma) * I(x, y, t) & \frac{\delta^2}{\delta yt}g(\sigma) * I(x, y, t) & \frac{\delta^2}{\delta t^2}g(\sigma) * I(x, y, t) \end{bmatrix}$$



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Temporal Robust Features (TRoF)

Inspiration on Speeded-Up Robust Features (SURF)

Integral Image

Data structure I_{Σ} computed from a given image I that shares the same resolution (i.e., same number of rows and of columns).

Each “pixel” of I_{Σ} has the following value:

$$I_{\Sigma}(x, y) = \sum_{i=0}^x \sum_{j=0}^y I(i, j)$$

i.e., it holds the sum of all the pixel values of I that spatially precede the position (x, y) .

RECAP



Temporal Robust Features (TRoF)

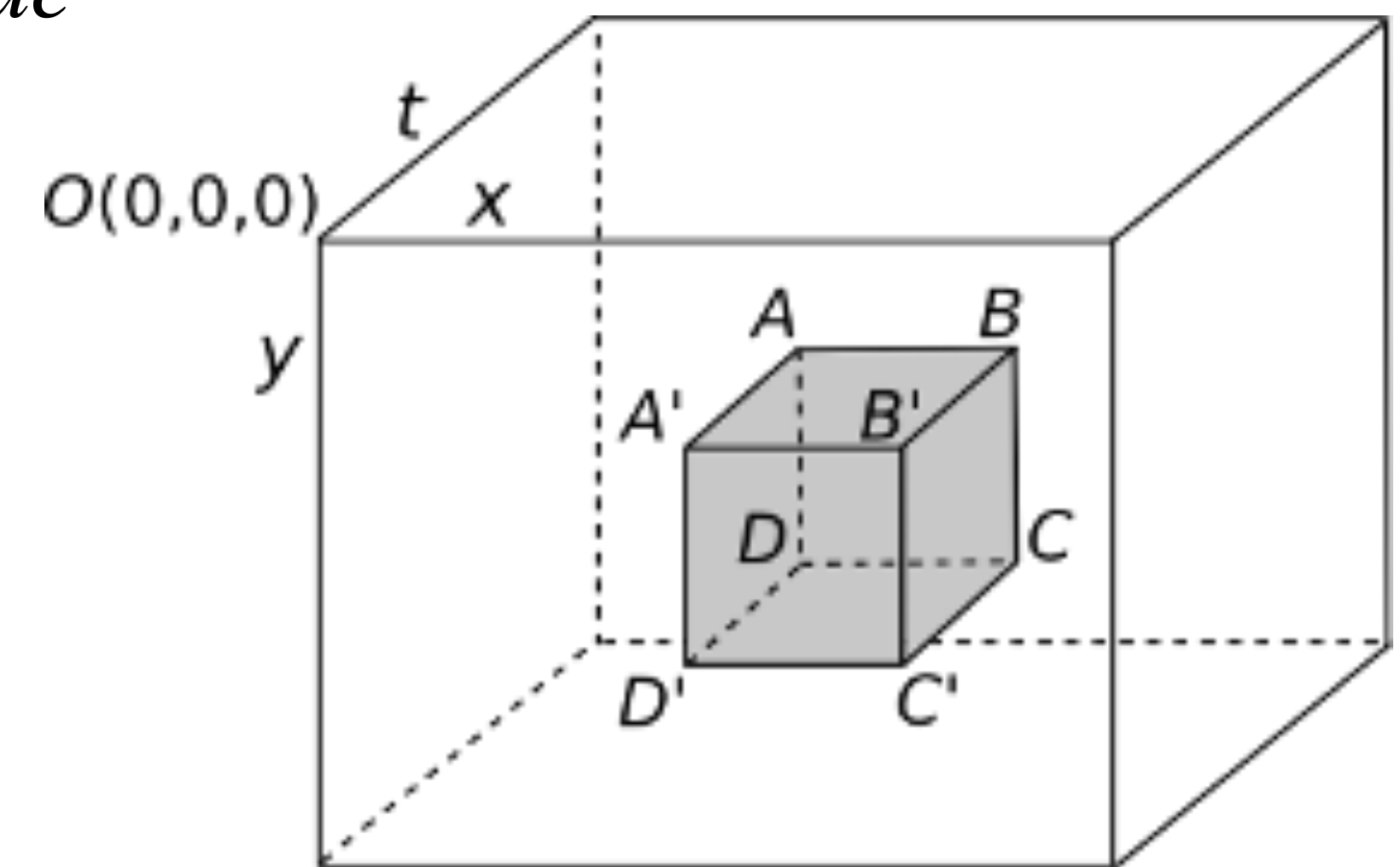
Inspiration on Speeded-Up Robust Features (SURF)

Integral **Video**

Convolutions supported by an integral video:

$$R = [(A + C) - (B + D) - (A' + C') + (B' + D')] \times filter_value$$

Eight accesses for any filter size.



Temporal Robust Features (TRoF)

Inspiration on Speeded-Up Robust Features (SURF)

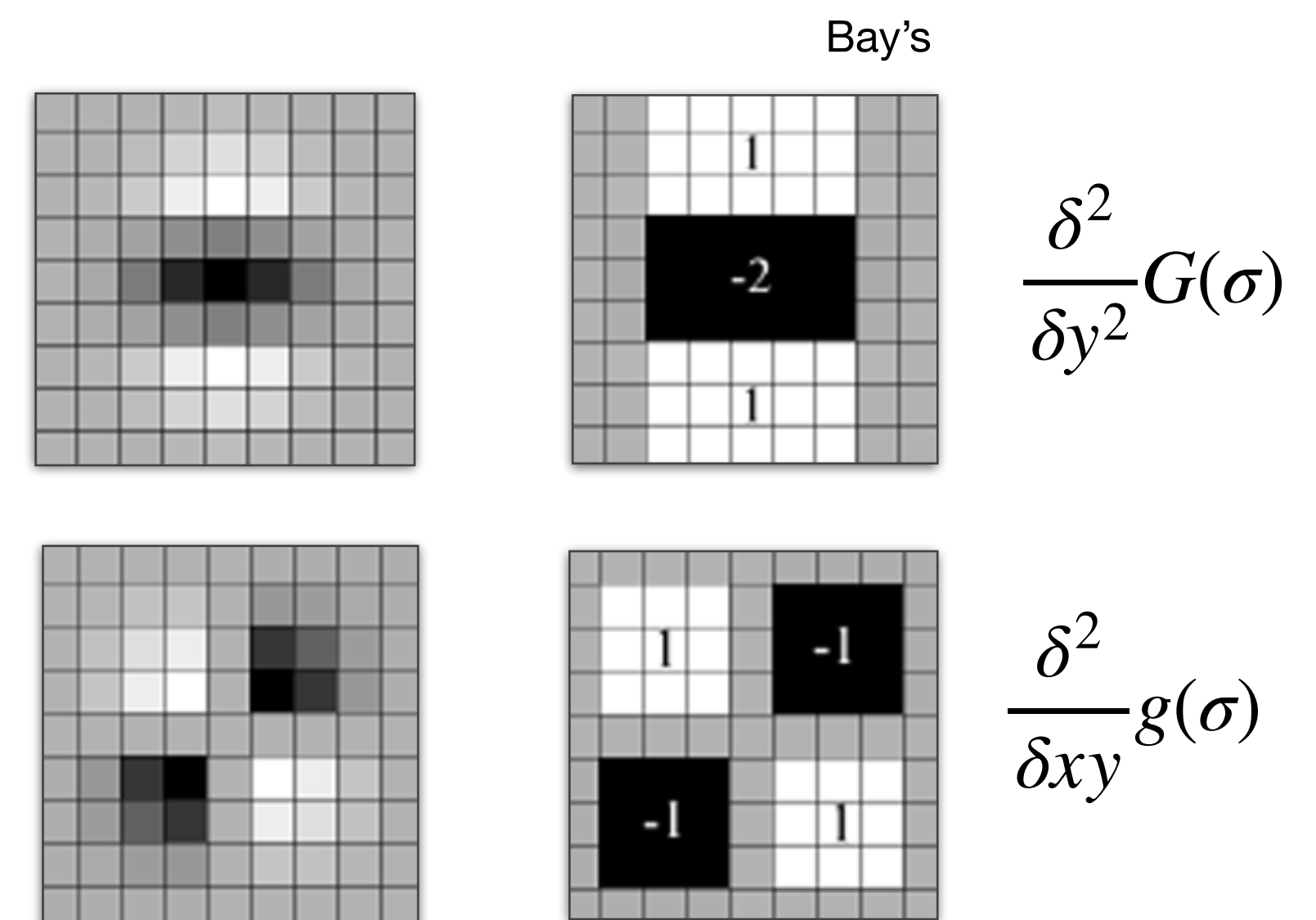
Box Filters

The Gaussian second order derivative functions $\frac{\delta^2}{\delta x^2}G(\sigma)$, $\frac{\delta^2}{\delta y^2}G(\sigma)$, and $\frac{\delta^2}{\delta xy}g(\sigma)$ can be approximated by box filters.

Compute the $\det(H)$ quickly by using the box filters and the integral image!

$$H(x, y, \sigma) = \begin{bmatrix} \frac{\delta^2}{\delta x^2}g(\sigma) * I(x, y) & \frac{\delta^2}{\delta xy}g(\sigma) * I(x, y) \\ \frac{\delta^2}{\delta xy}g(\sigma) * I(x, y) & \frac{\delta^2}{\delta y^2}g(\sigma) * I(x, y) \end{bmatrix}$$

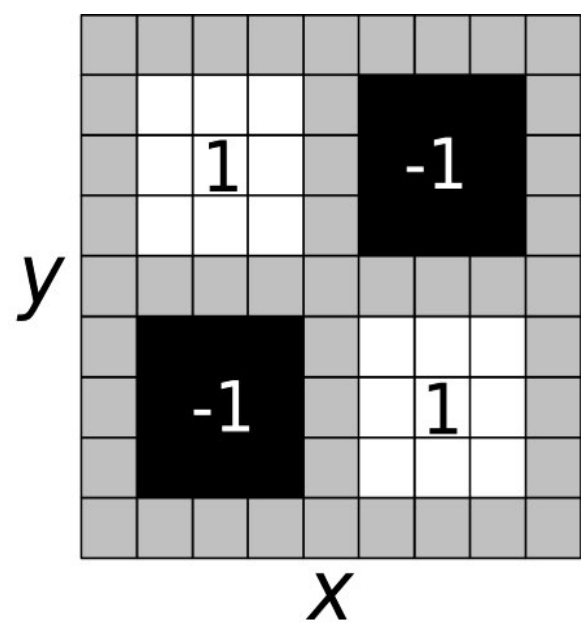
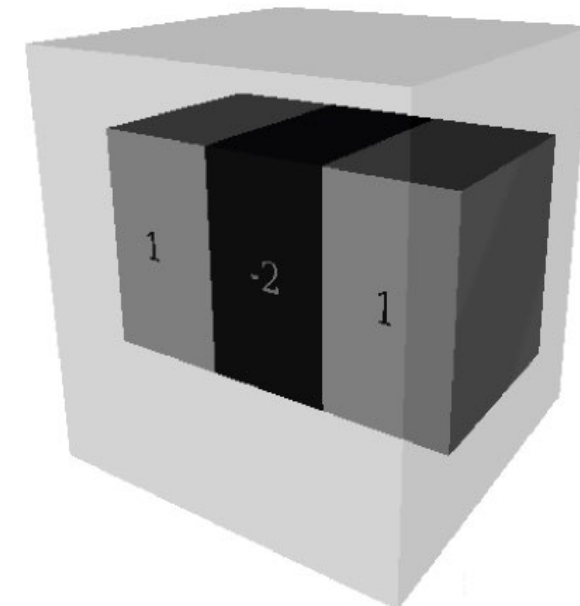
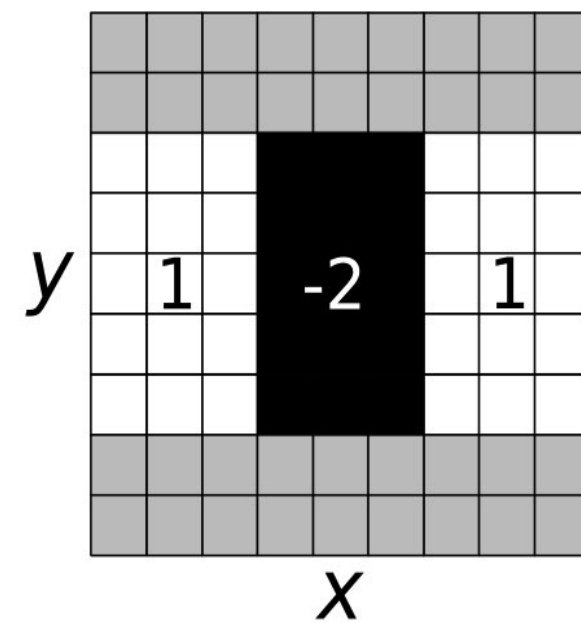
RECAP



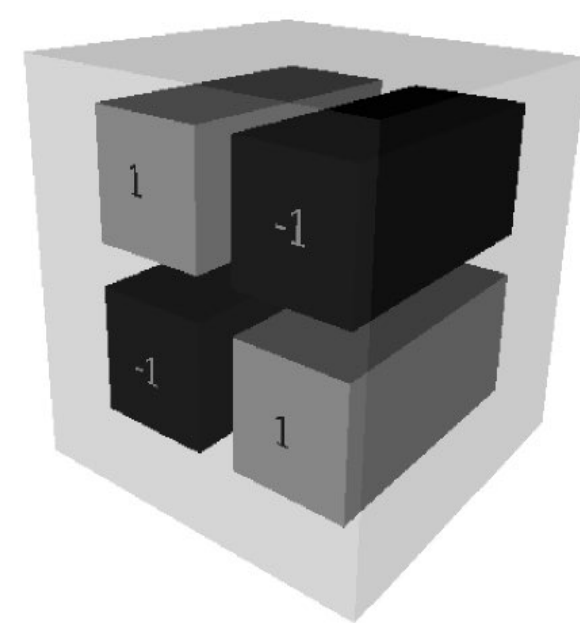
Temporal Robust Features (TRoF)

Inspiration on Speeded-Up Robust Features (SURF)

3D Box Filters



SURF

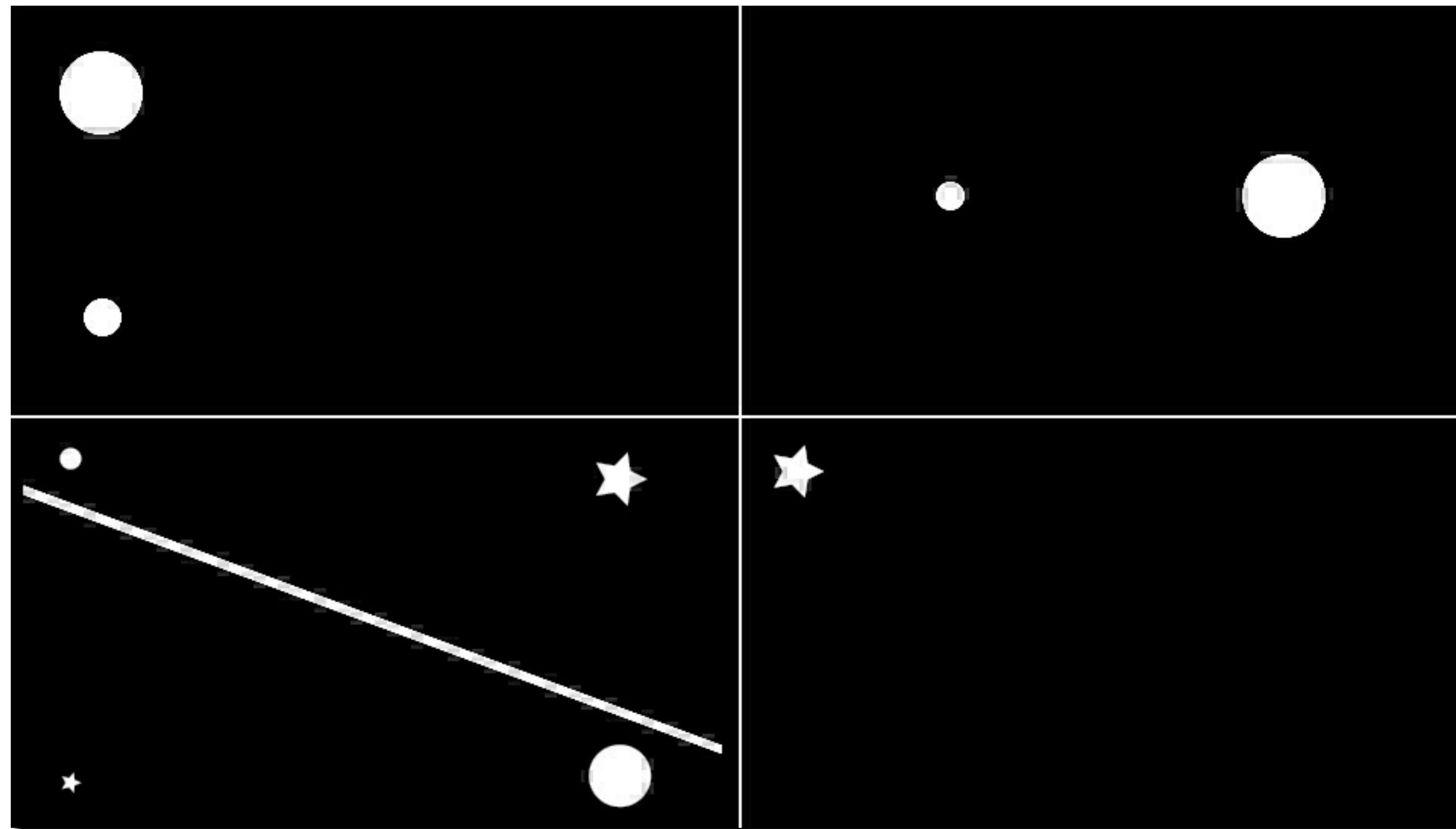


TRoF



Temporal Robust Features (TRoF)

TRoF Detector



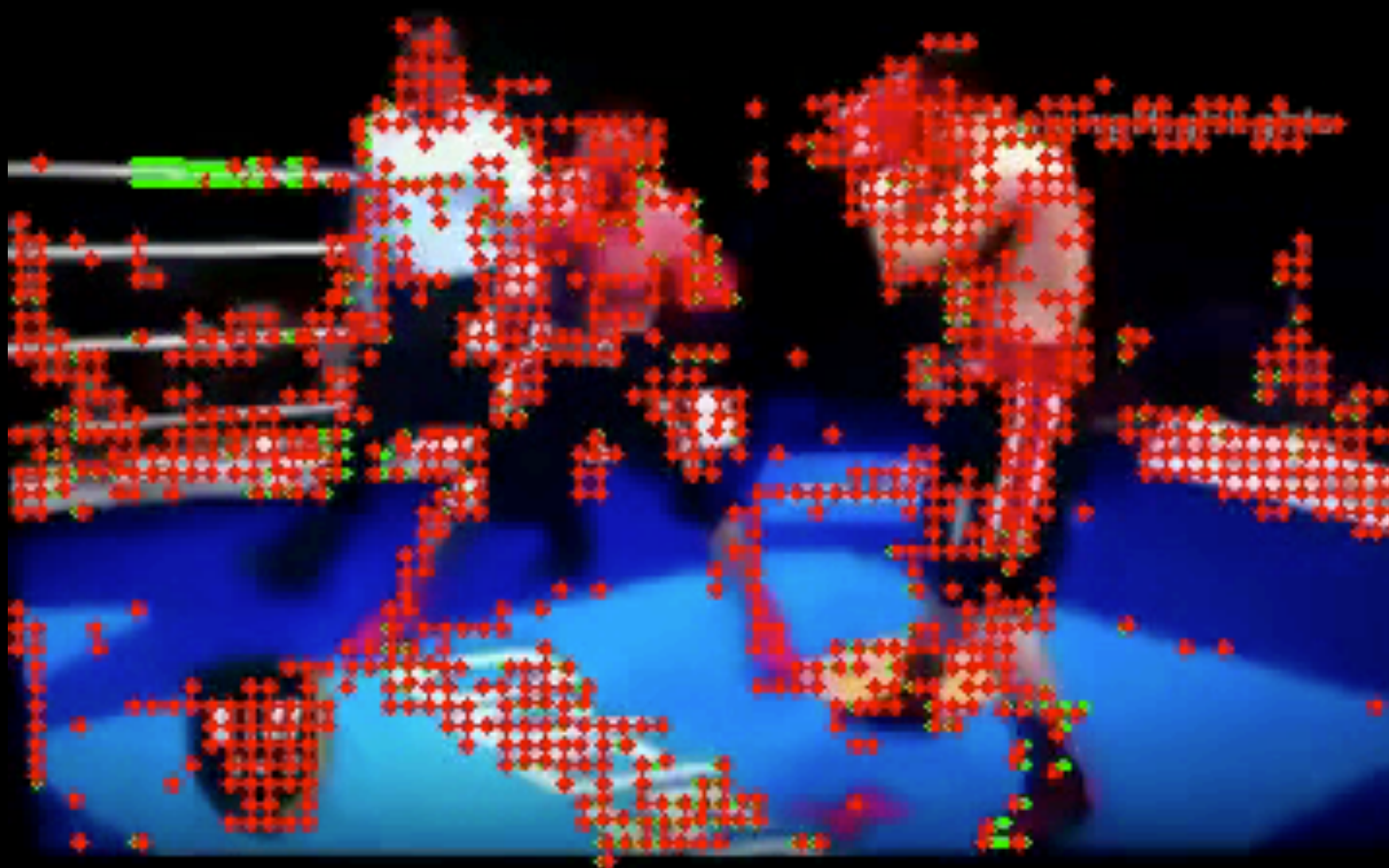
Original



TRoF



Dense
Trajectories
(Wang et al., 2013)



STIP
(Laptev et al., 2008)



Temporal Robust Features (TRoF)

Inspiration on Speeded-Up Robust Features (SURF)

Keypoint Description

For each rotated keypoint, sample a 4 x 4 window on its neighborhood, according to the keypoint scale.

