LIFAT laboratory
University of Tours

Performance Evaluation for Scalable Partial Video Copy Detection

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Presented by LE Van Hao

Jury Members

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Outline

Introduction to partial video copy detection (PVCD)

Introduction (1/3)

- Partial video copy detection (PVCD) aims at finding one/more short video segments which have been transformed into a longer video.

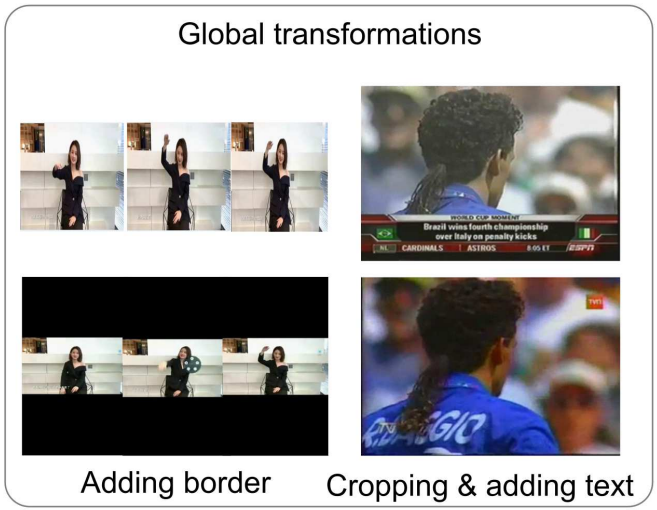
2 short video segments a long video

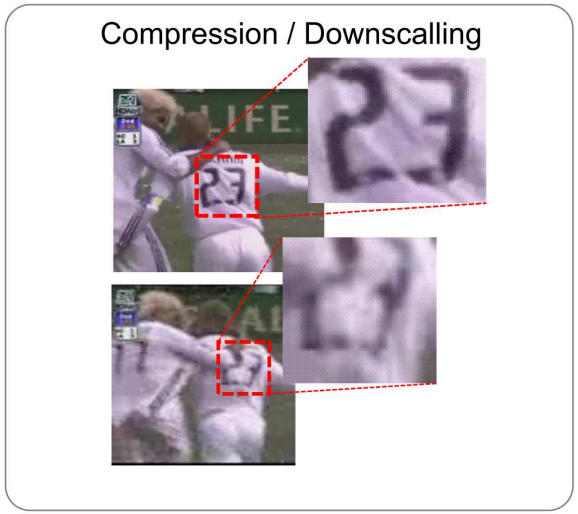
- Applications: copyright protection, video retrieval & monitoring, etc.
- A key topic in Computer Vision [Guzman, 2019; Liu, 2021; Tan, 2022], Meta AI contest 2023[1]

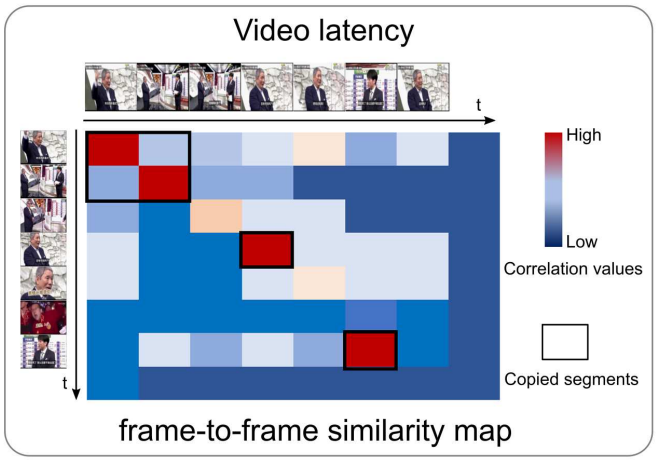
[1] CVPR: https://sites.google.com/view/vcdw2023/video-similarity-challenge

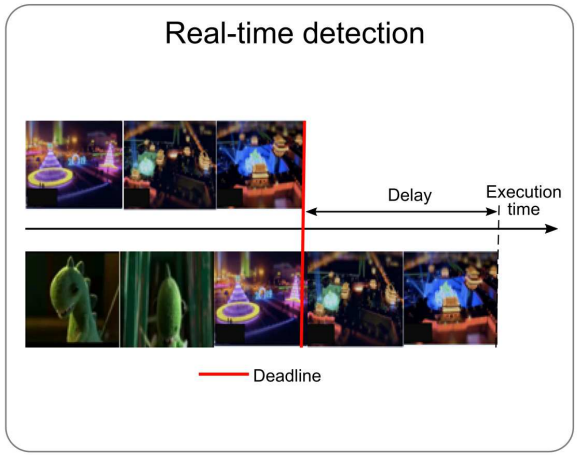
Introduction (2/3)