For each one of the 4 x 4 cells, compute 4 sums:

(1) $\sum d_x$, (2) $\sum |d_x|$, (3) $\sum d_y$, and (4) $\sum |d_y|$.

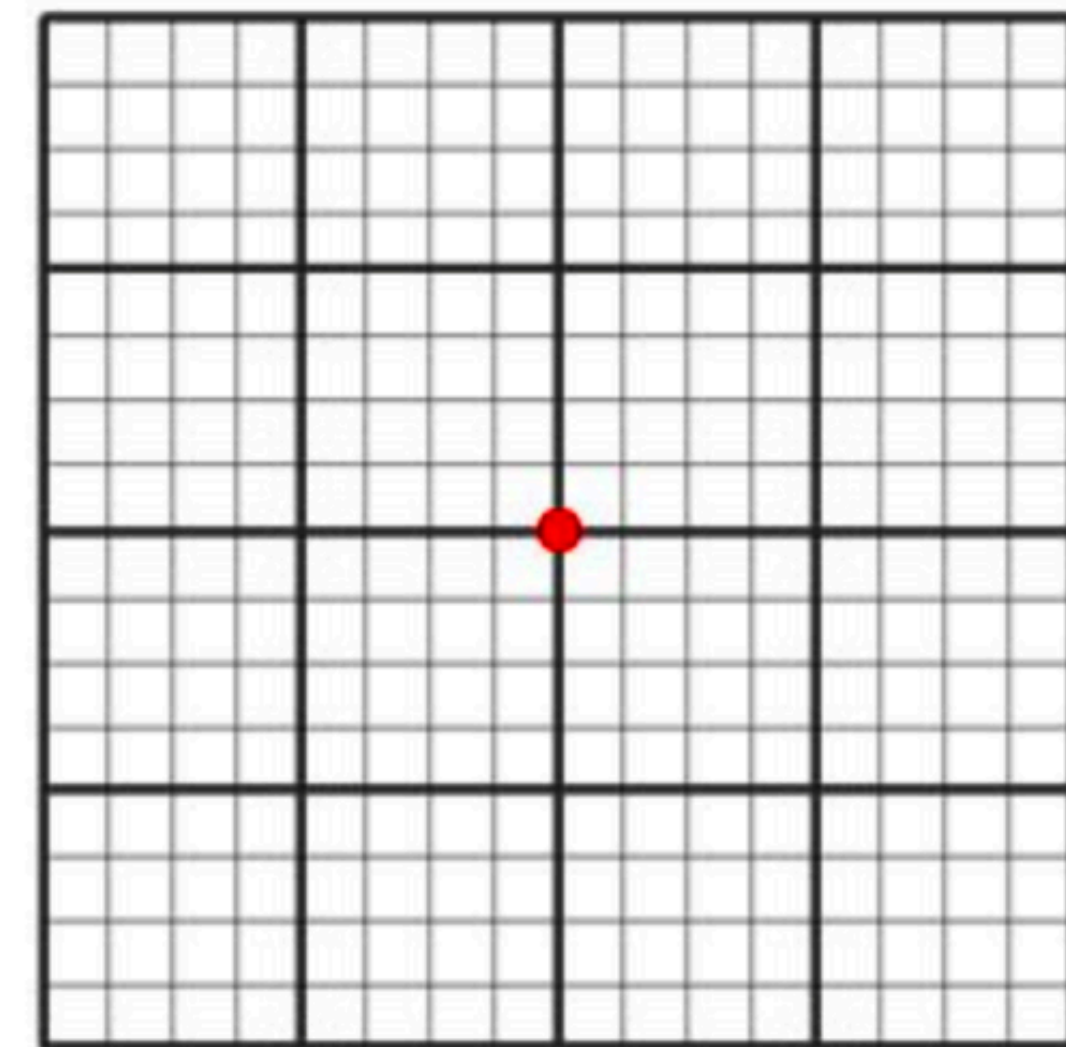
Fill out a feature vector with the 4 x 4 x 4 = 64 values.



d_x



d_y

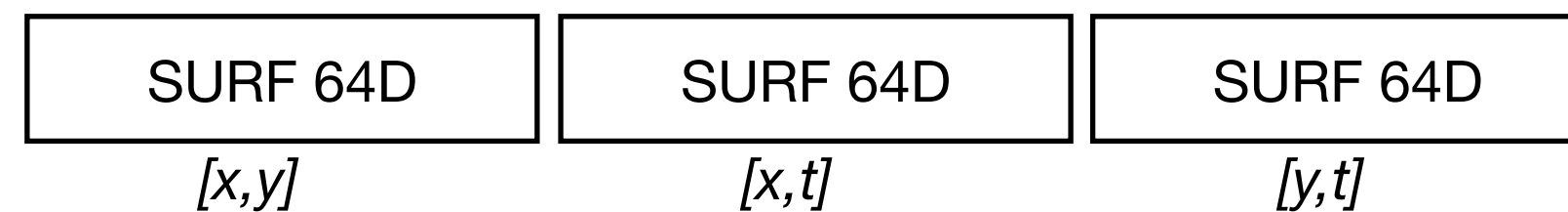
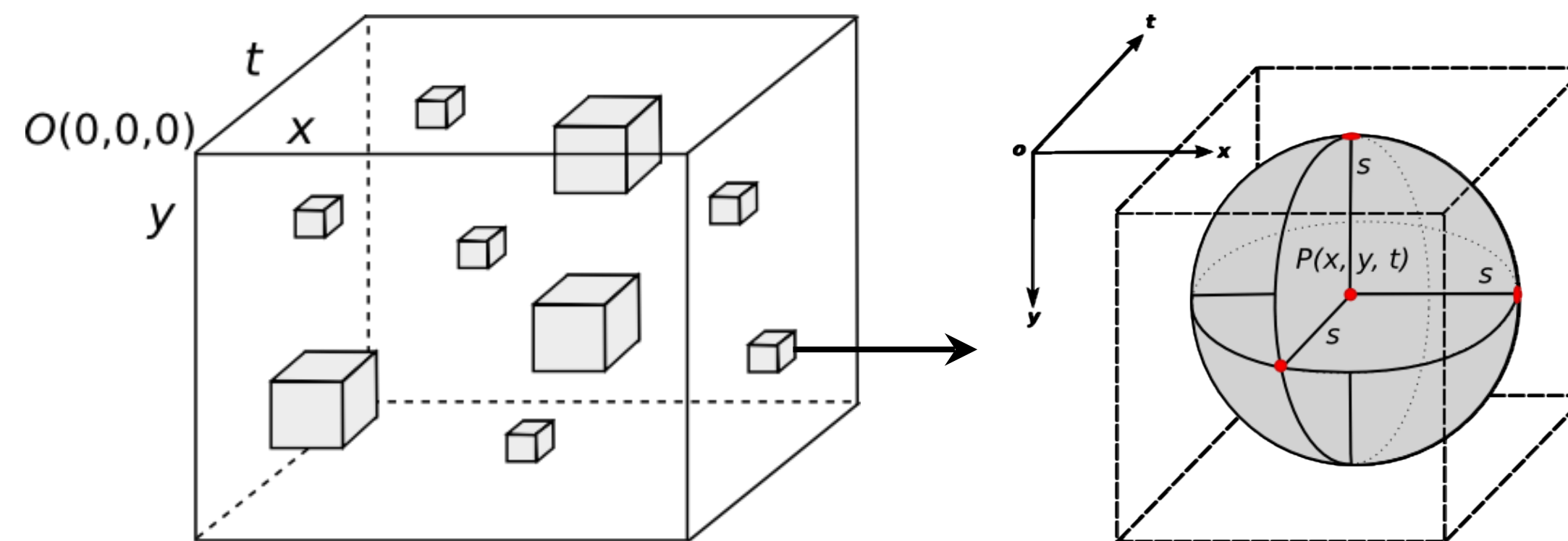


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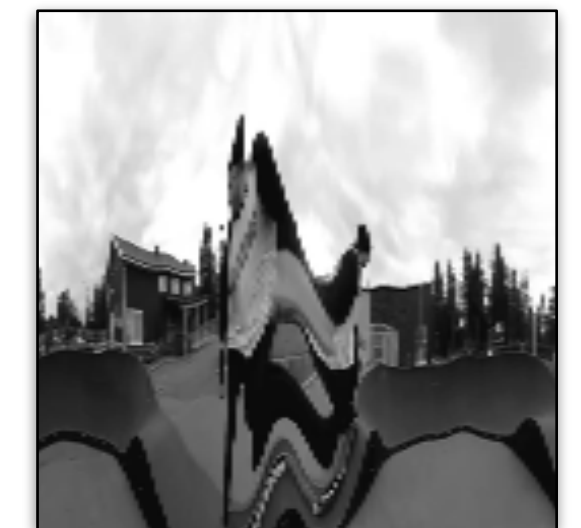
Temporal Robust Features (TRoF)

TRoF Descriptor

How to describe each detected blob?

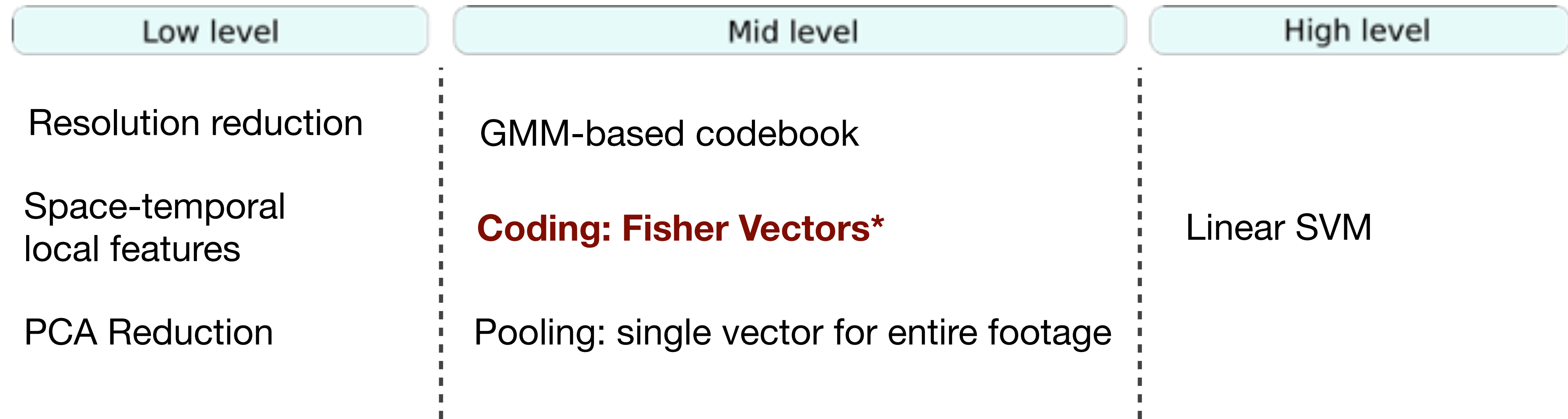


192 D



Proposed Solution

Based on Bags of Visual Words that (BoVW)



*Perronnin et al., 2010

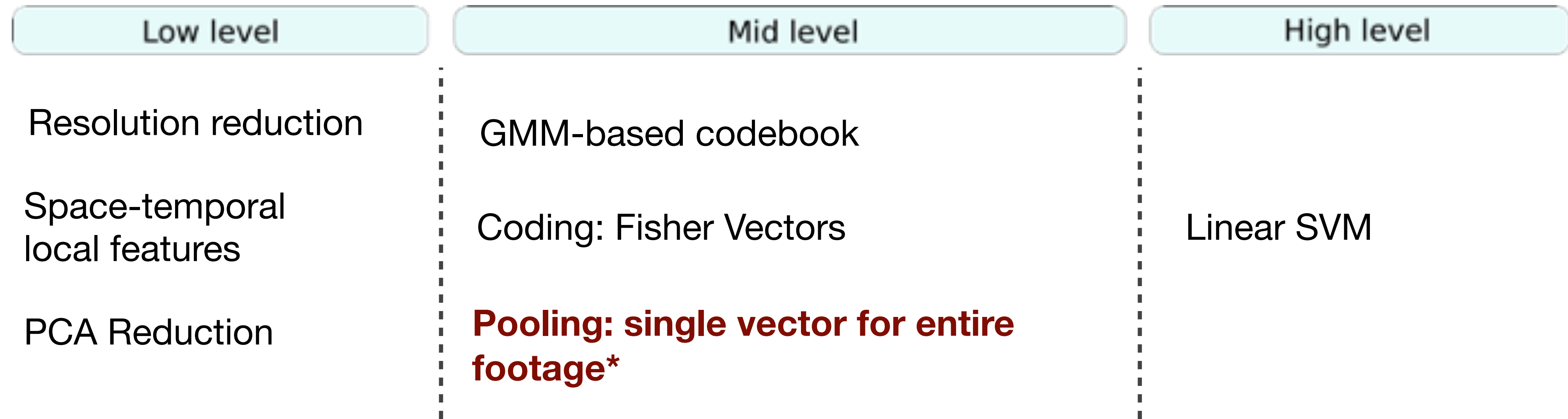
Perronnin, F., Sanchez, J., and Mensink, T.
Improving the fisher kernel for large-scale image classification
European Conference on Computer Vision (ECCV), 2010



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Proposed Solution

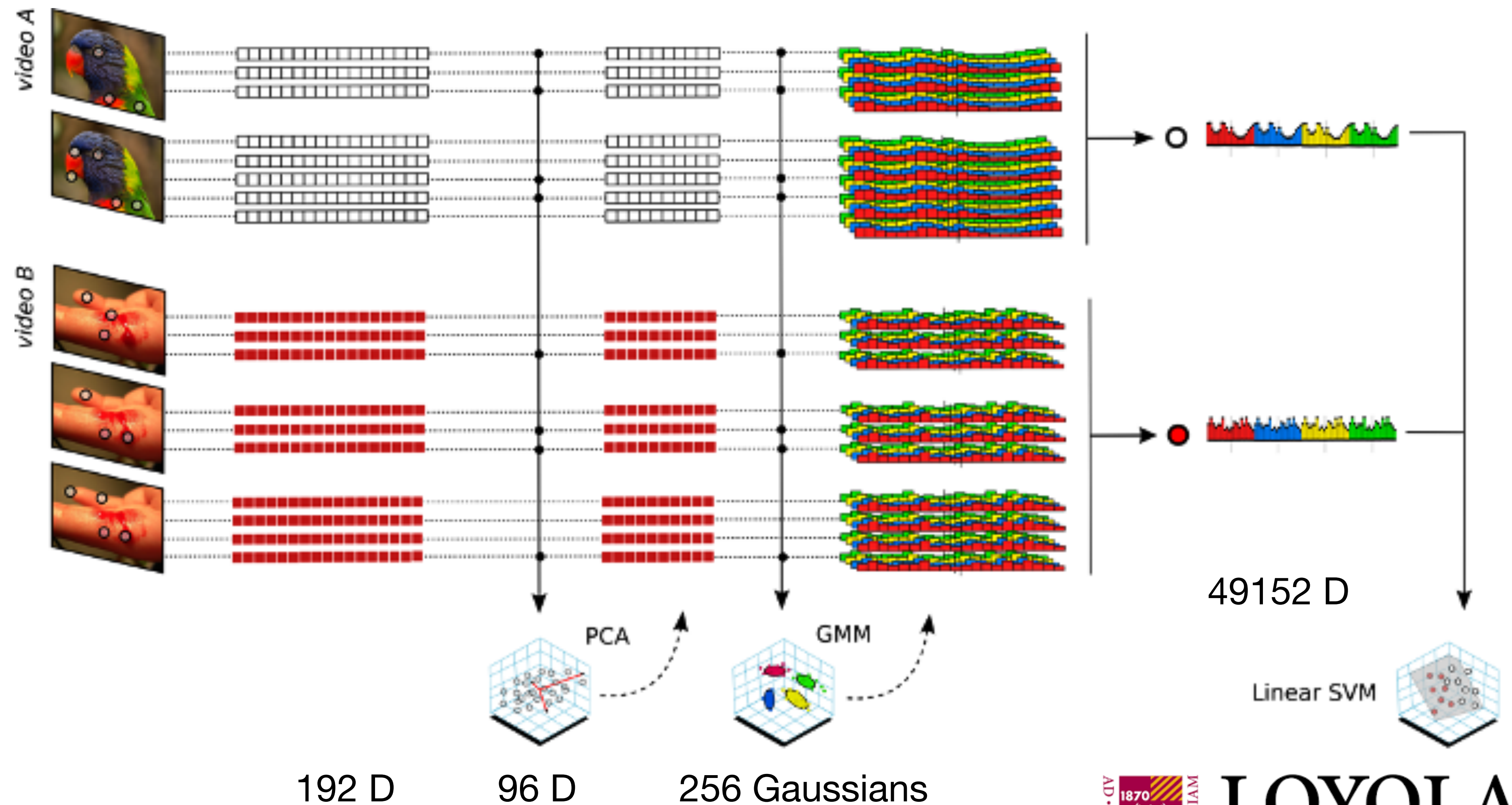
Based on Bags of Visual Words that (BoVW)



*Average Pooling

Proposed Solution

Inference
Time



Violence Results

Dataset

MediaEval 2013



“Content one would not let a child see.” [2]

Training: 18 movies
Test: 7 movies



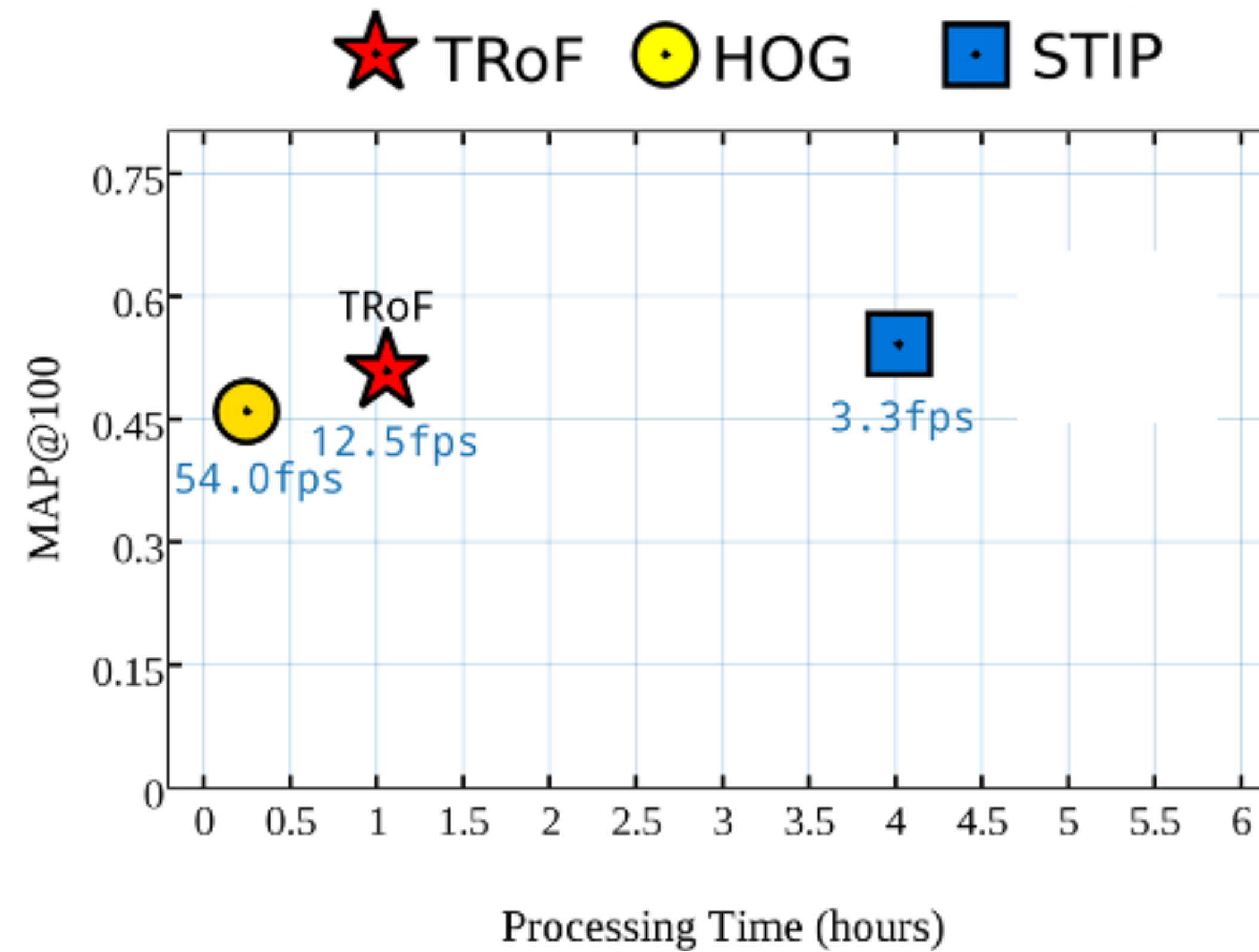
Shot-based
segmentation
and classification.

Metric: Mean Average
Precision (MAP)

[2] Demarty et al., *Benchmarking Violent Scenes Detection in Movies*. In IEEE CBMI, 2014

Violence Results

MAP vs. Runtime



2013 MediaEval Dataset

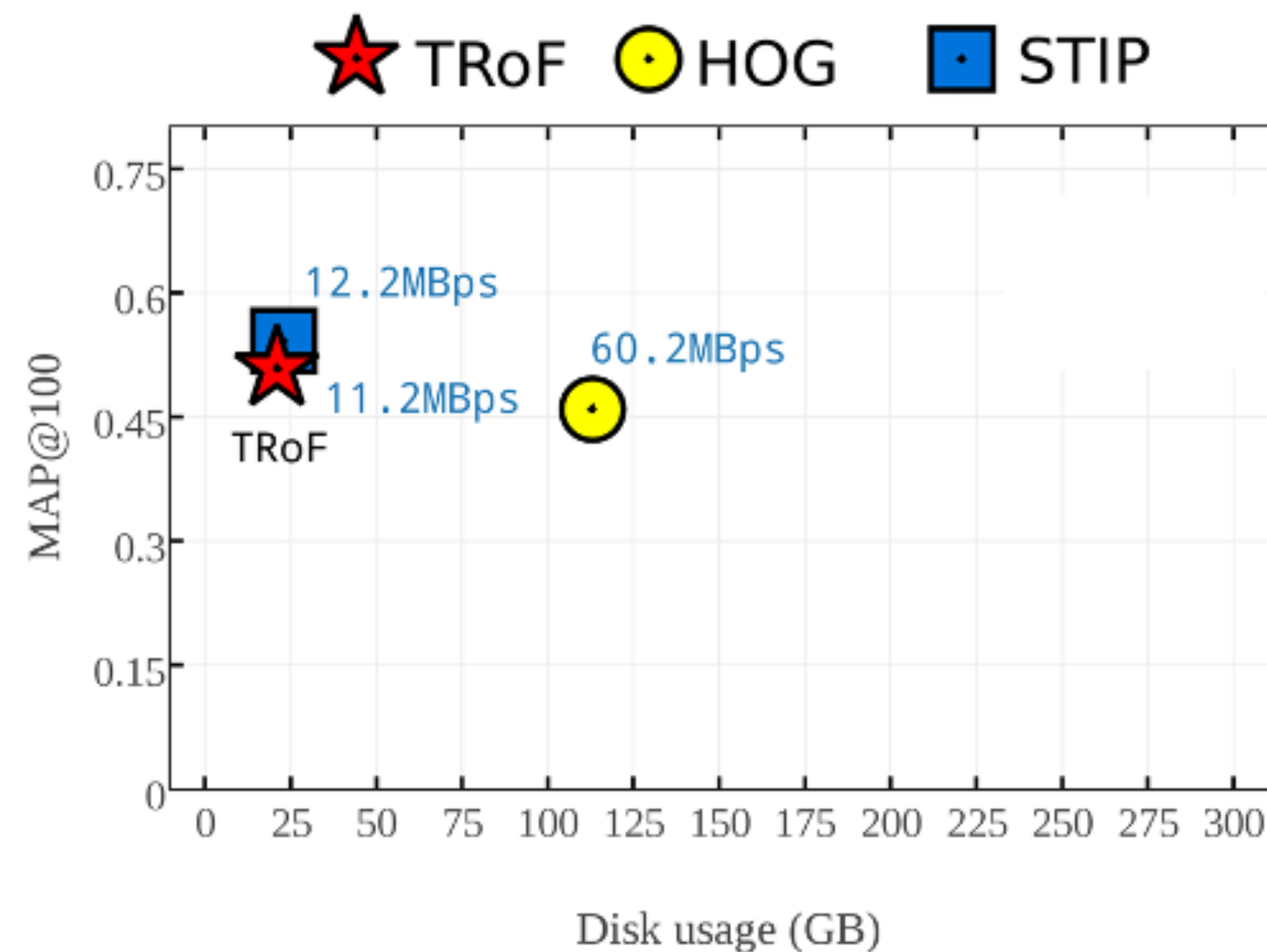


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Violence Results

MAP vs. Memory Footprint

2013 MediaEval Dataset



Violence Results

True Positive Sample



Violence Results

False Negative Sample



Violence Results

False Negative Sample



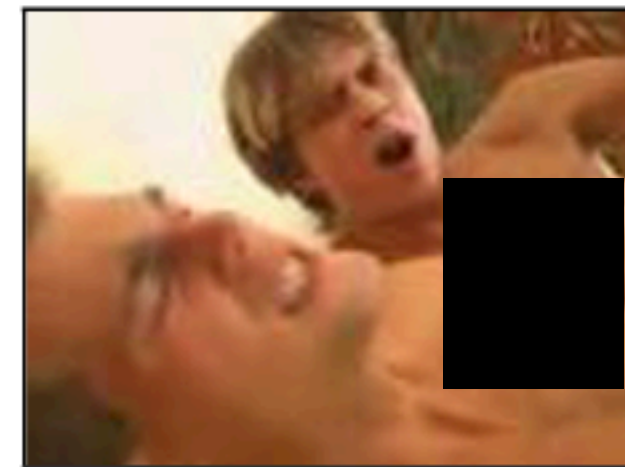
Pornography Results

Dataset

Porn-2k



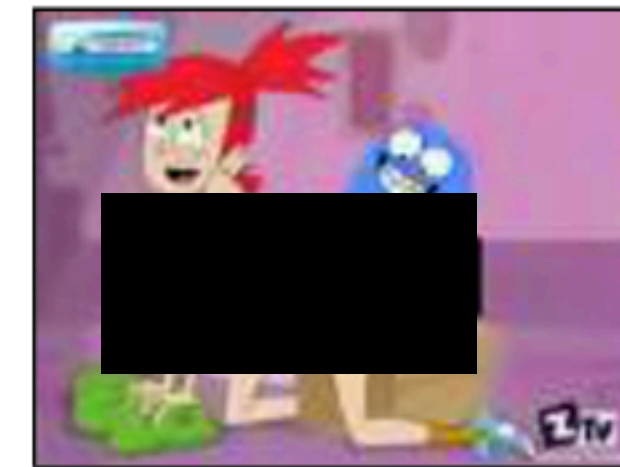
(a)



(b)



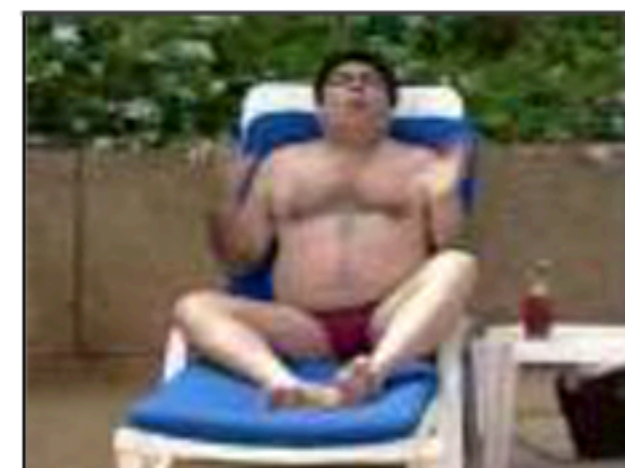
(c)



(d)



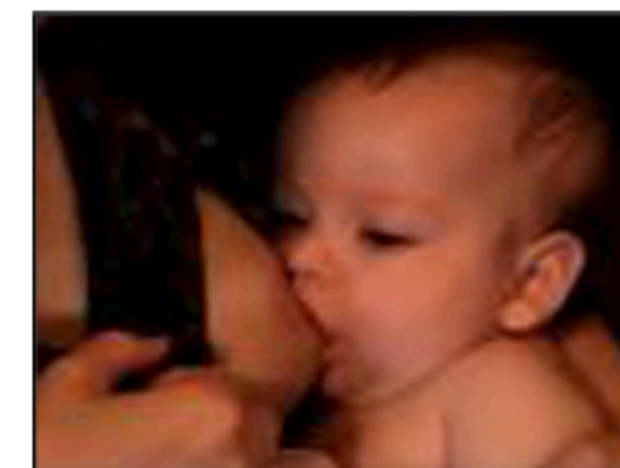
(e)



(f)



(g)



(h)

“Any explicit sexual matter with the purpose of eliciting arousal.” [1]

140h of video
1000 porn clips
1000 non-porn clips

Metric: Classification Accuracy

YouTube

Vine

vimeo

Porn sites

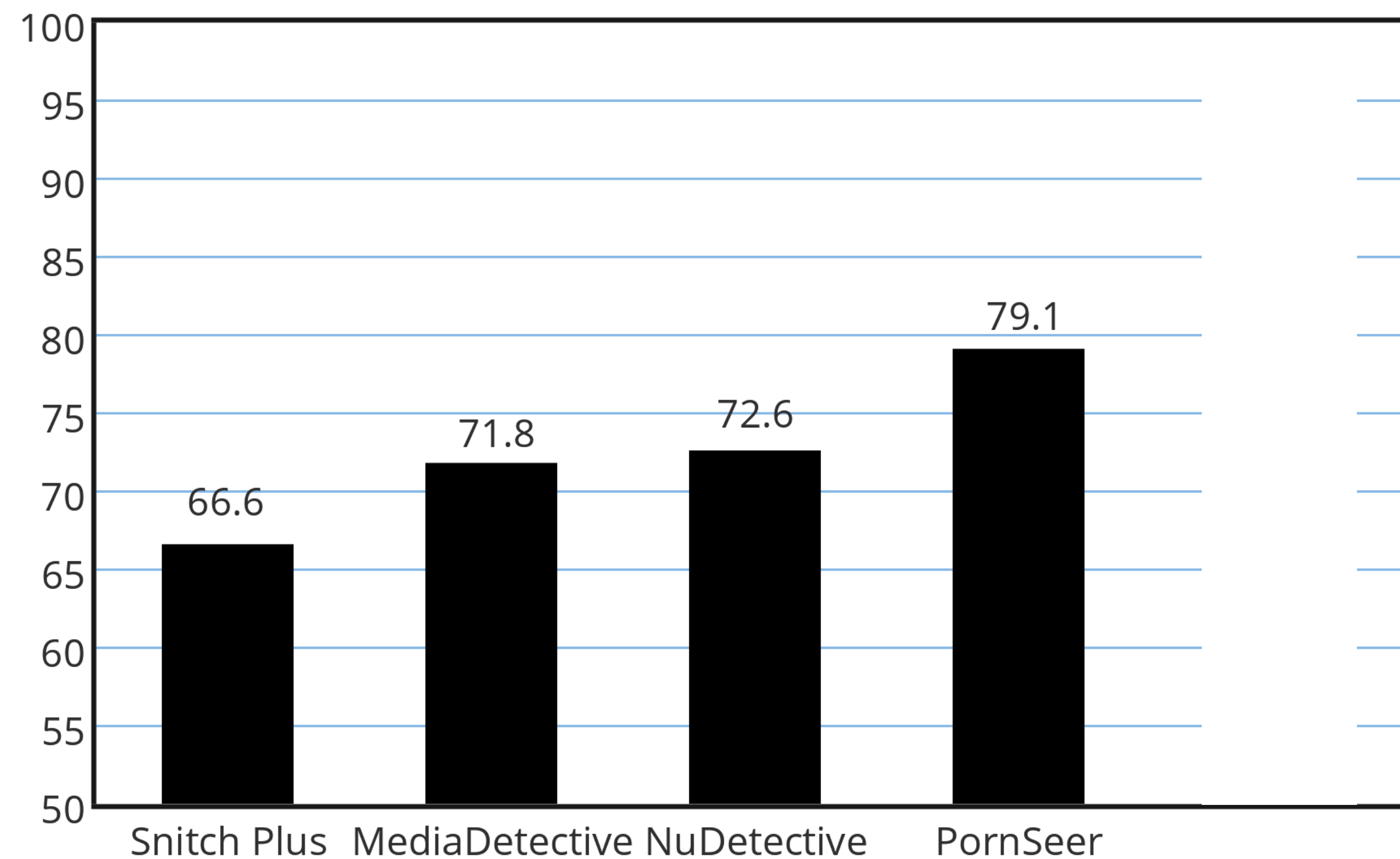
[1] Short et al., *A review of internet pornography use research: Methodology and content from the past 10 years*. Cyberpsychology, Behavior, and Social Networking 15, 2012