- Diversity in detection problems [Kordopatis, 2017; Liu, 2021; Tan, 2022]



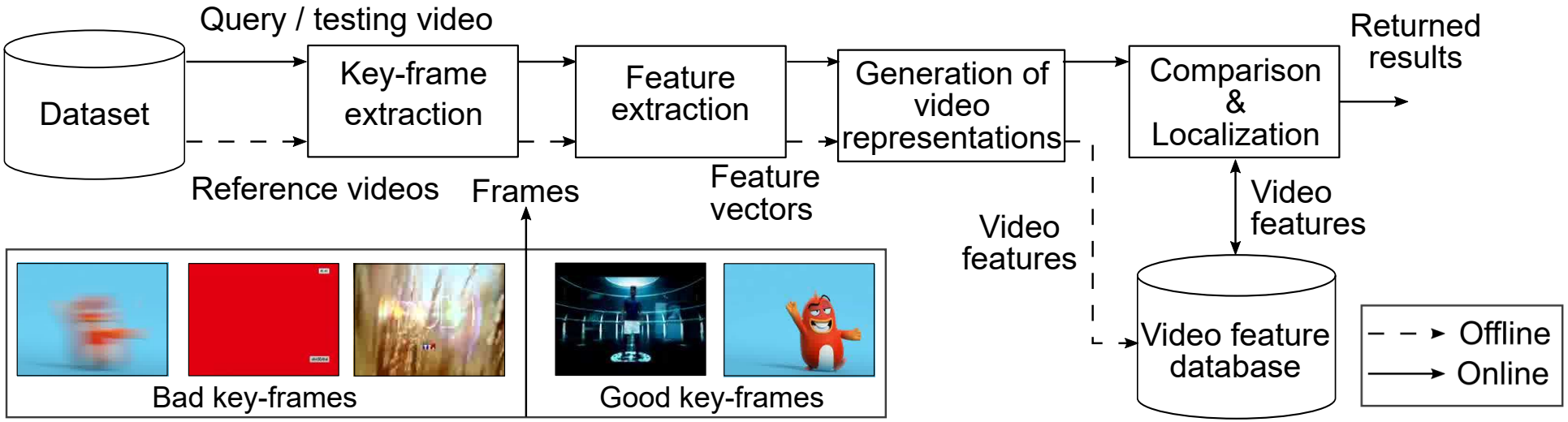






Introduction (3/3)

- Common components of a typical PVCD system [Jiang, 2016; Hu, 2019]



- Top competitive systems use 2D CNNs [Han, 2021; He, 2022].
- Little discussion on improvement & characterization of these features [Kordopatis-Zilos, 2017; Hu, 2019]
- Dataset's limitations[2] avoid fine characterization/training [He, 2022]