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Pornography Results

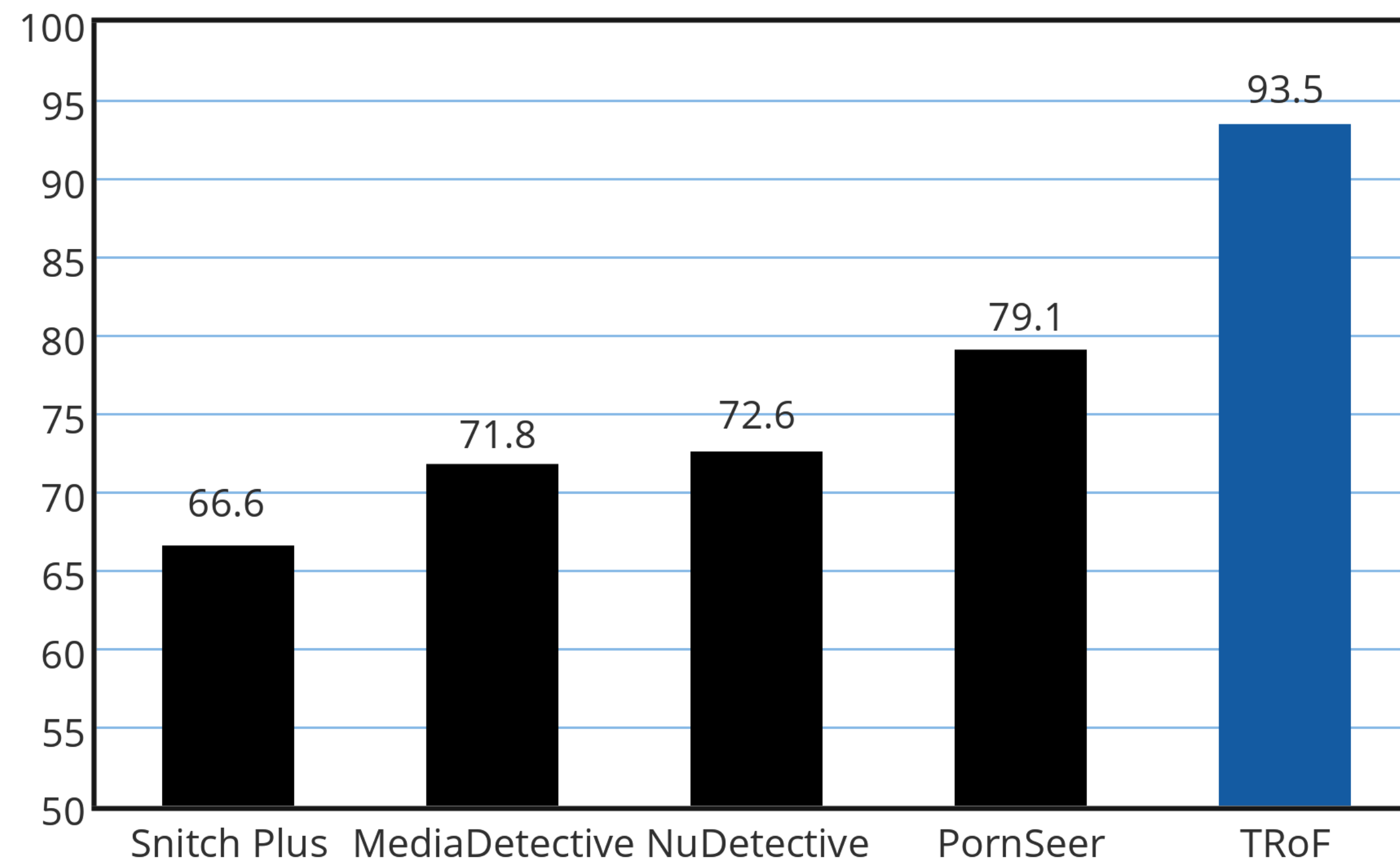
Classification Accuracy



Porn-2k Dataset

Pornography Results

Classification Accuracy



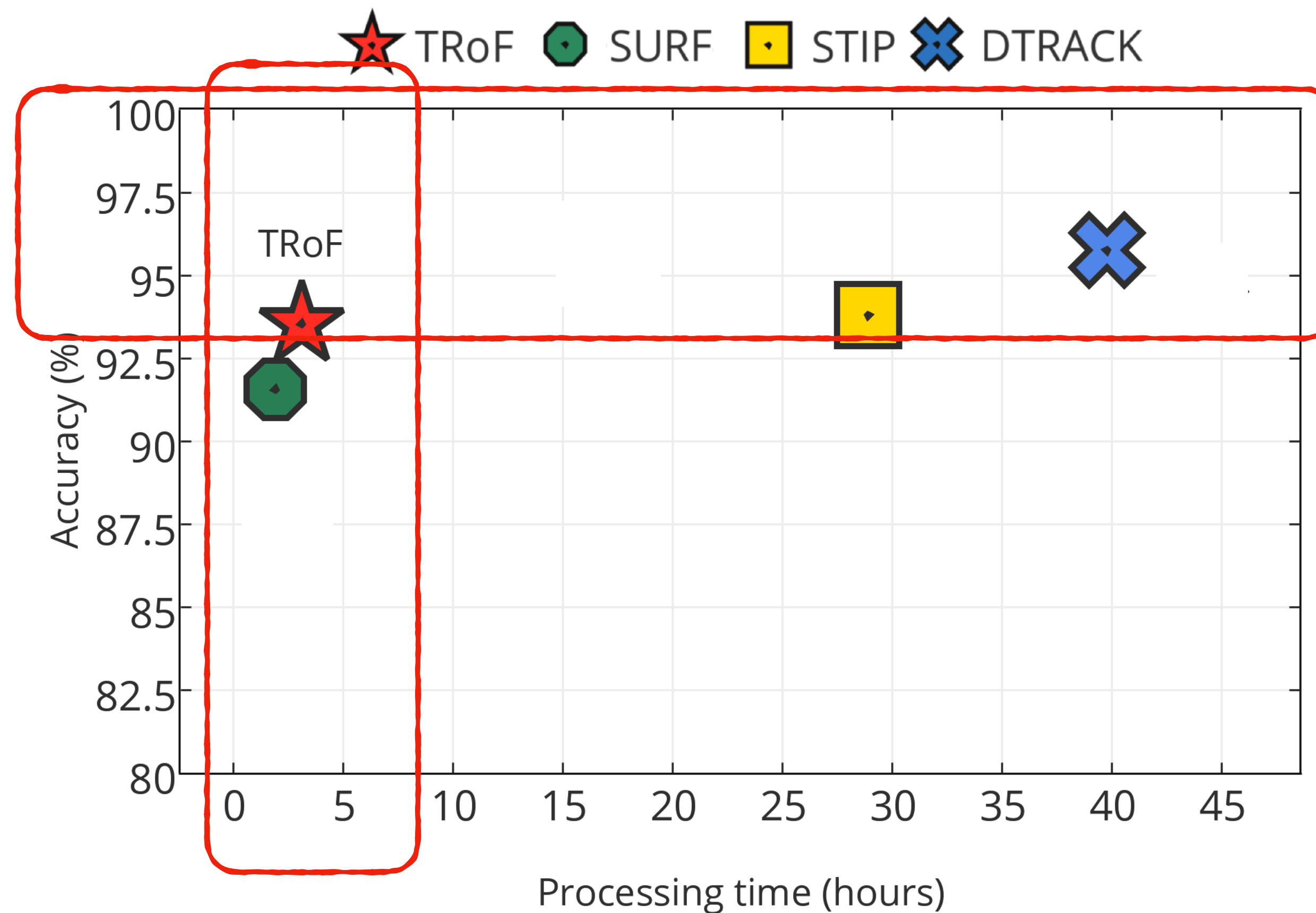
Porn-2k Dataset



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Pornography Results

Accuracy vs. Runtime



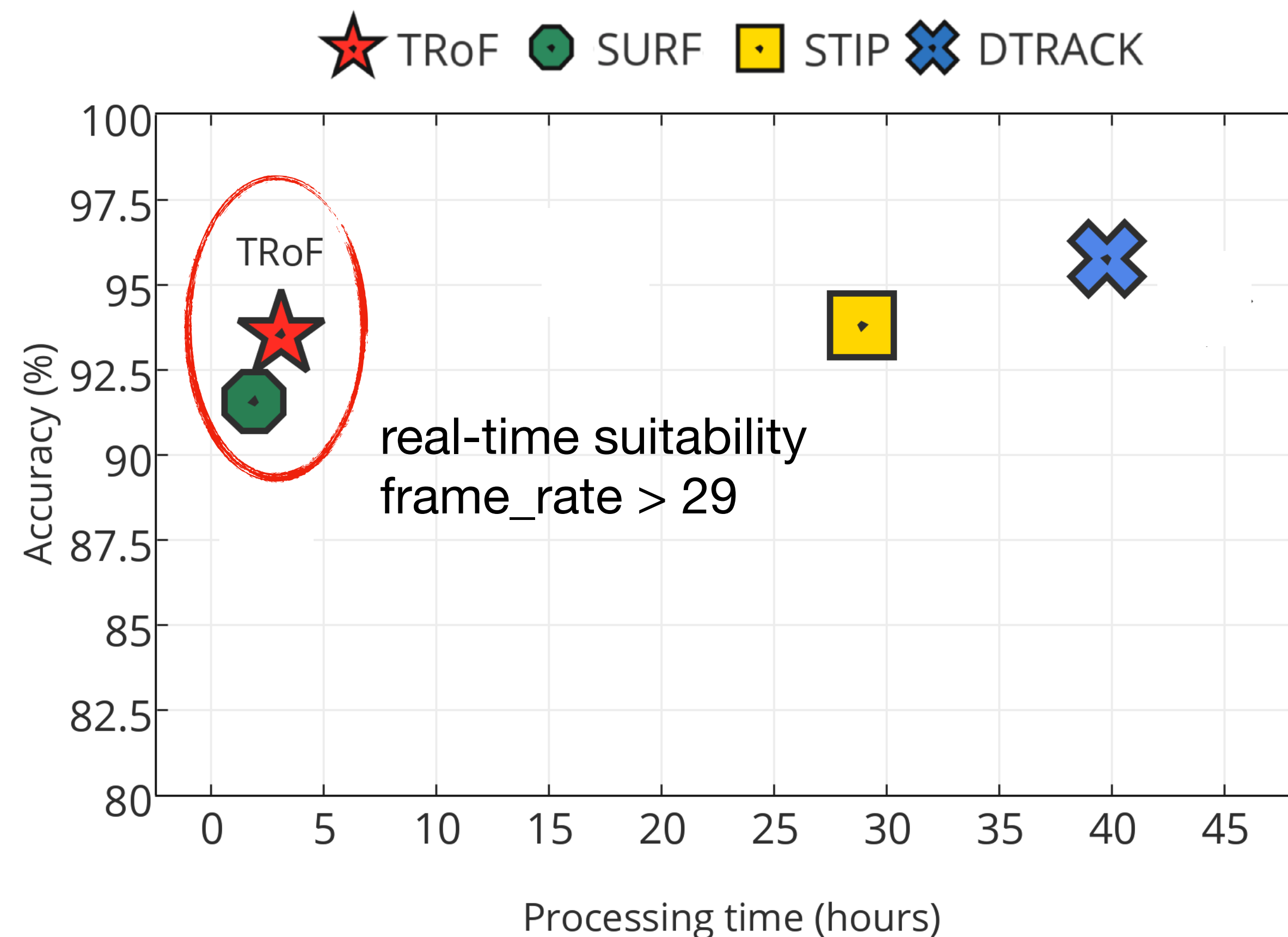
Porn-2k Dataset



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Pornography Results

Accuracy vs. Runtime



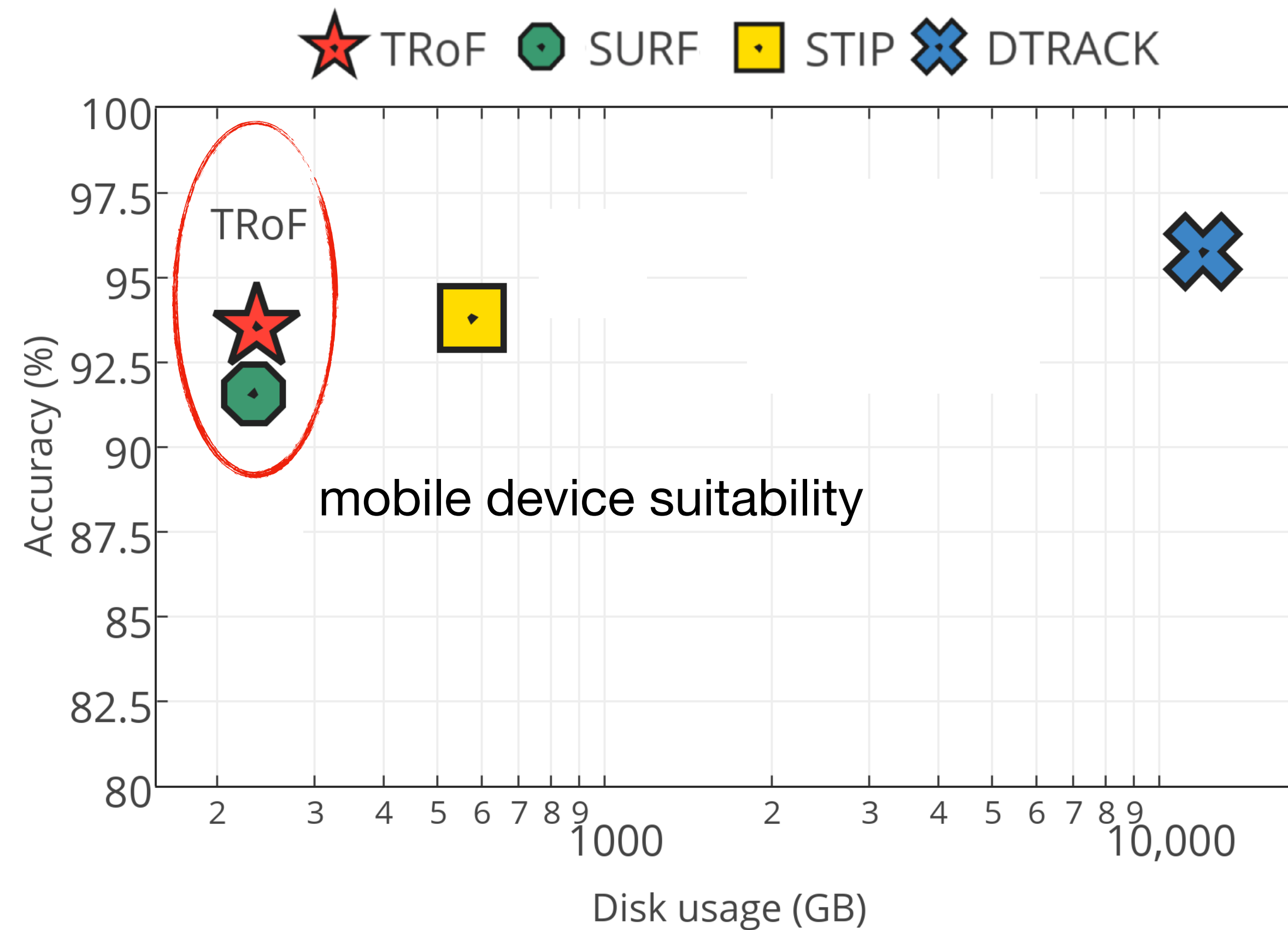
Porn-2k Dataset



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Pornography Results

Accuracy vs. Memory Footprint



Porn-2k Dataset



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Training Protocol

Folding Blurb

5x2-fold cross validation

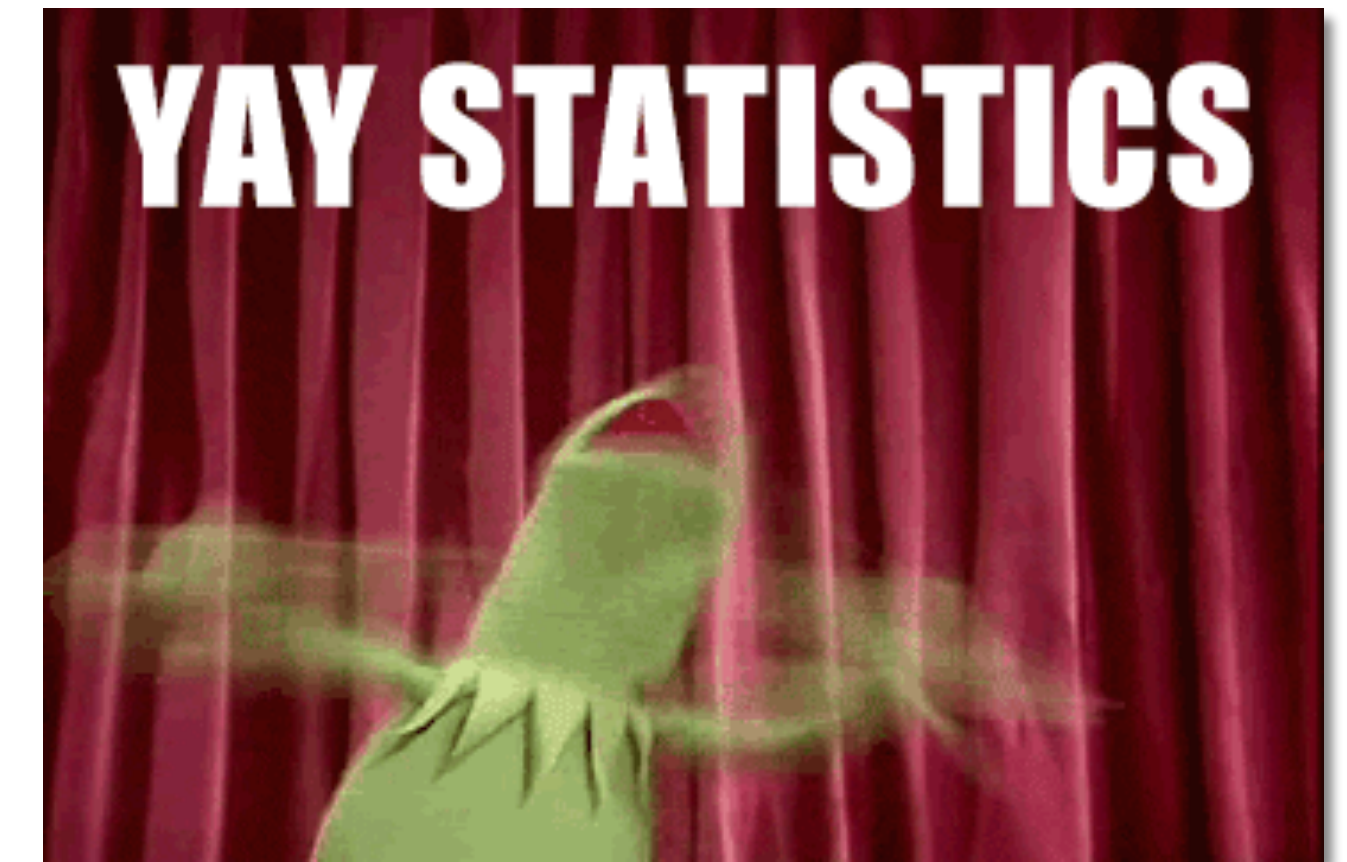
Non-parametric pairwise Wilcoxon signed-rank test,
with Bonferroni's p -correction

Reference

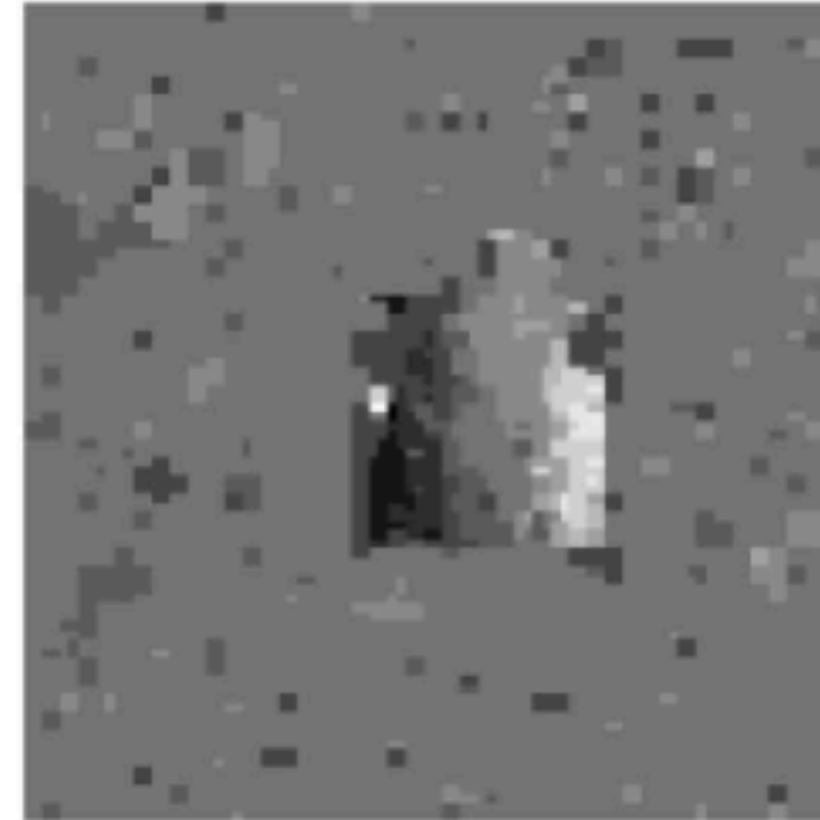
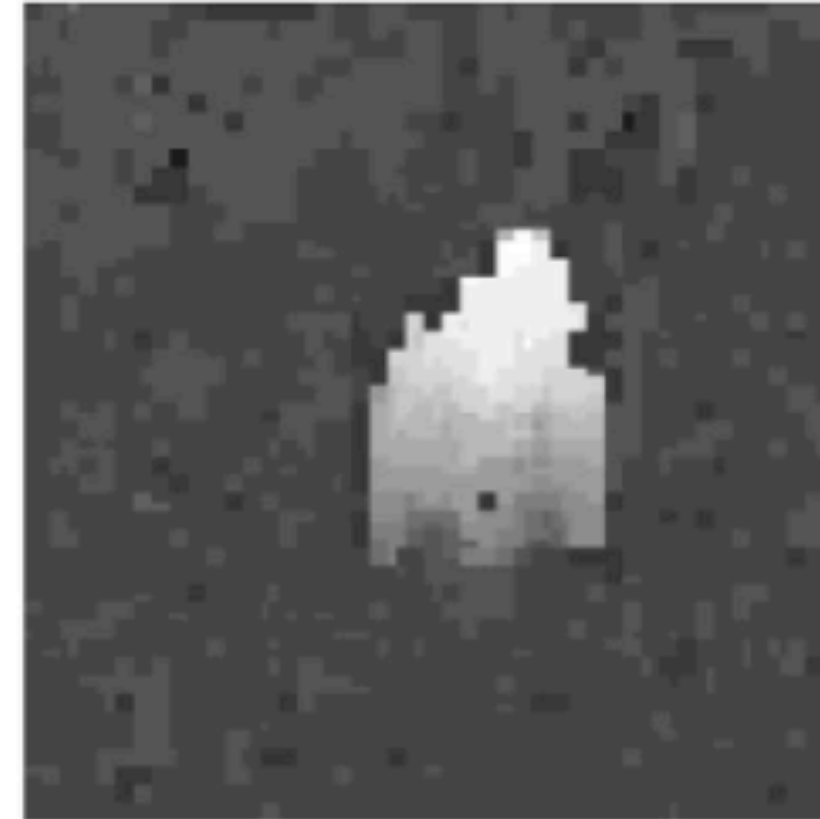
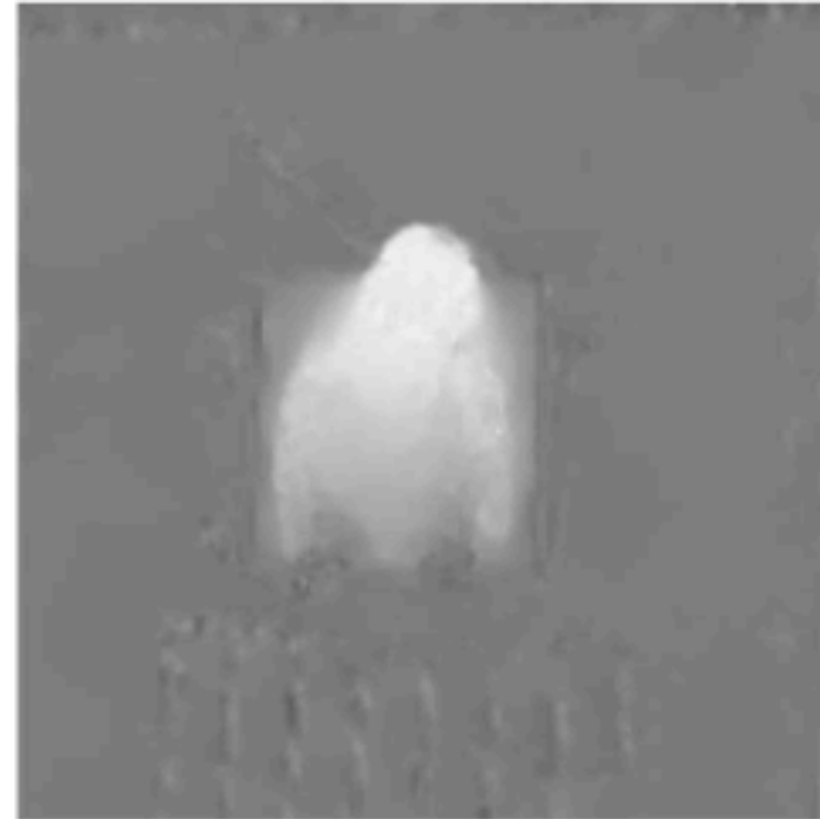
Demšar, J.

Statistical comparisons of classifiers over multiple data sets

ACM Journal of Machine Learning Research (JMLR) 7 (1), 2006



Deep Learning?



(a) Sequential Raw frames

(b) Optical Flow

(c) Motion Vectors

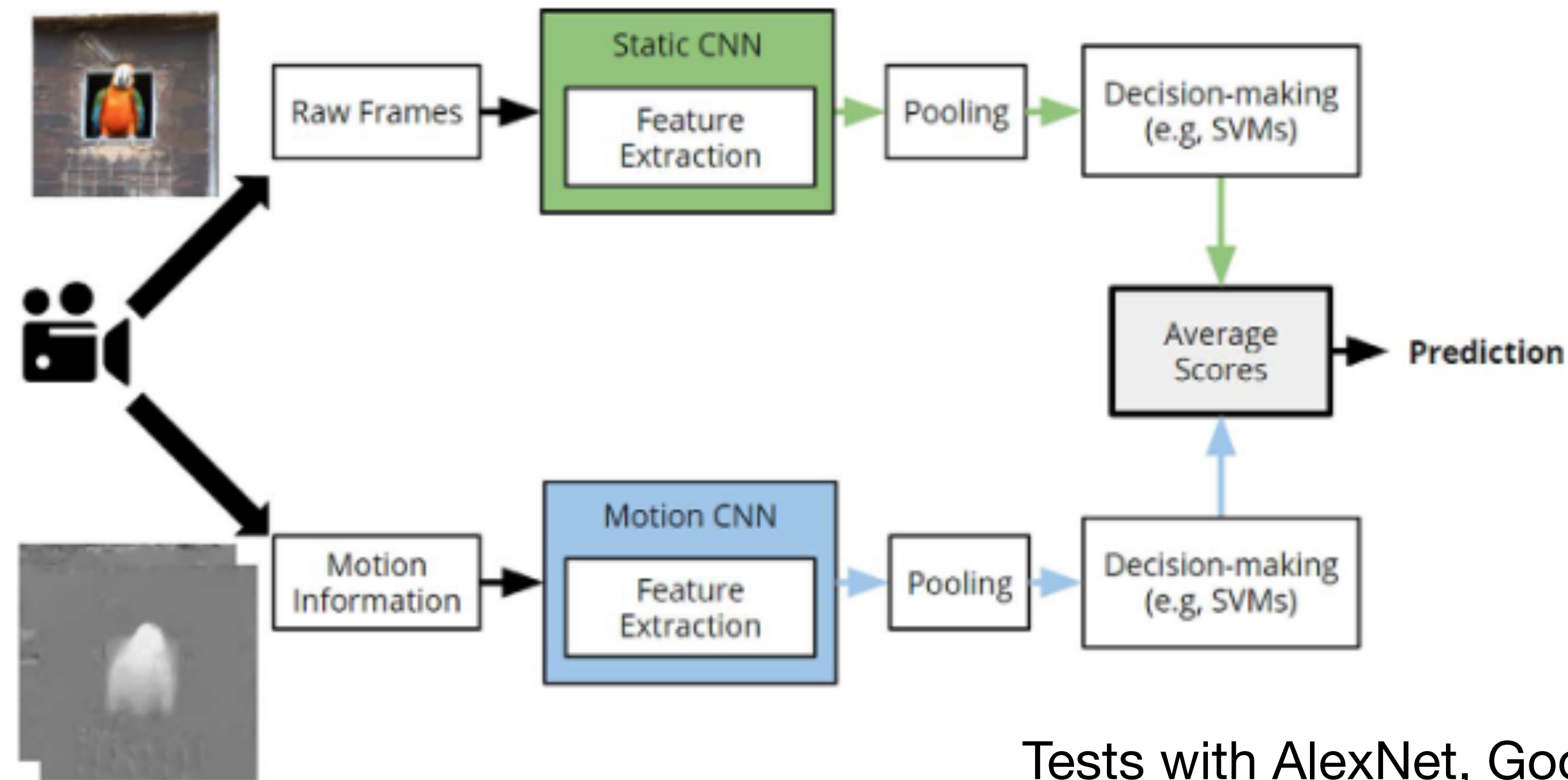
Perez, M., et al.
Video pornography detection through deep learning techniques and motion information

Elsevier Neurocomputing 230, 2017



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Deep Learning?



Tests with AlexNet, Googlenet, and VGG.
Best results so far.
Portable to mobile devices?

Tasks

Part I: Sensitive Video Classification

Part II: Sensitive Video Detection

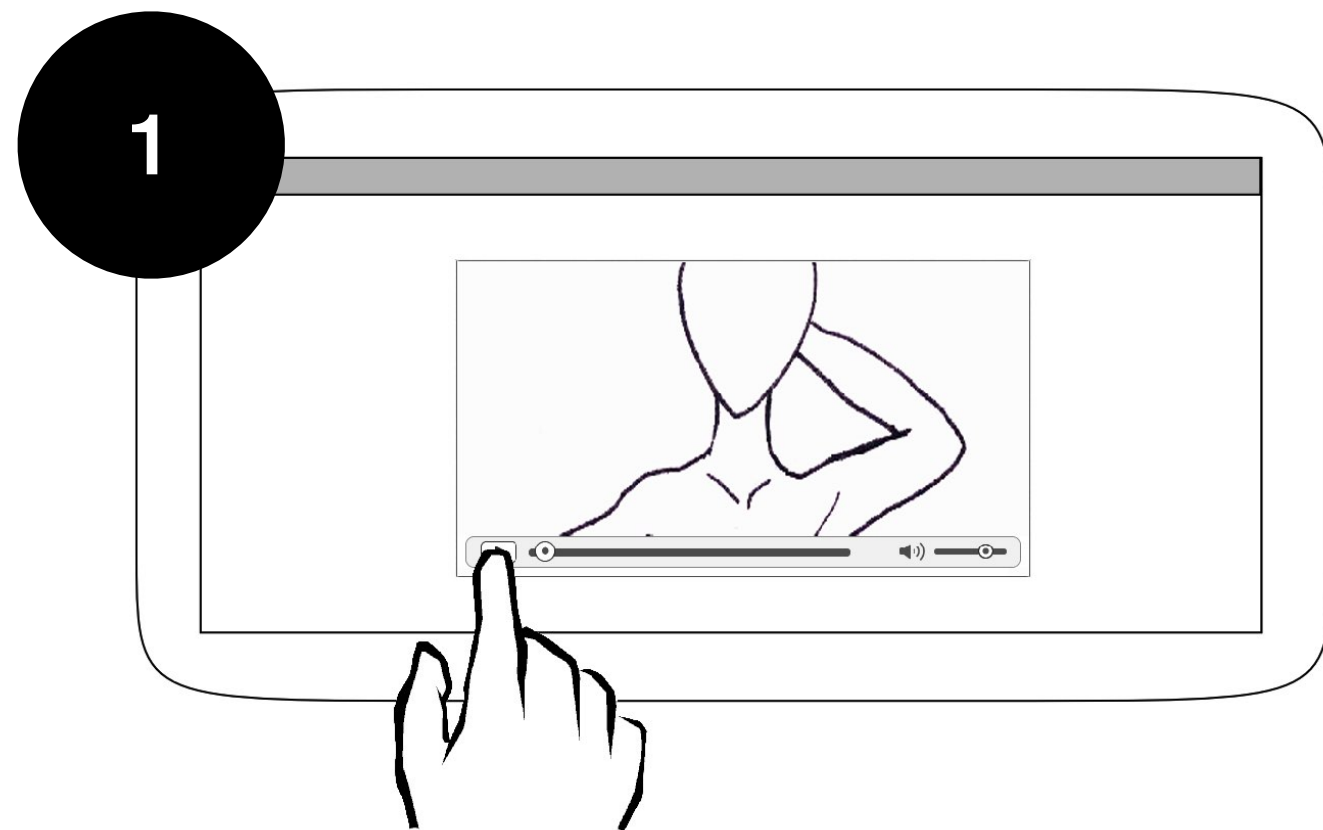
Sensitive Video Detection



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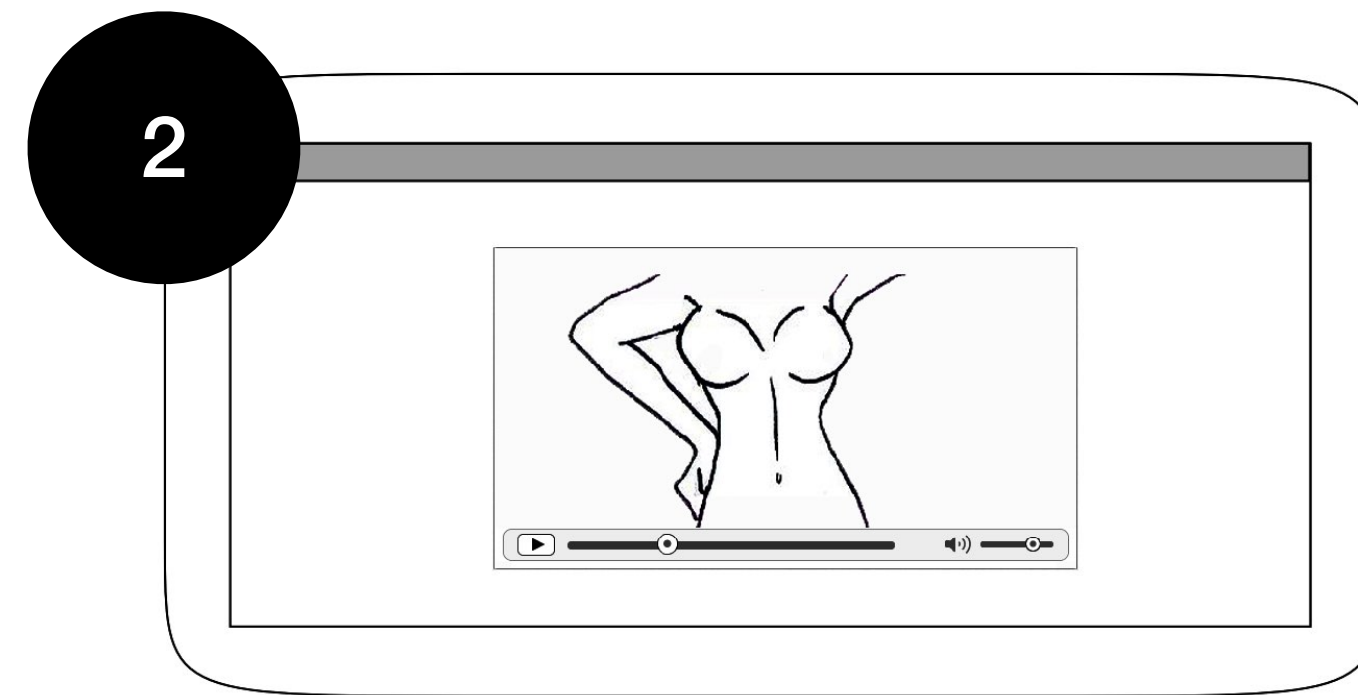
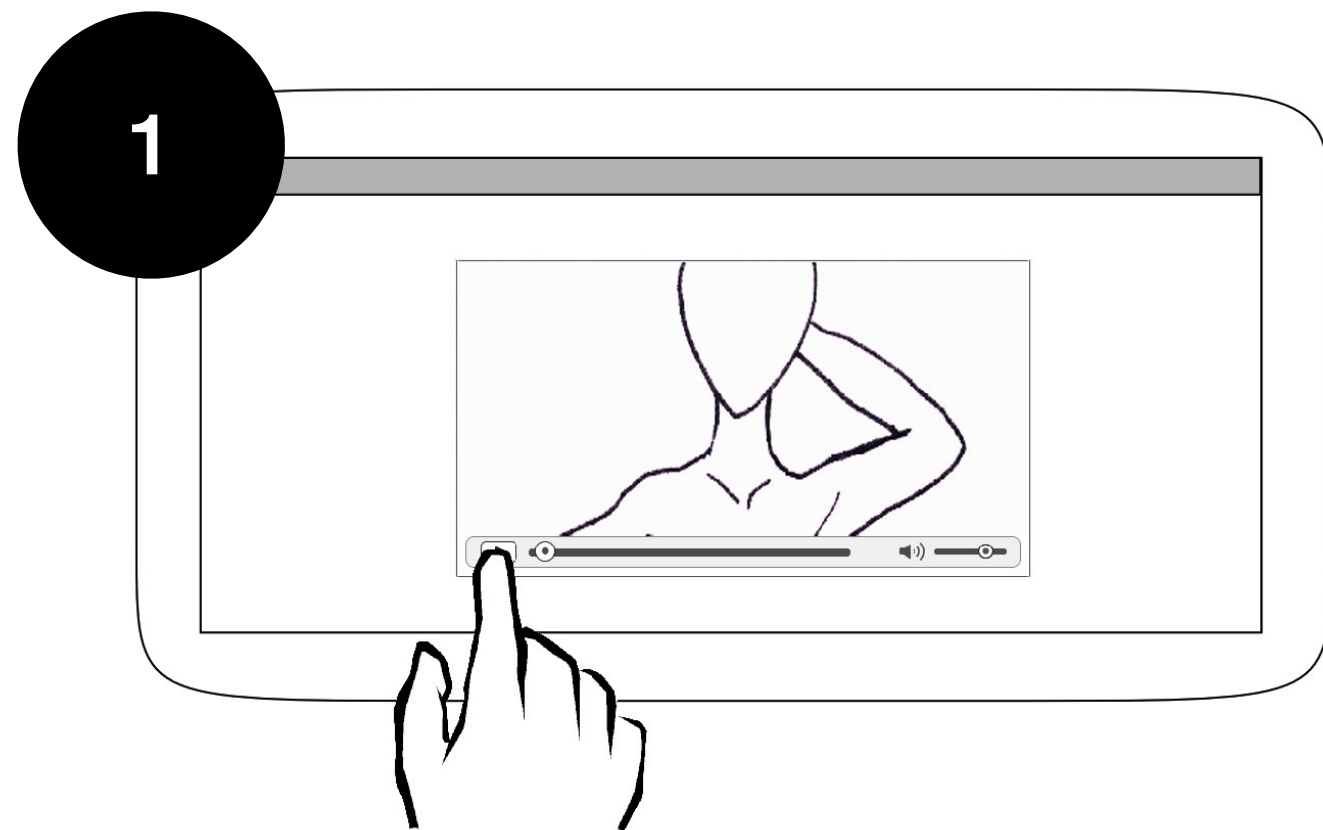
Task

Can a computer detect (or localize) sensitive scenes within the video timeline?



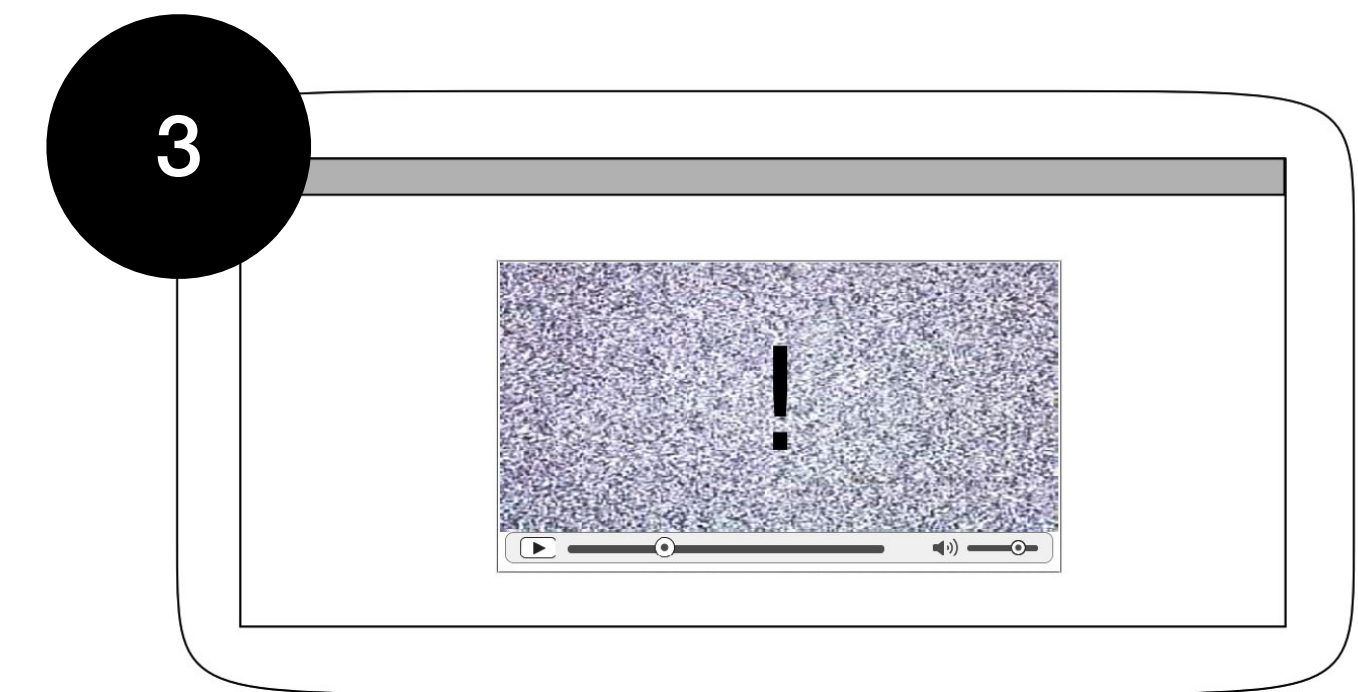
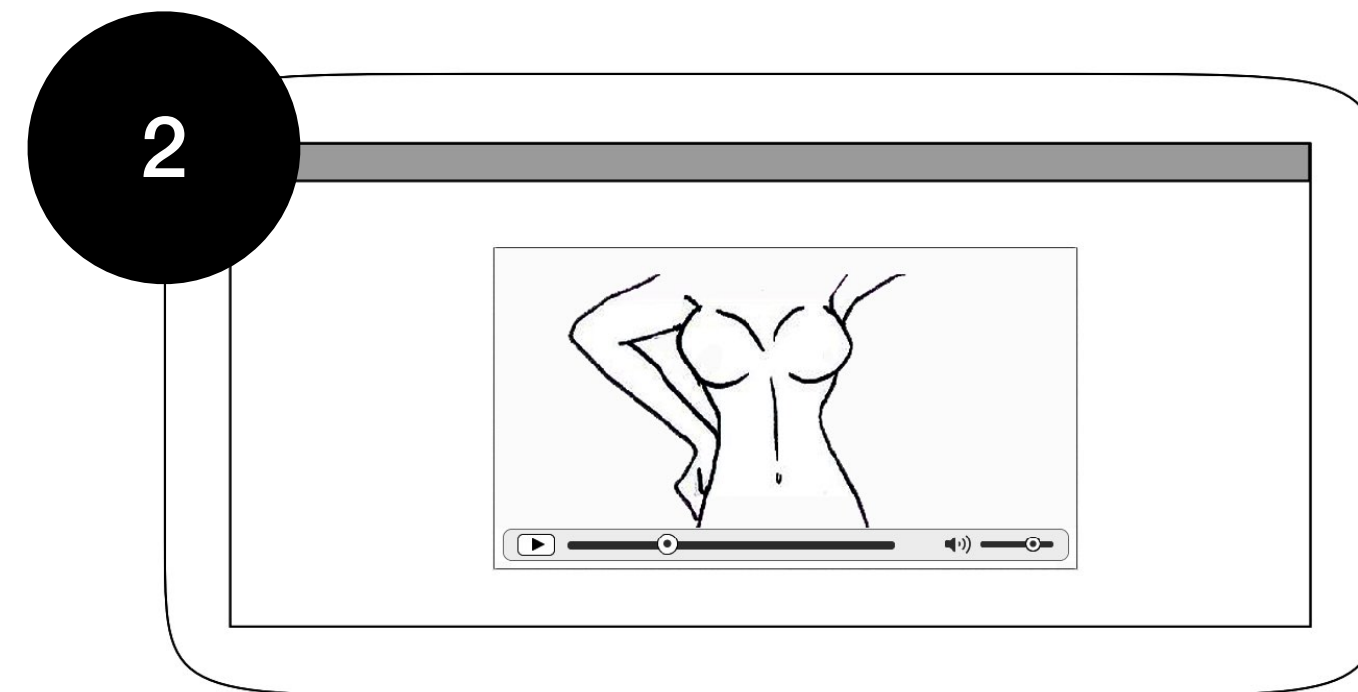
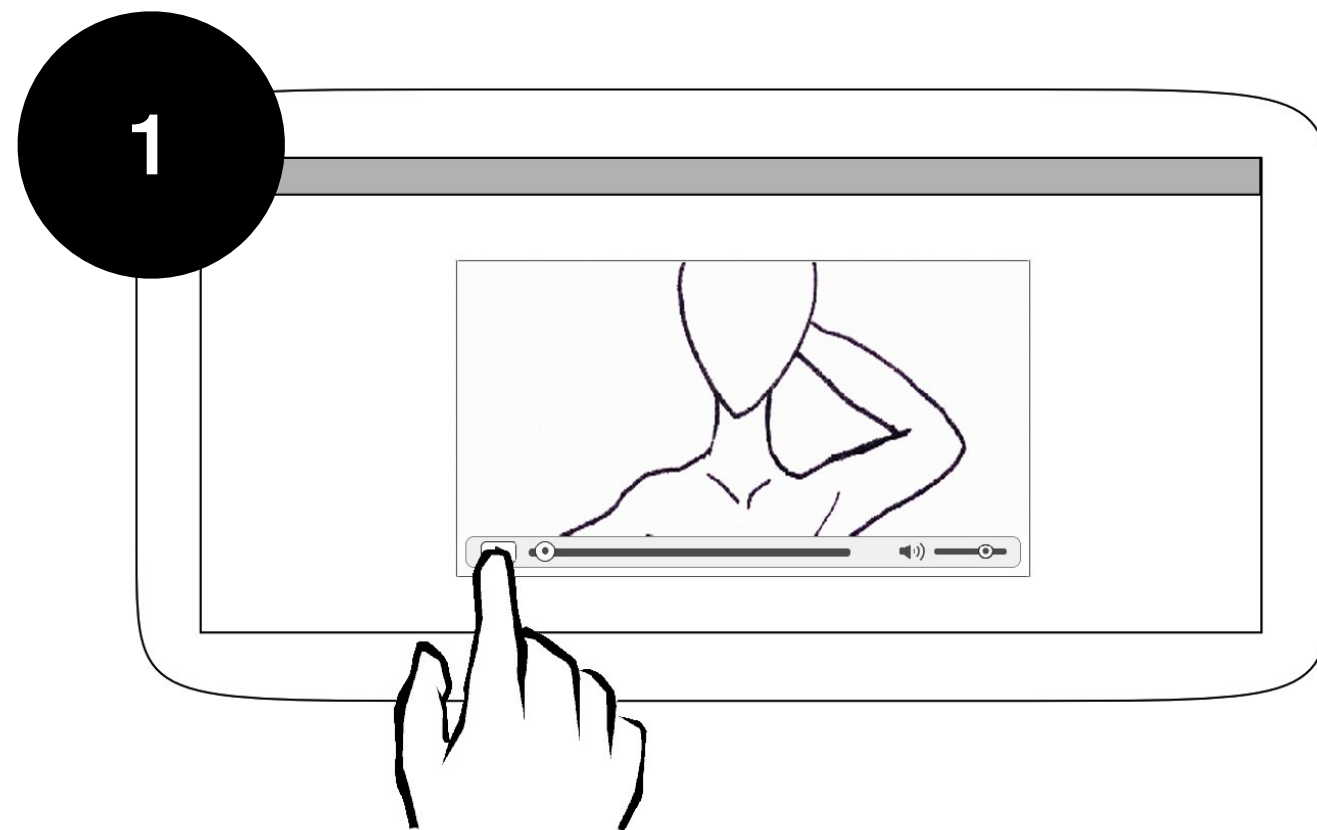
Task

Can a computer detect (or localize) sensitive scenes within the video timeline?



Task

Can a computer detect (or localize) sensitive scenes within the video timeline?



Why do we care?