[2] low scalability, imbalanced, temporal accuracy, uncontrolled noise

Part I: A large-scale TV dataset for PVCD

Part I: state-of-the-art PVCD datasets

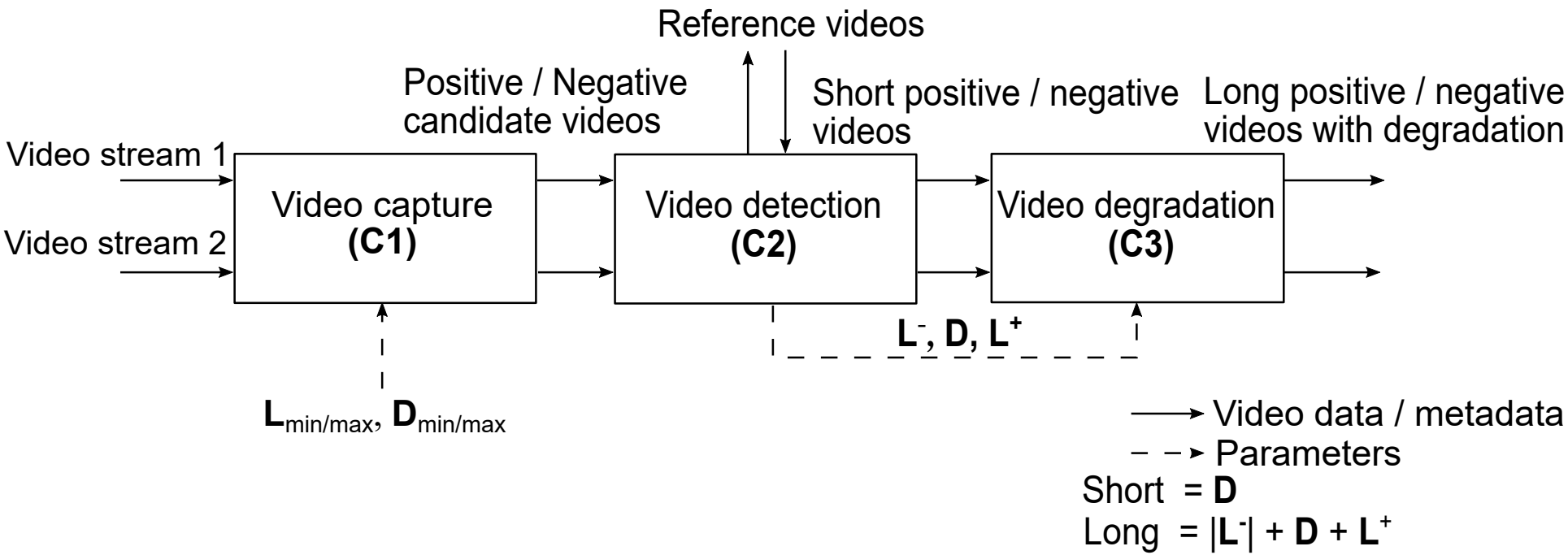
- 3 relevant datasets: VCDB, FIVR-PVCD, VCSL
- Protocols: Web videos with real degradations, manual annotation

Dataset	VCDB [Jiang, 2014]	FIVR-PVCD [Han, 2021]	VCSL [He, 2022]
References	small	small	small
Positive pairs	small	middle	**large**
Annotation cost	+	++	+++
Negative videos	middle	no	no
Overall scale	middle	middle	**large**
Degradation	real	real	real
Annotation level	segment	segment	segment
Timestamps (s)	1	1	1

- None of them fully reflect the real-world complexities of PVCD.

Part I: Our protocol (1/7)

- We propose a new protocol extended from [Joly, 2007; Law-To, 2007].
- 3 main components of our protocol:
  - **(C1)** captures videos with a TV workstation,
  - **(C2)** annotates reference, positive, and negative videos,
  - **(C3)** generates test sets with synthetic degradations.



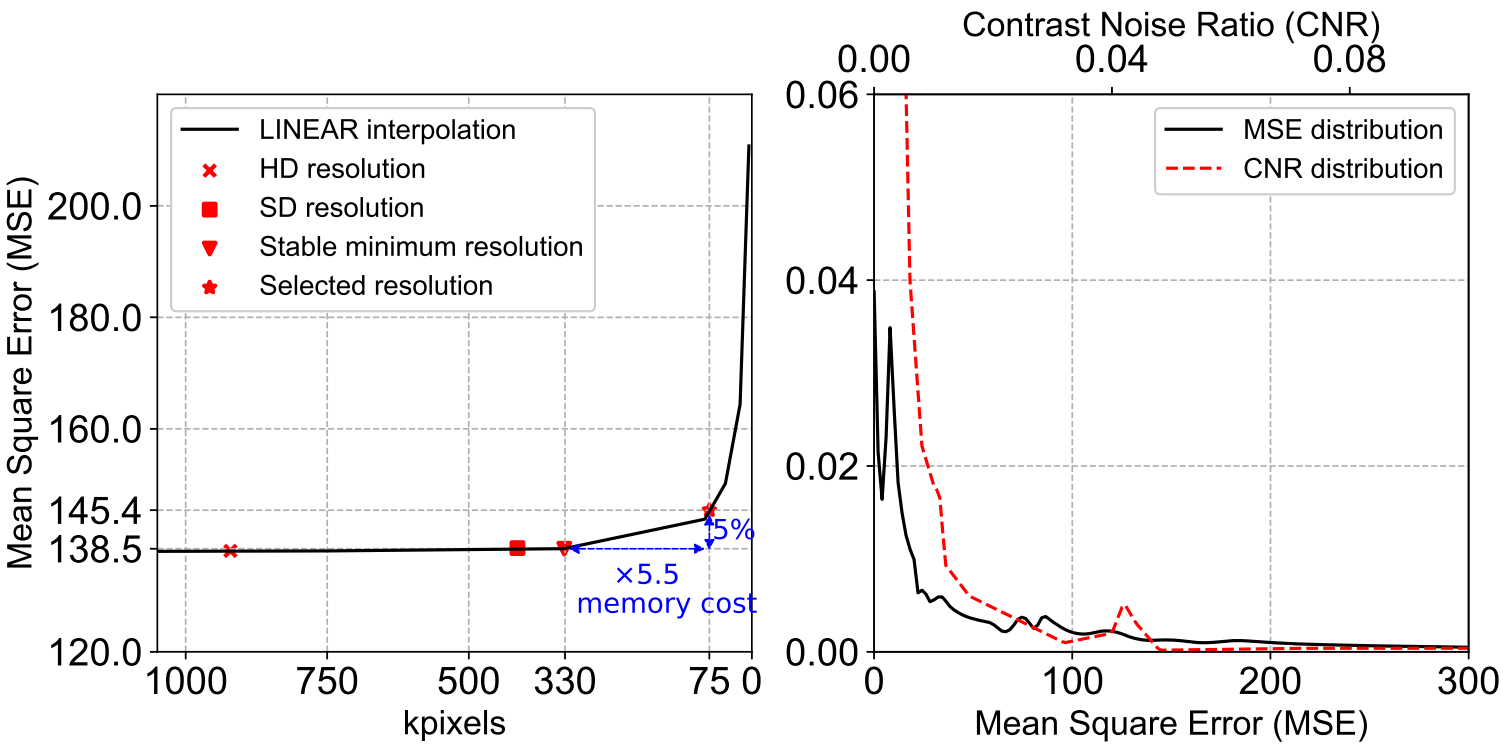
Part I: Our protocol (2/7)

Video capture **(C1)**

- It captures French TVs (MPEG-4/H264) using a TV workstation.

Channels per month	Daily file: Resolution	kbps	Aspect ratio	Length	FPS	Full capture: Months	Files	Size
8	320×240	560	4 : 3	20 h	30	3	720	**3.46 TB**

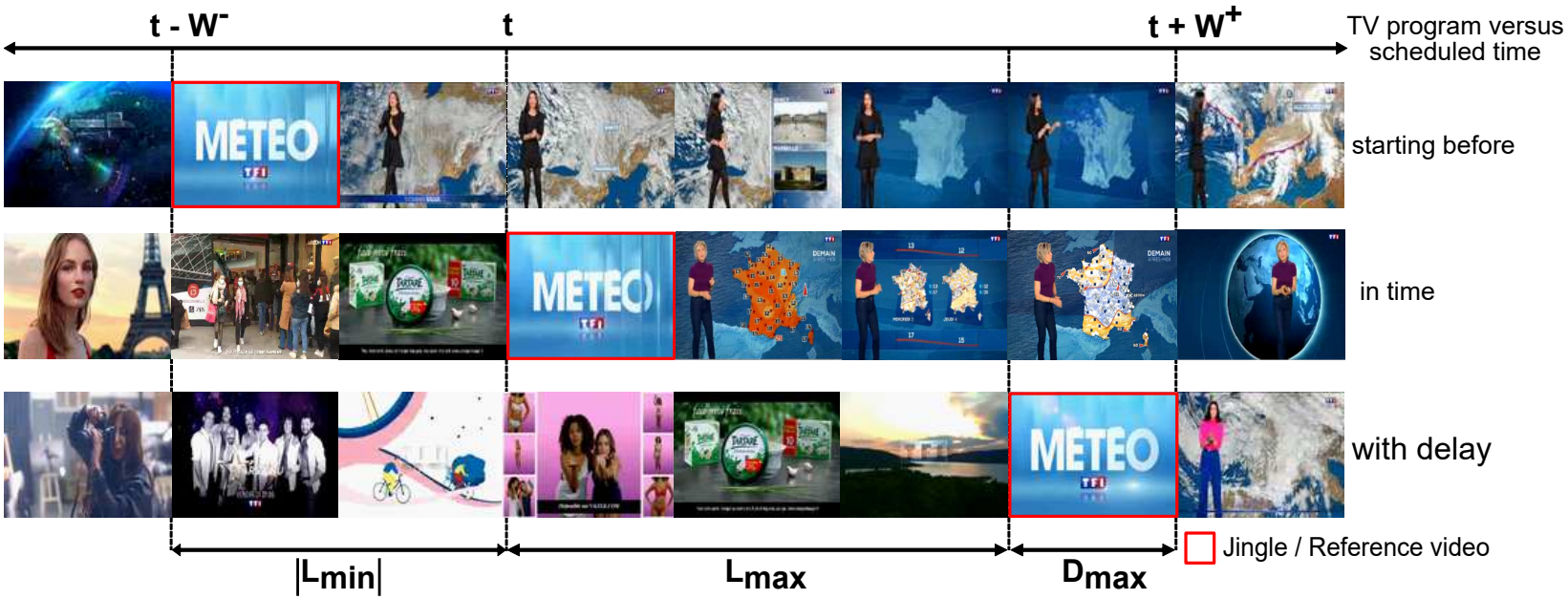
- An optimal strategy for memory cost and noise level