The Intersect **The Washington Post**

A 12-year-old girl live-streamed her suicide.
It took two weeks for Facebook to take the

The New York Times

Teenager Is Accused of Live-Streaming a Friend's Rape


SOUTH FLORIDA

Miami Herald

Another girl hangs herself while
streaming it live — this time in N

CNN BUSINESS Markets Tech Media Success Perspectives Video

Seven weeks later, videos of New Zealand attack still
circulating on Facebook and Instagram

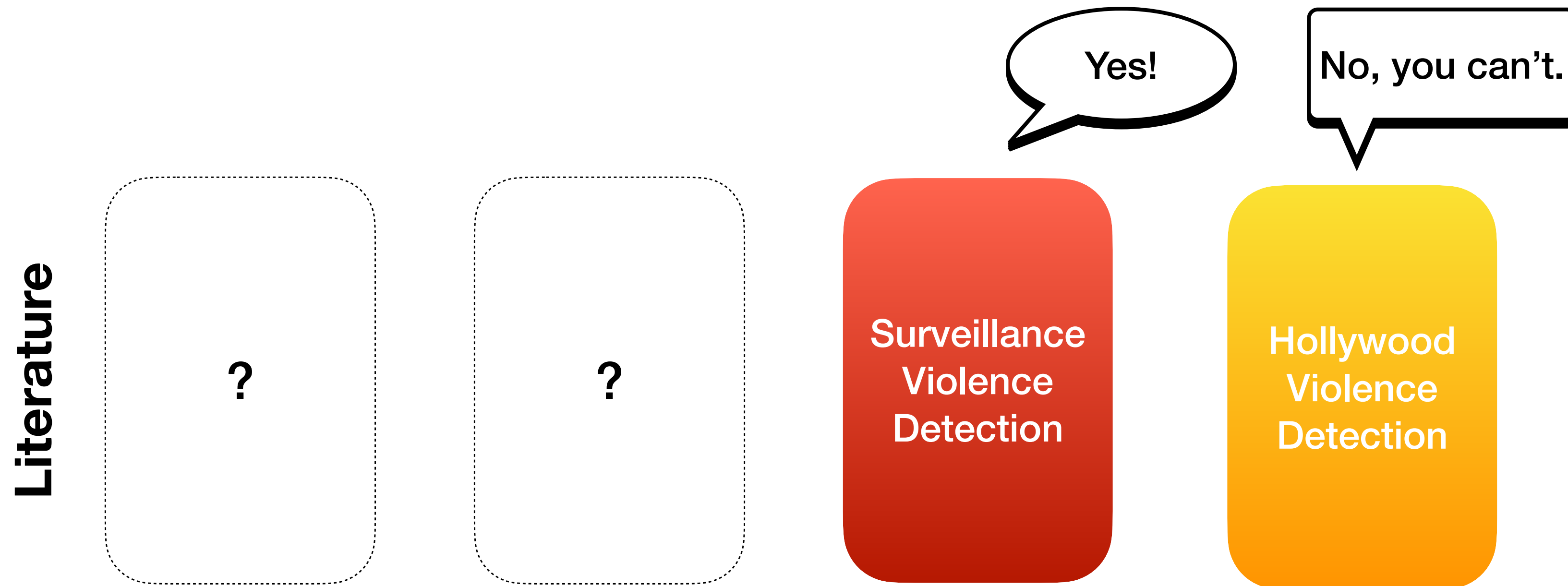
Man shot, killed 
while live-streaming



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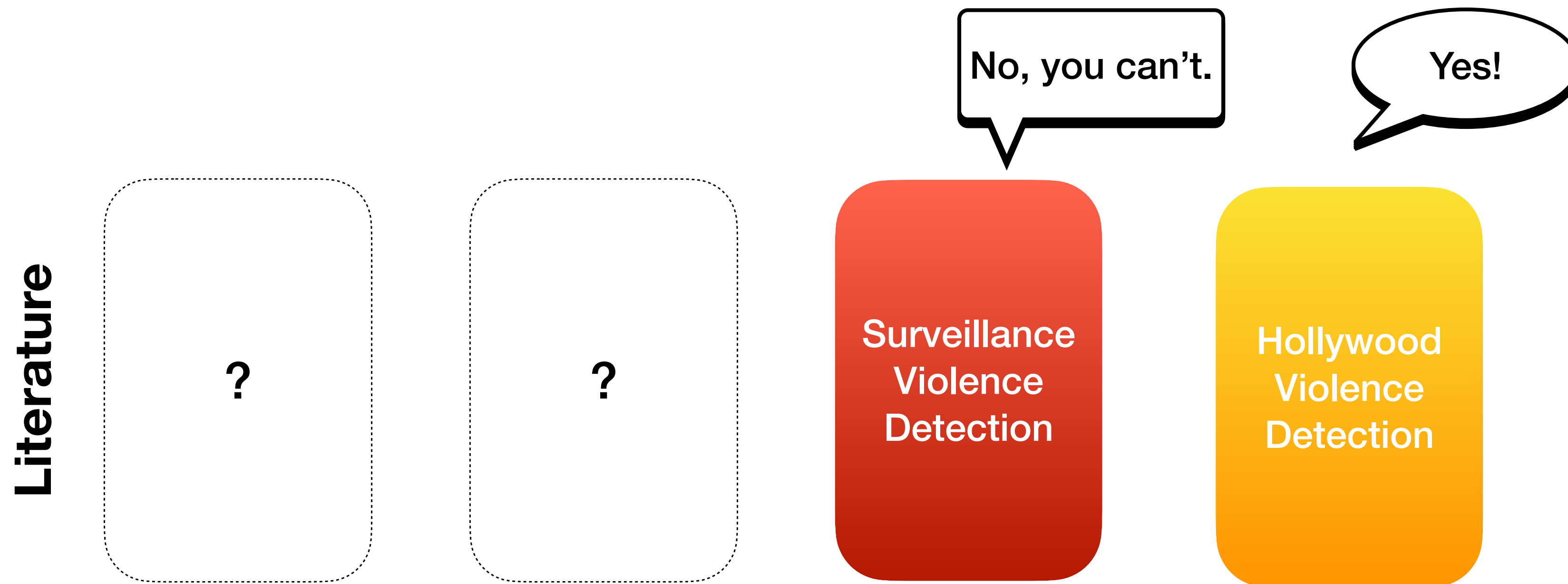
State of the Art

Can a computer detect (or localize) sensitive scenes within the video timeline?



State of the Art

Can a computer detect (or localize) sensitive scenes within the video timeline?



Sponsor's Challenge

Can a computer detect sensitive content other than violence?

Literature

?

?

Surveillance
Violence
Detection

Hollywood
Violence
Detection

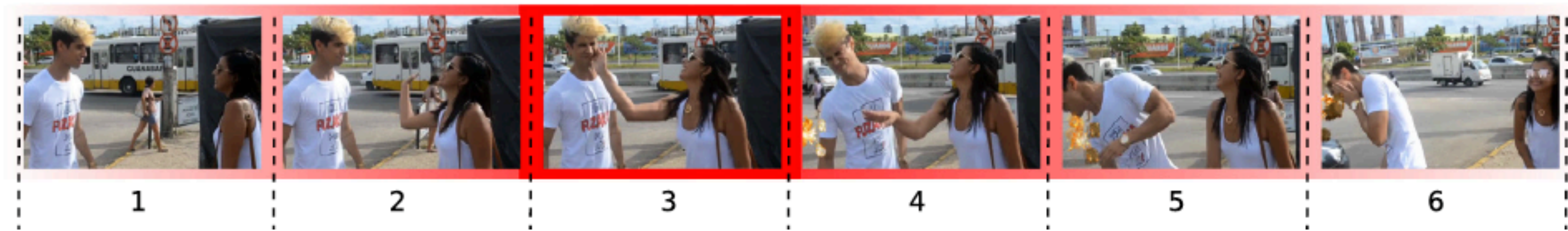
Sponsor's Challenge

Can a computer detect sensitive content other than violence?