Part I: Our protocol (3/7)

Video capture **(C1)**

- Selection of positive candidates using metadata information:
  - collecting the TV metadata from EPG[3],
  - selecting daily programs with high frequency,
  - hashing/encoding the names of these programs.
- The windows model to extract candidate & reference videos

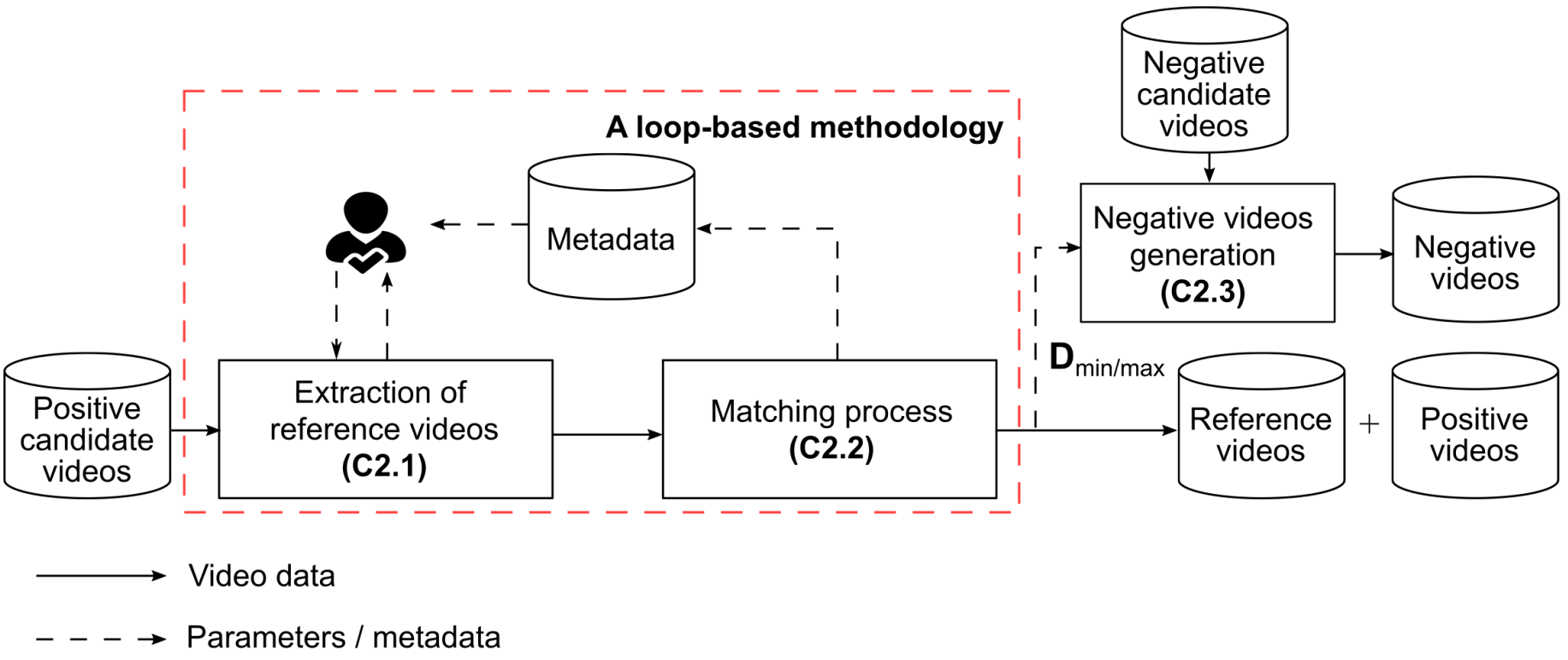


[3] EPG: Electronic Program Guide, e.g., https://xmltv.ch

Part I: Our protocol (4/7)

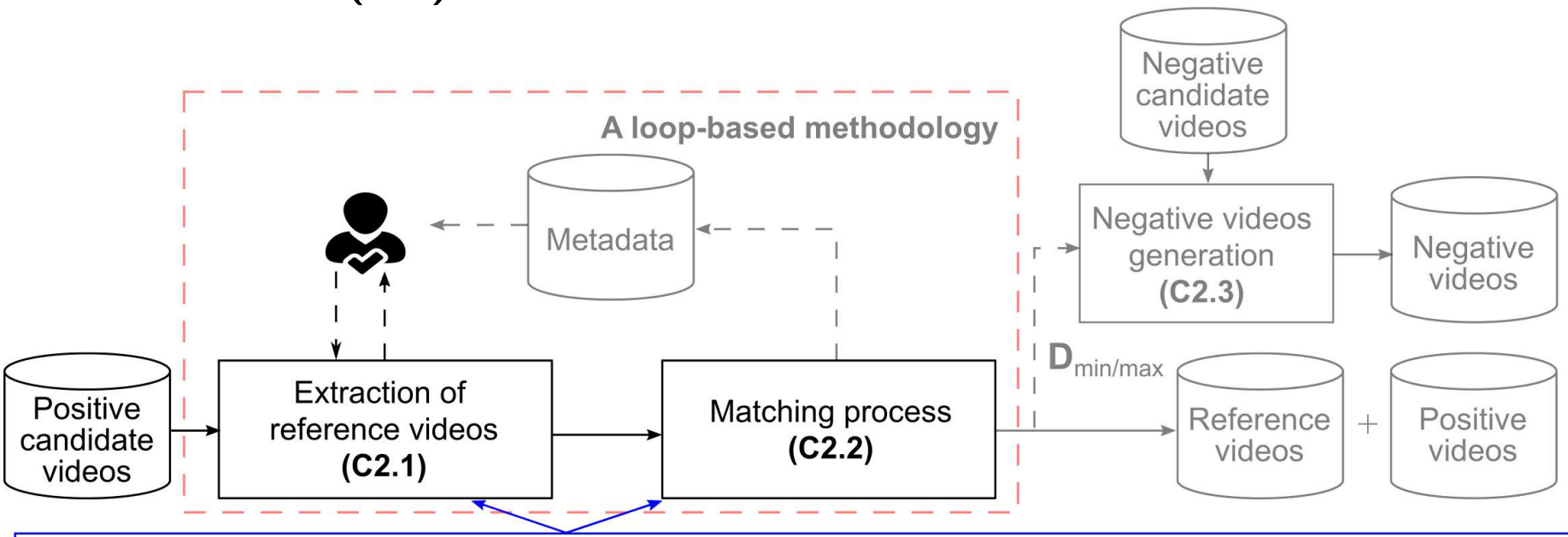
Video detection **(C2)**

- A semi-automatic annotation process with:
  - 3 sub-components **(C2.1), (C2.2), (C2.3)**,
  - **a loop-based methodology** to generate reference, positive videos,
  - an experiment-based procedure to generate negative videos.