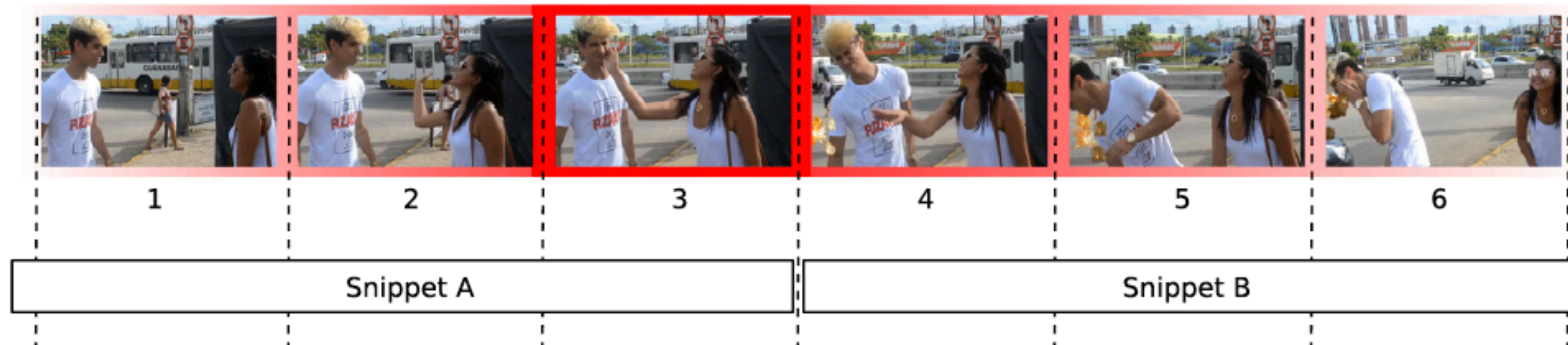
Proposed Solution

Video Snippet Segmentation



Proposed Solution

Video Snippet Segmentation



Non-overlapping Snippets

Proposed Solution

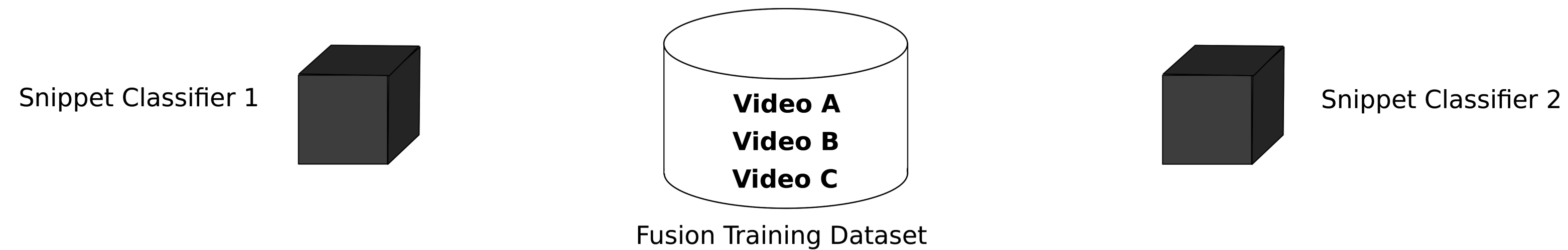
Video Snippet Segmentation



Overlapping Snippets

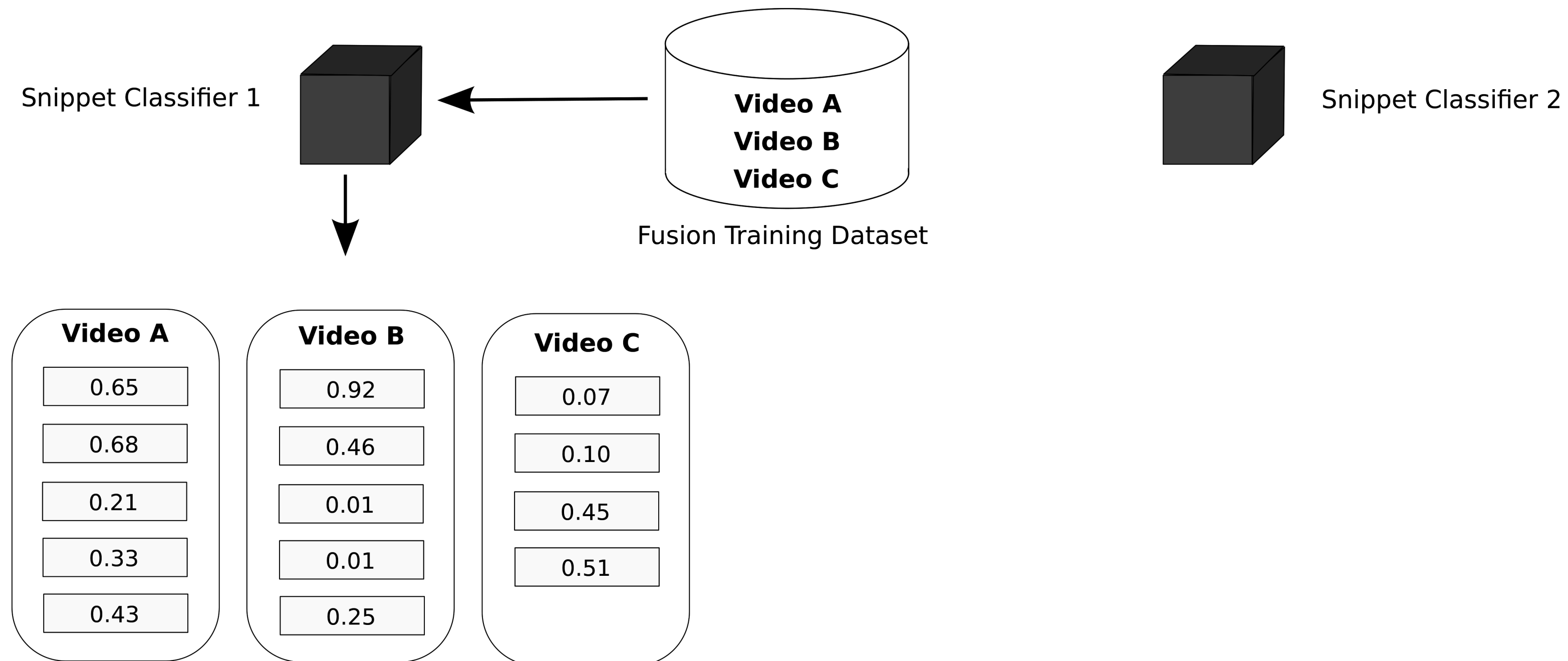
Proposed Solution

Snippet Classification



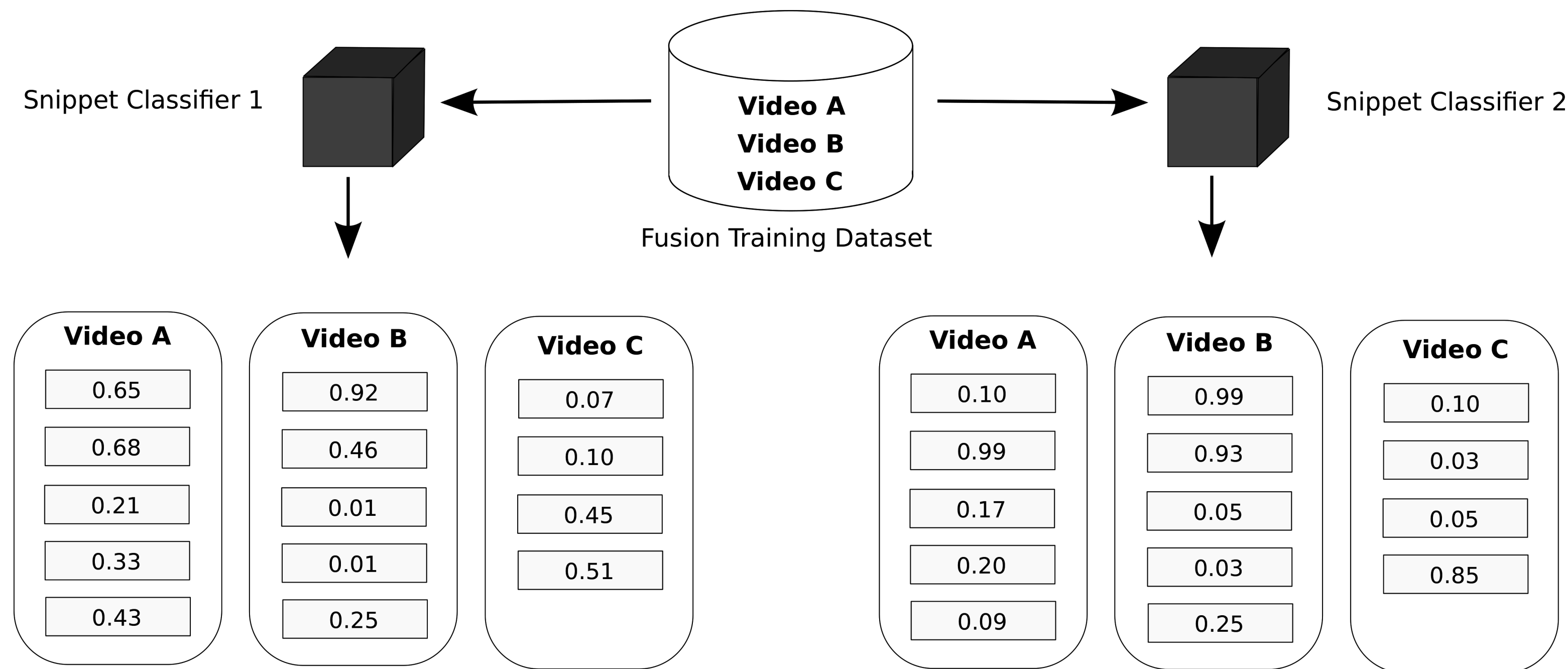
Proposed Solution

Snippet Classification



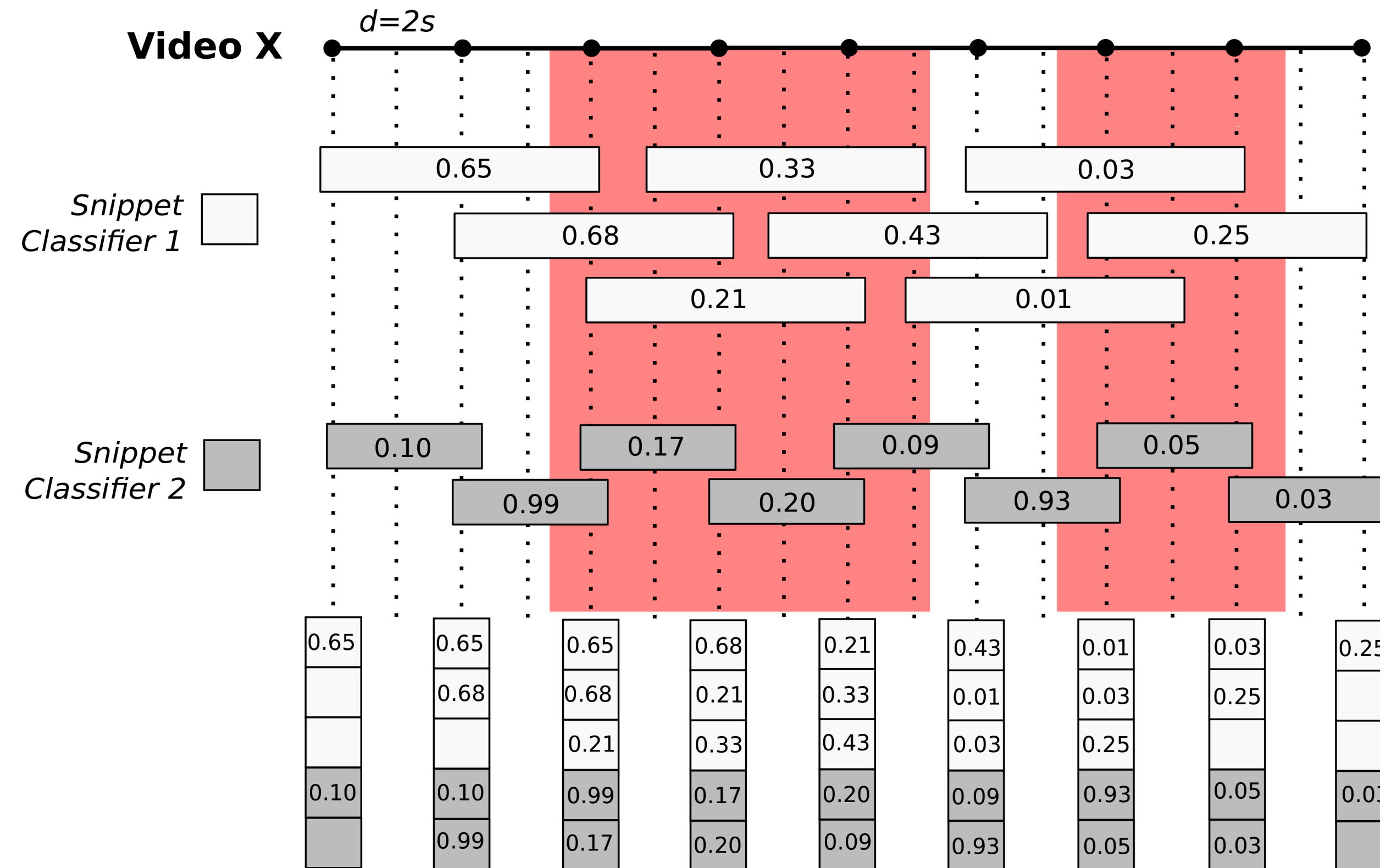
Proposed Solution

Snippet Classification



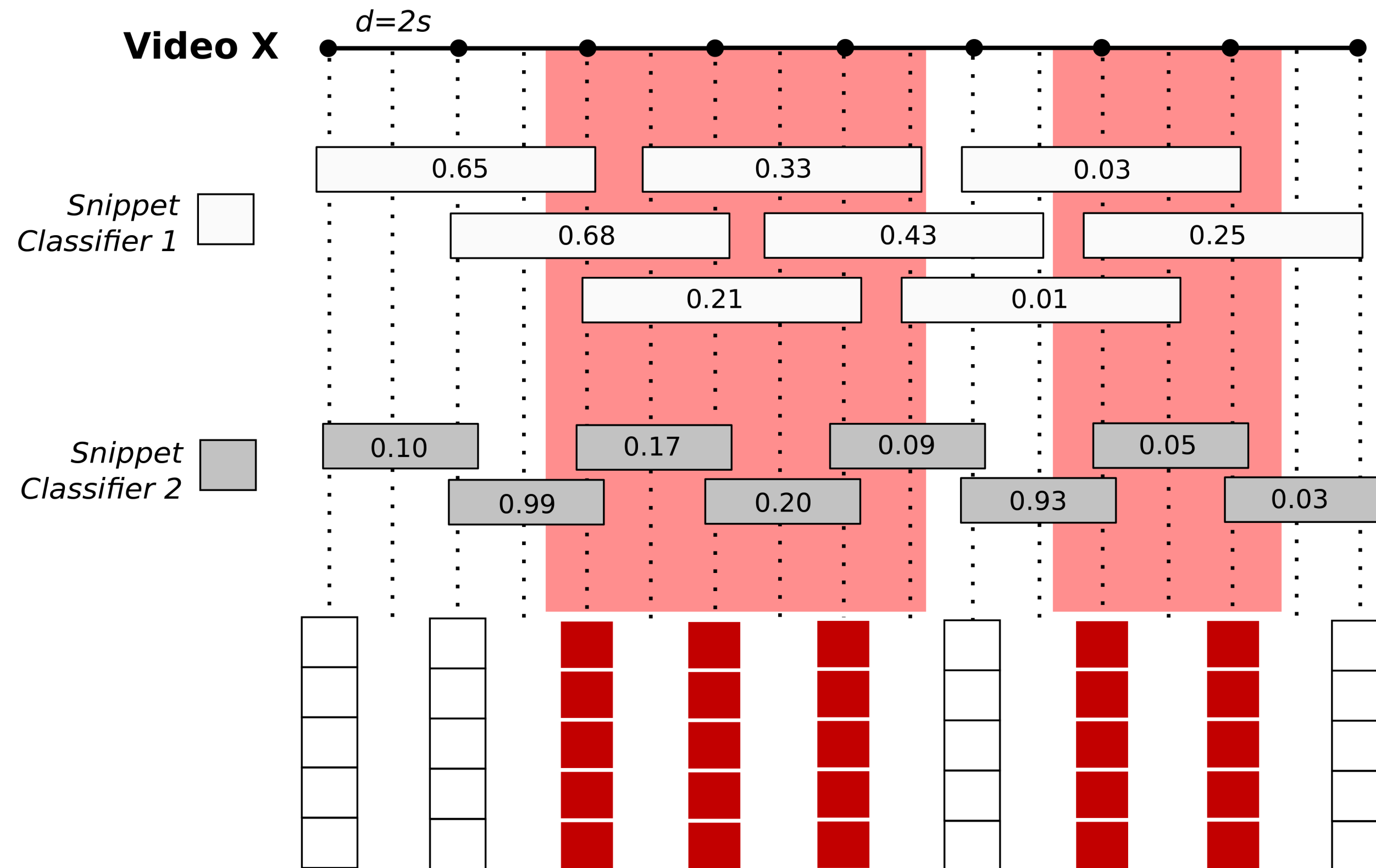
Proposed Solution

Late Fusion of Snippet Classifiers



Proposed Solution

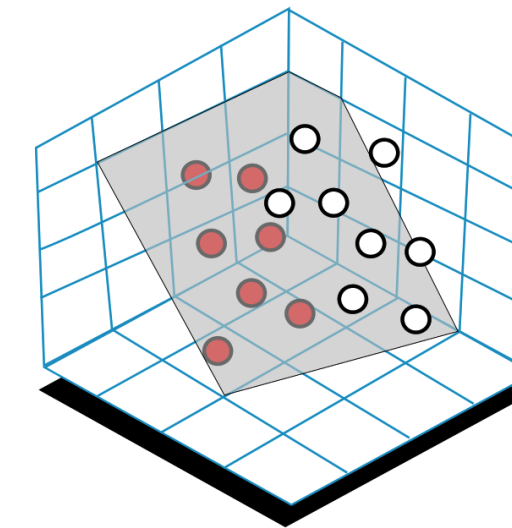
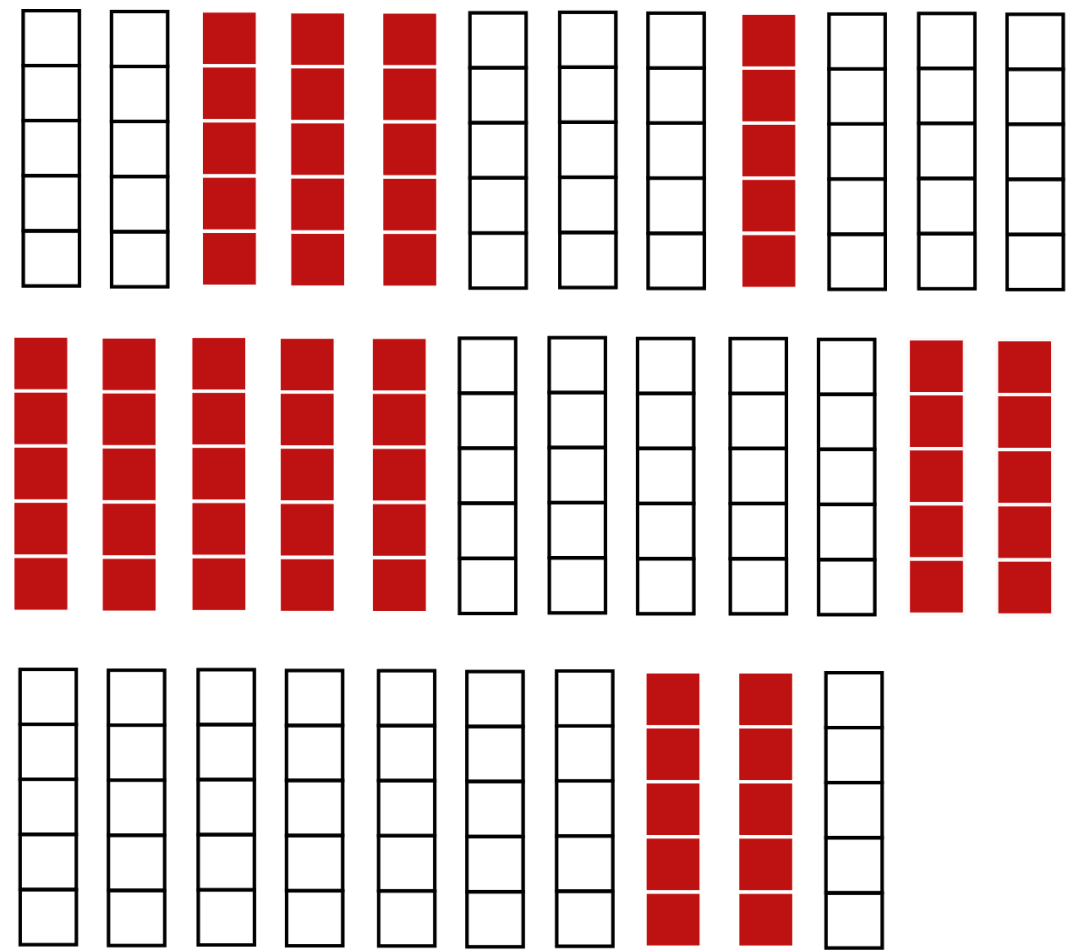
Late Fusion of Snippet Classifiers