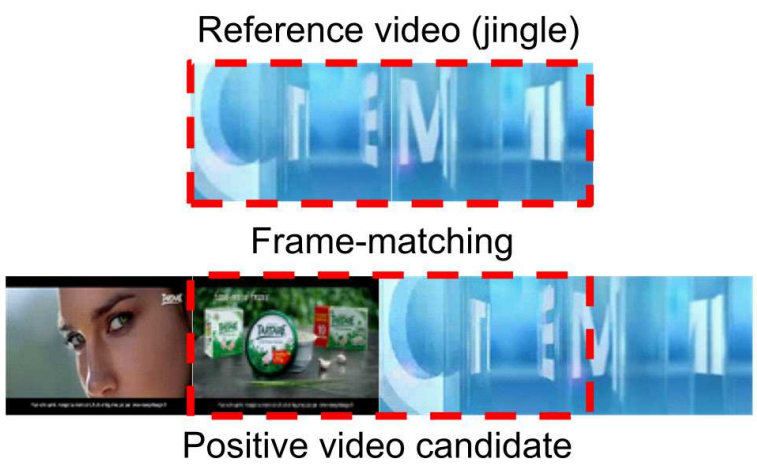


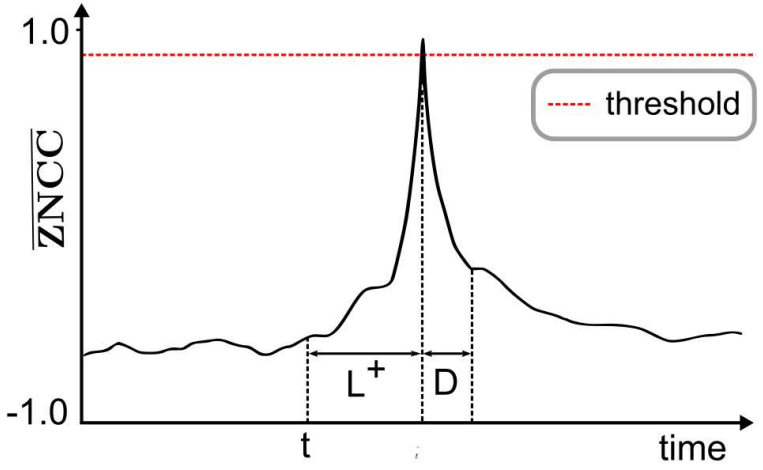
Part I: Our protocol (5/7)

Video detection (C2)



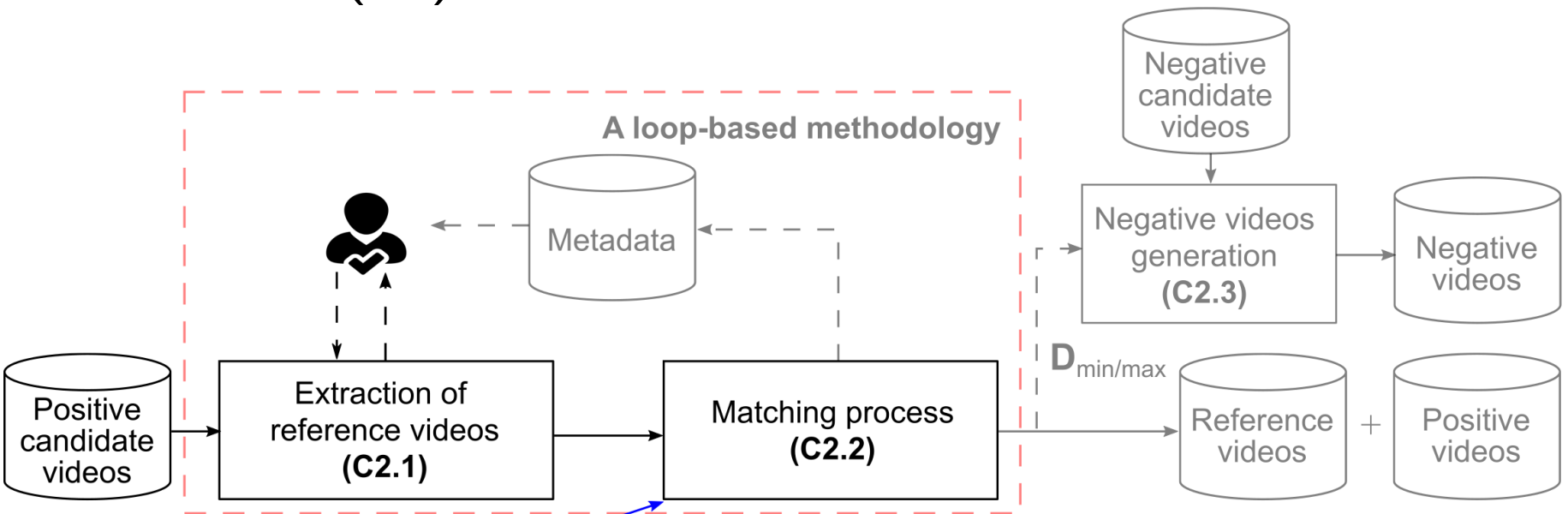
Frame-matching by a weighted method of Zero-mean Normalized Cross Correlation (ZNCC)



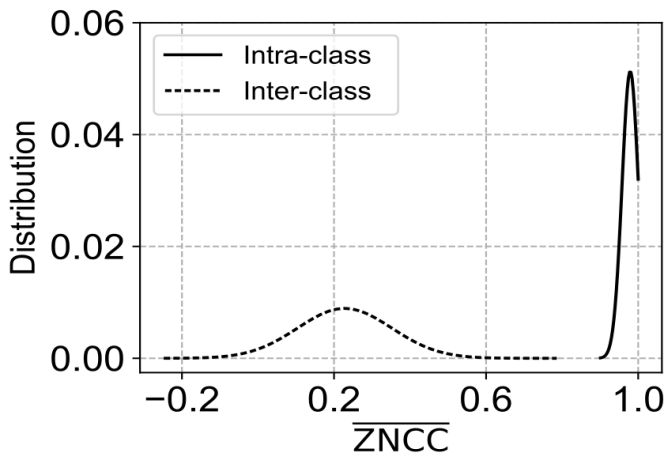


Part I: Our protocol (5/7)