Proposed Solution

Classification of Fusion Vectors

Training Time

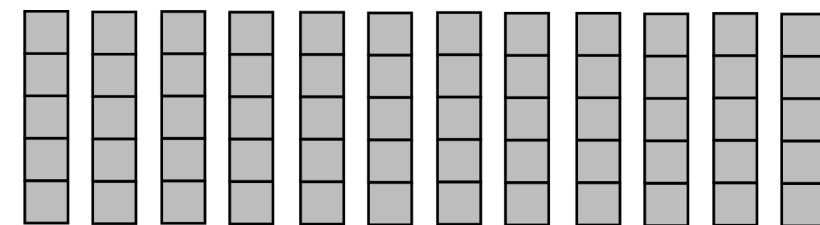


fusion classification model

Proposed Solution

Classification of Fusion Vectors

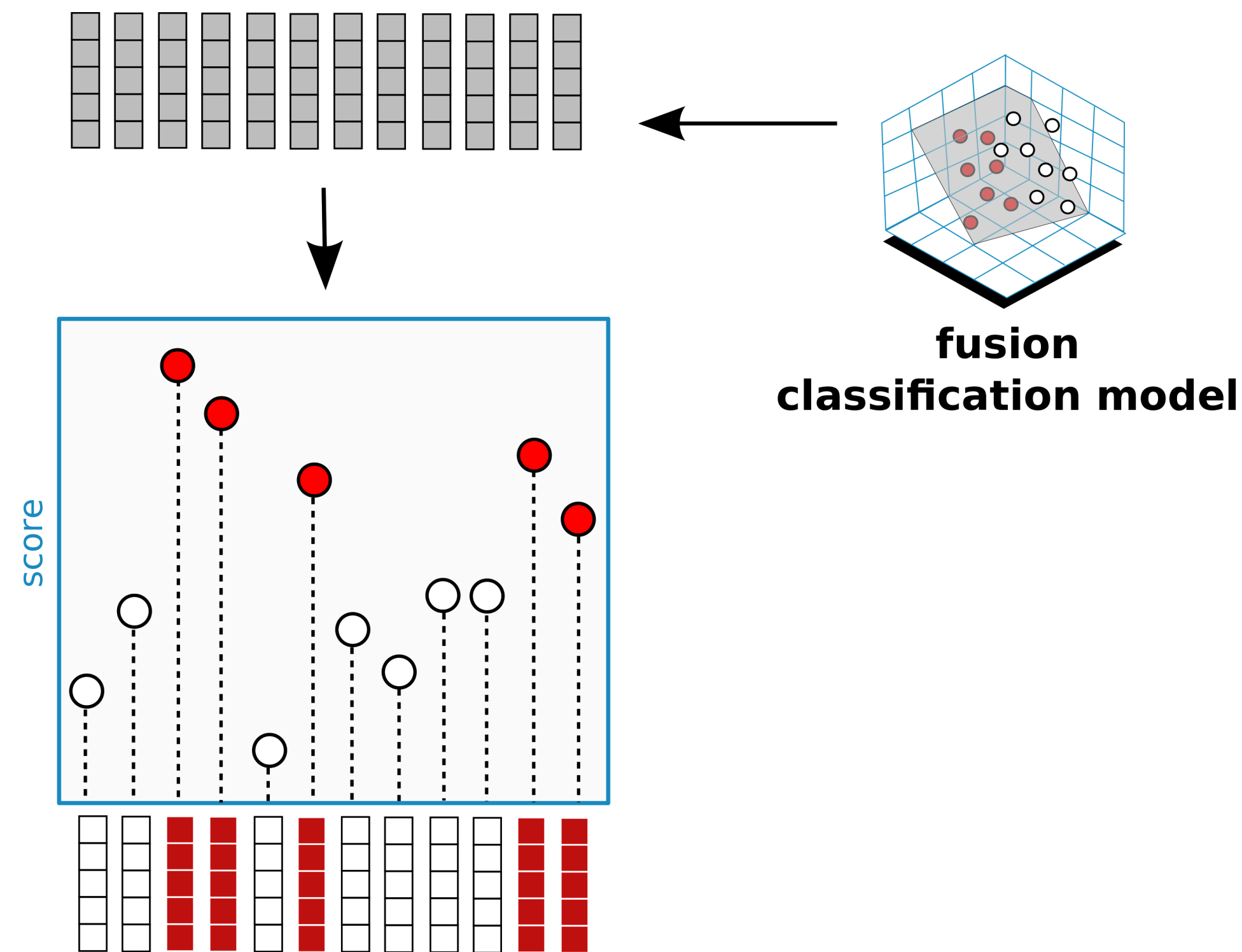
Inference Time



Proposed Solution

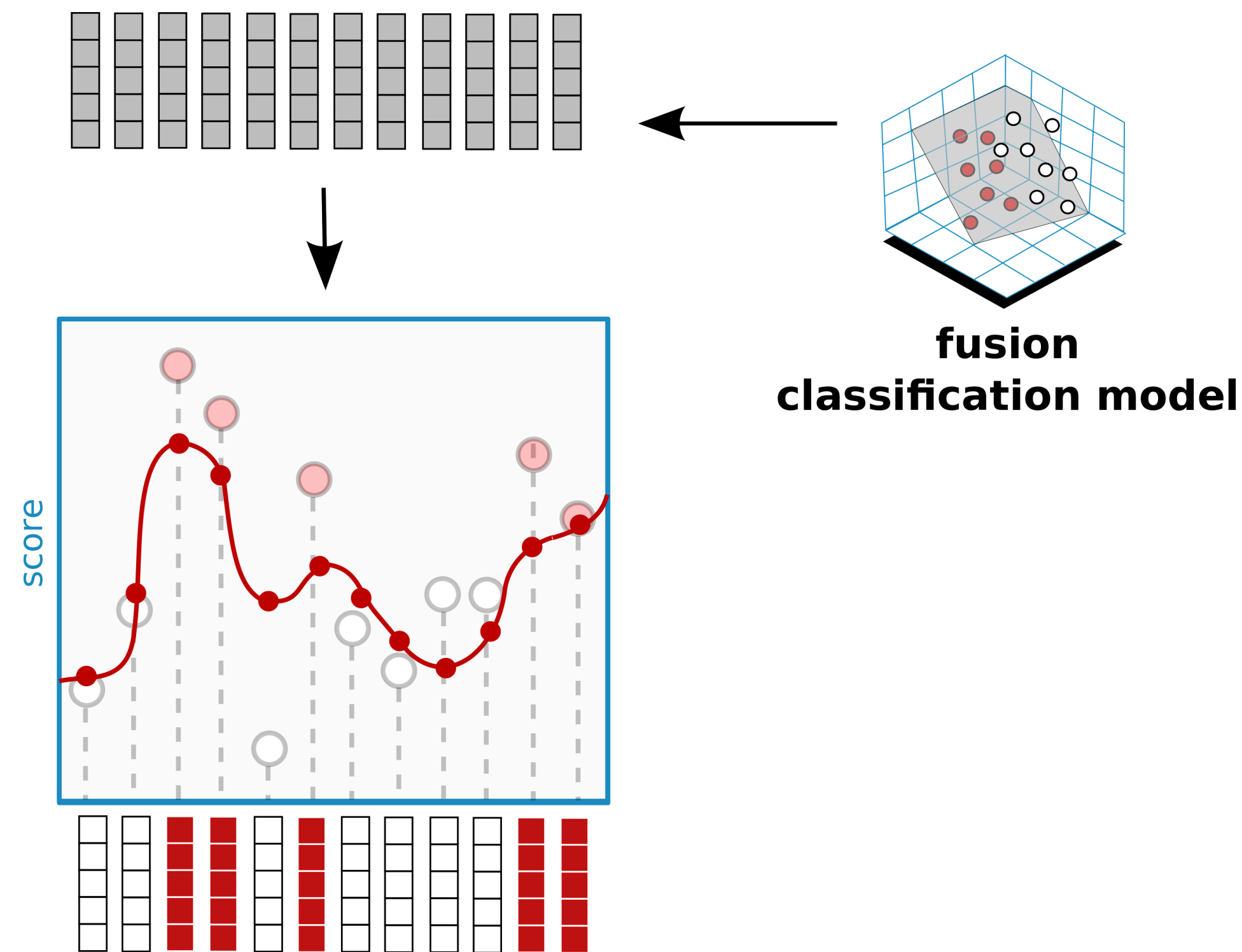
Classification of Fusion Vectors

Inference Time



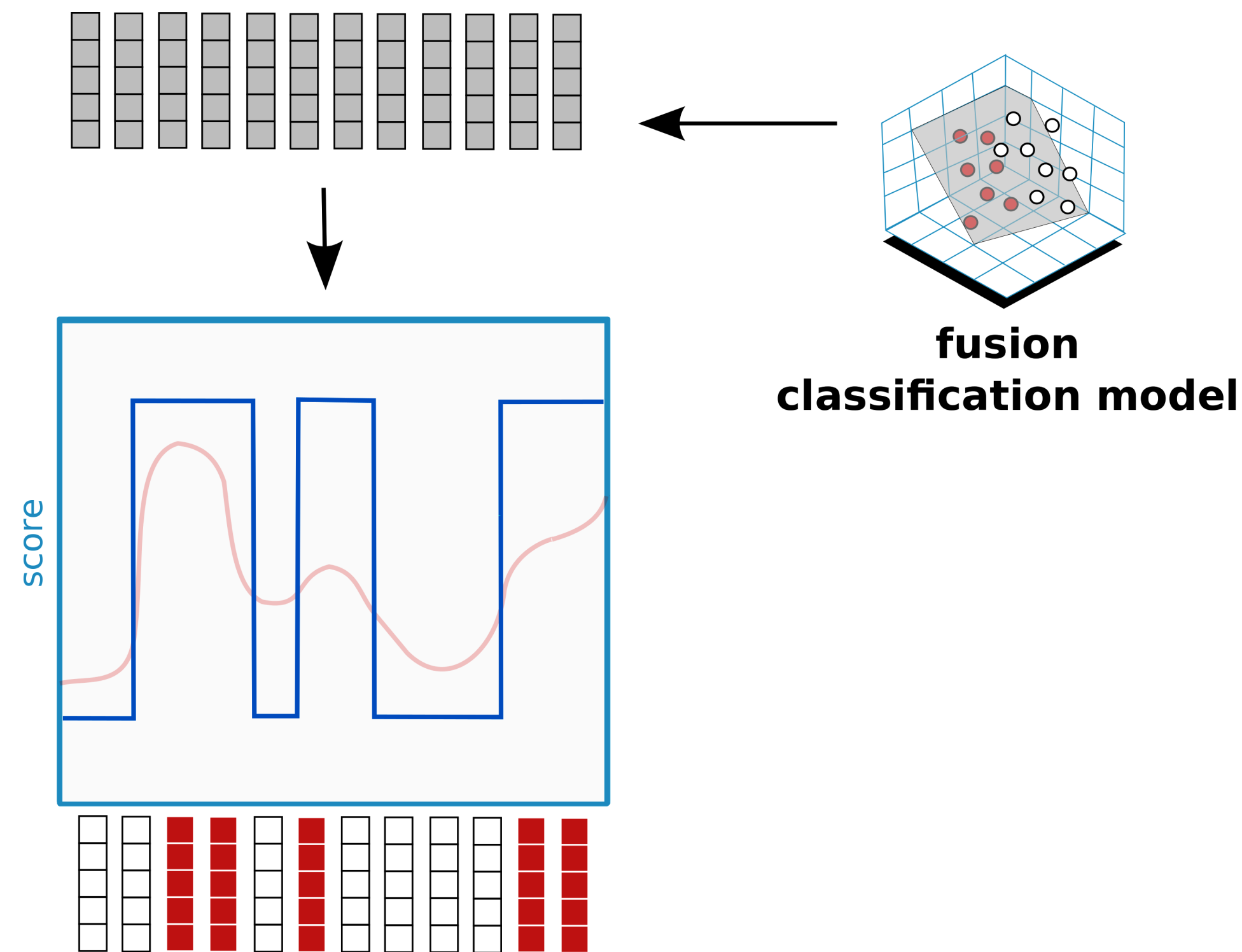
Proposed Solution

Classification Score Smoothing Inference Time



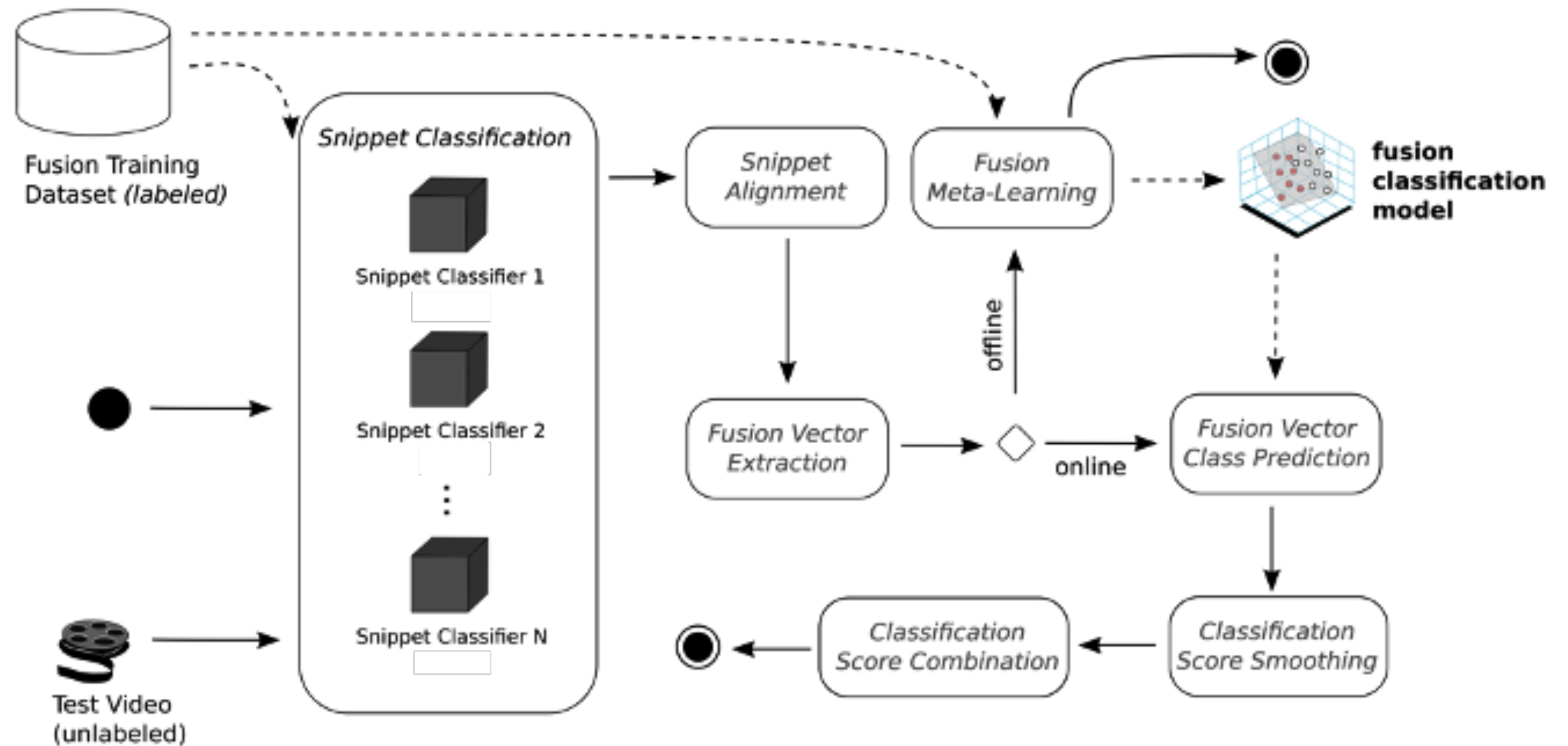
Proposed Solution

Classification Score Combination Inference Time



Proposed Solution

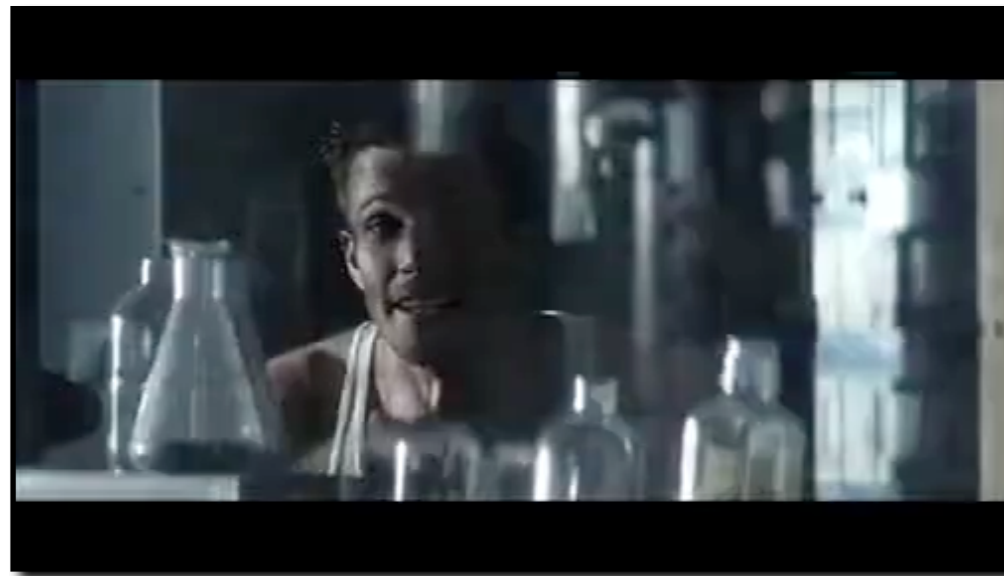
Summary



Violence Results

Dataset

MediaEval 2014



“Content one would not let a child see.” [2]

Training: 24 movies
Test: 7 movies



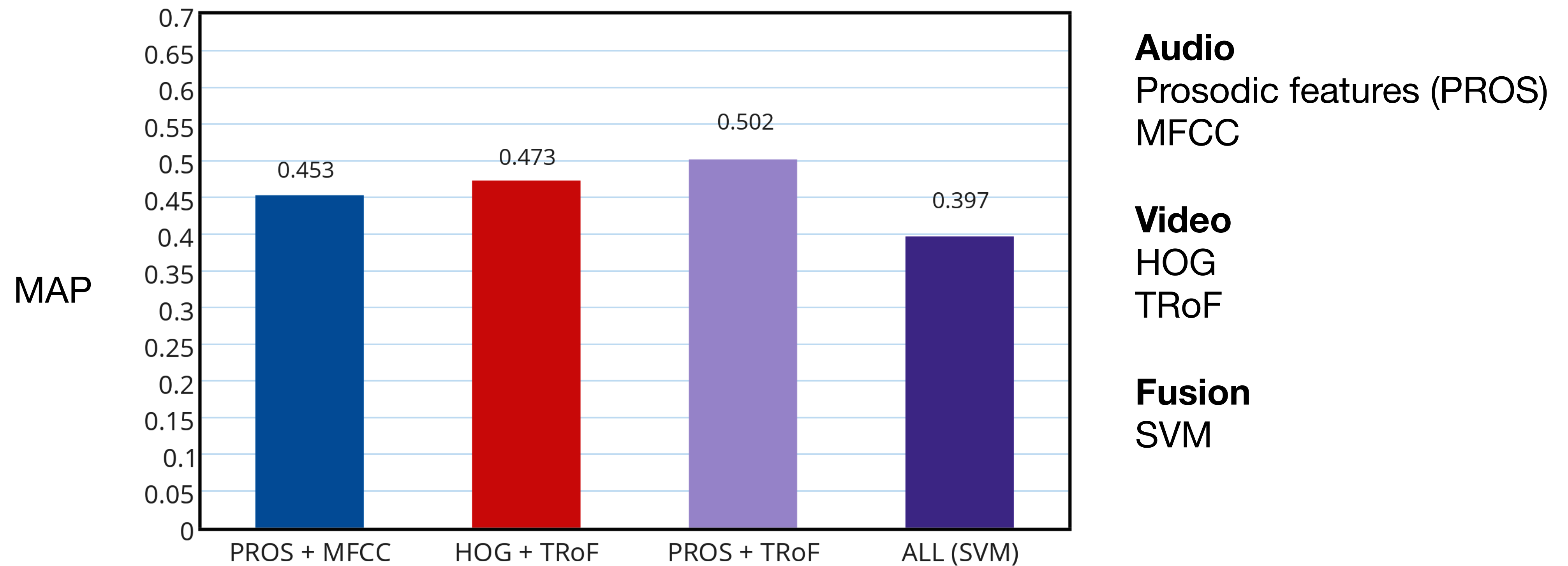
Frame-level
annotation.

Metric: Mean Average
Precision (MAP)

[2] Demarty et al., *Benchmarking Violent Scenes Detection in Movies*. In IEEE CBMI, 2014

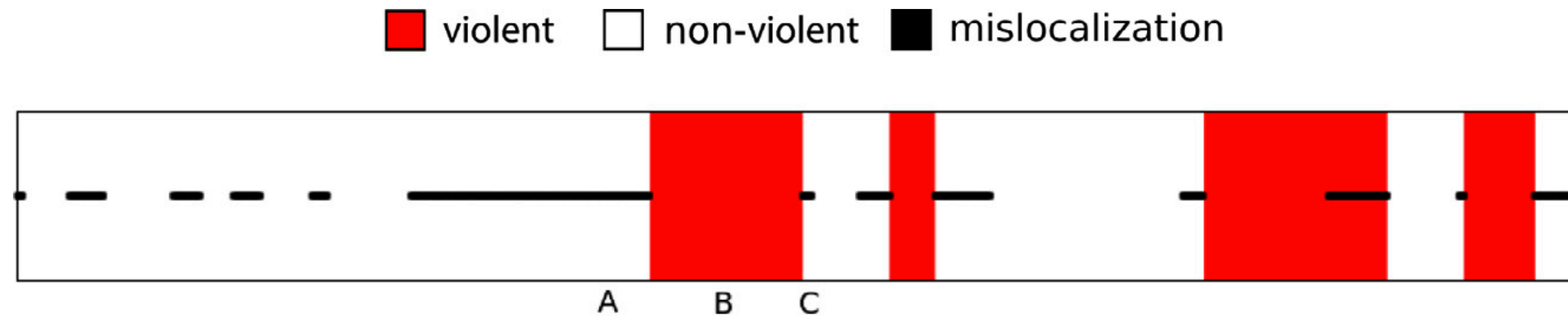
Violence Results

Multimodal Fusion (Audio + Video)



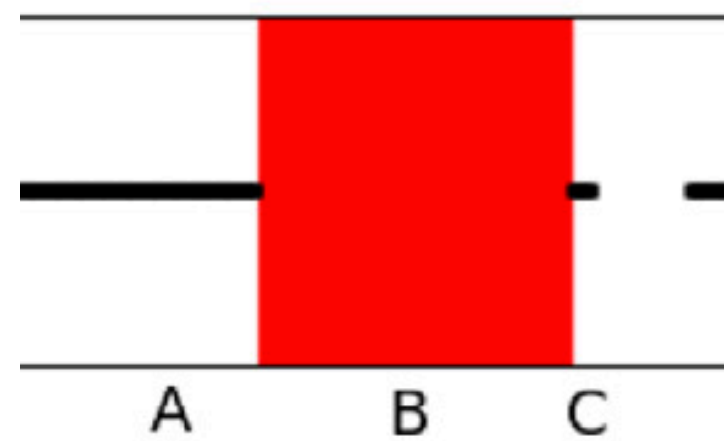
Violence Results

Qualitative Results



Violence Results

Qualitative Results



(a) A_1 : non-violent



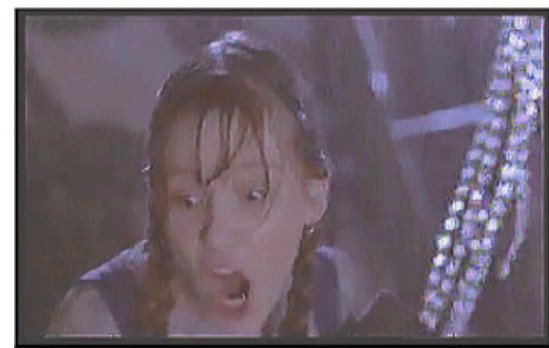
(b) A_2 : non-violent



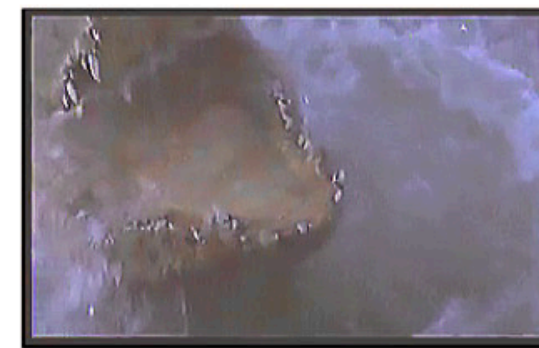
(c) A_3 : non-violent



(d) A_4 : non-violent



(e) B_1 : violent



(f) B_2 : violent



(g) B_3 : violent



(h) B_4 : violent



(i) C_1 : non-violent



(j) C_2 : non-violent



(k) C_3 : non-violent



(l) C_4 : non-violent

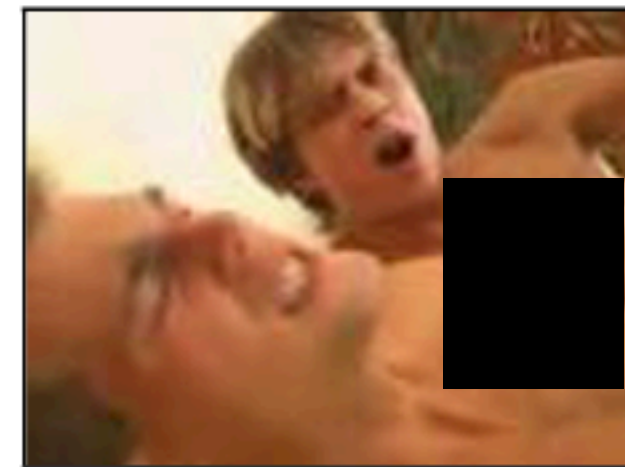
Pornography Results

Dataset

Porn-2k



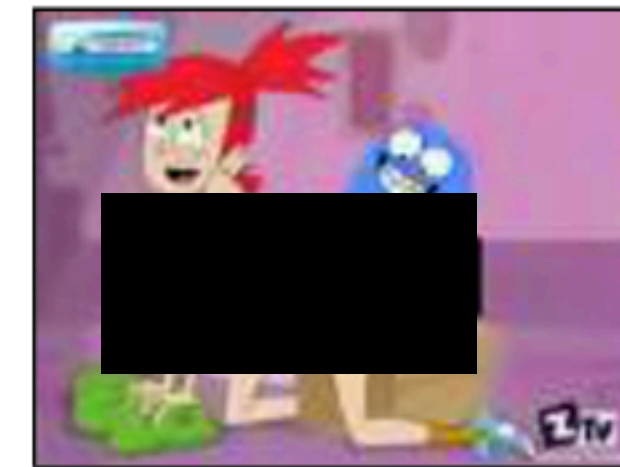
(a)



(b)



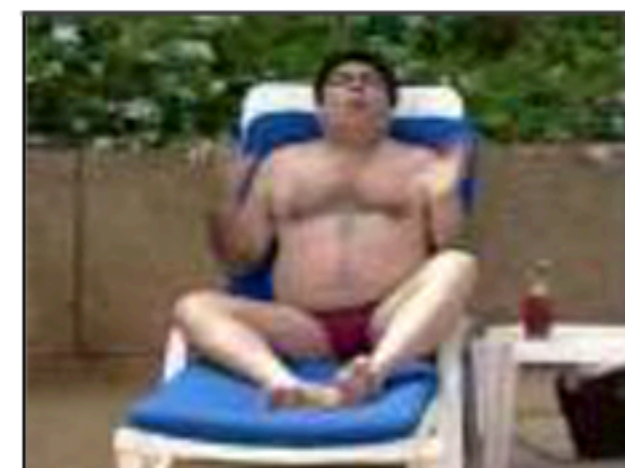
(c)



(d)



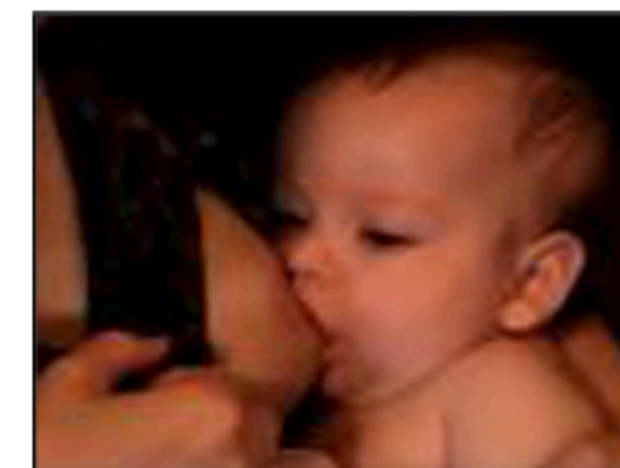
(e)



(f)



(g)



(h)

“Any explicit sexual matter with the purpose of eliciting arousal.” [1]

140h of video

Frame-level annotation

Metric: frame-level classification accuracy.

YouTube

Vine

vimeo

Porn sites

[1] Short et al., *A review of internet pornography use research: Methodology and content from the past 10 years*. *Cyberpsychology, Behavior, and Social Networking* 15, 2012



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Pornography Results

Dataset

Porn-2k

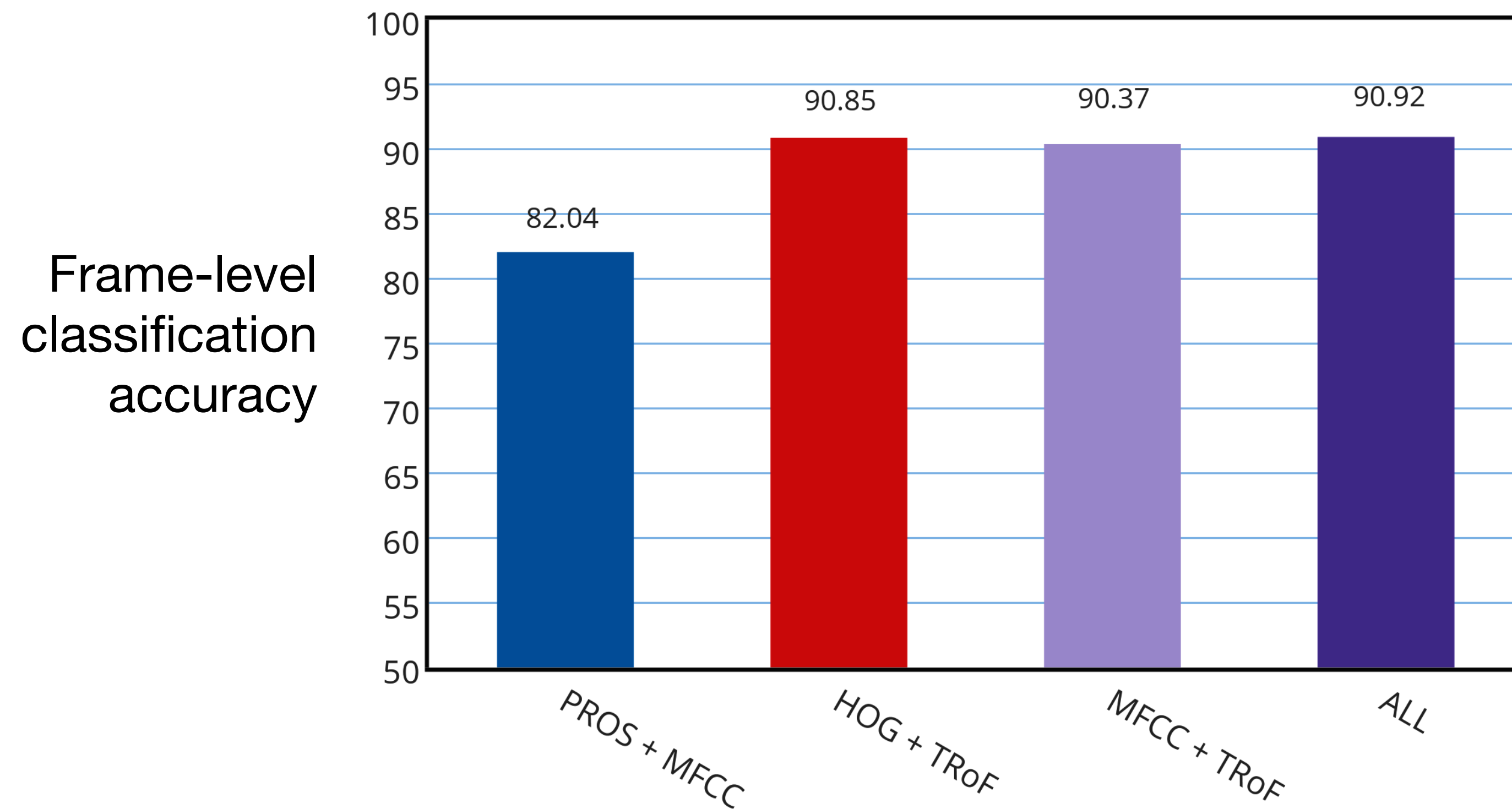


Frame-level
annotation tool.

Pornography Results

Multimodal Fusion

(Audio + Video)



Audio

Prosodic features (PROS)

MFCC

Video

HOG

TRoF

Fusion

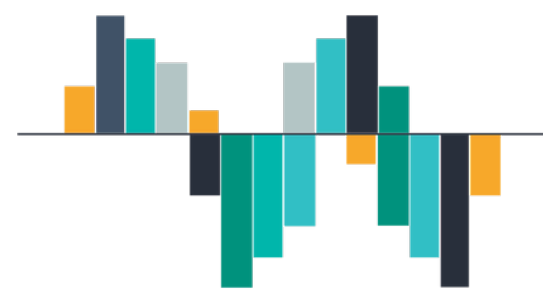
SVM



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Pornography Results

Qualitative Results



The solution misses 5 minutes
in every hour of pornographic content

PROS



MFCC



HOG



TRoF



ALL



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Accomplishments



3 Journals



3 Conference Papers



1 patent



Frame-level annotated
porn video dataset



Violent Scenes
Detection Competition



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Future Work

Cryptography and Machine Learning

Can Machine Learning techniques be trained over sensitive encrypted data?

Advantages

Human intelligibility is destroyed by encryption.

Applications

Child pornography detection and other sensitive data.

Hint

<https://bit.ly/2YGEOmD>