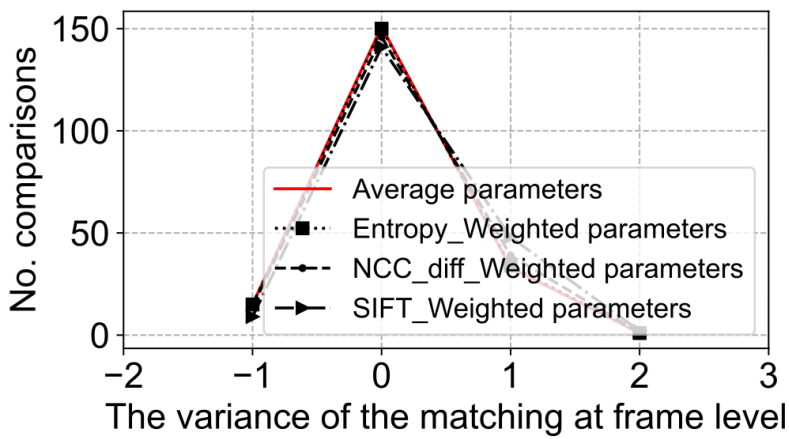
Video detection (C2)



The separation between the inter-class and intra-class distribution

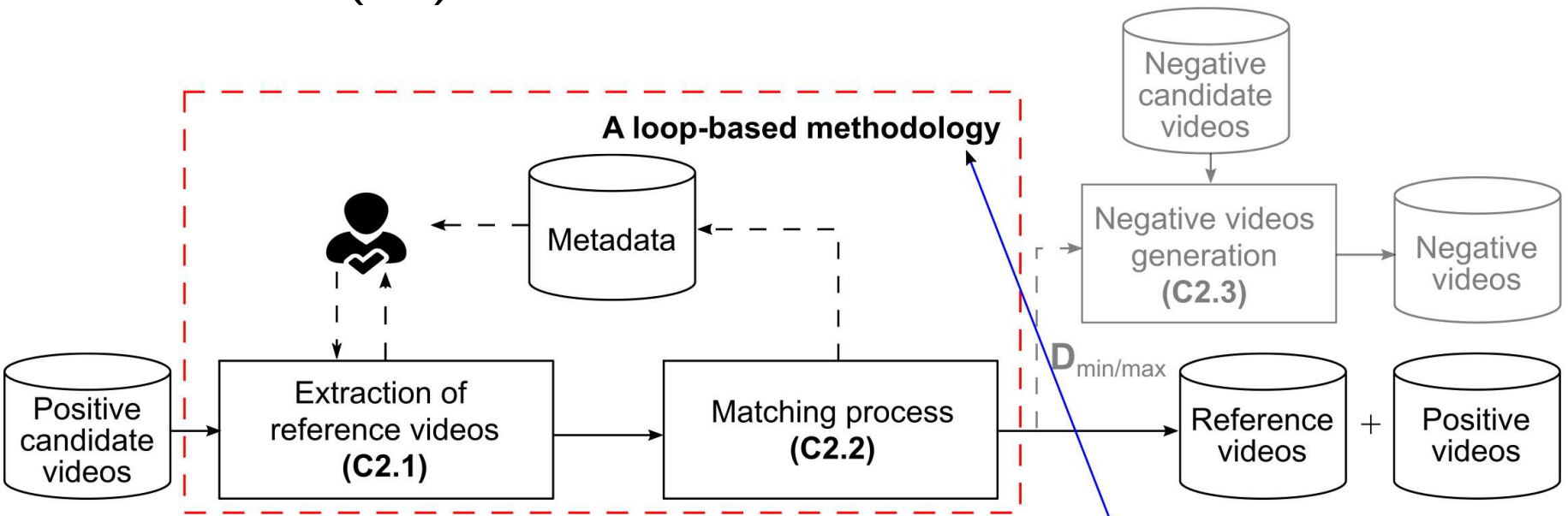


The accuracy of weighting methods for timestamping



Part I: Our protocol (5/7)

Video detection (C2)



A loop-based methodology to select/correct the reference videos to label while minimizing the user interaction cost.

different visual content

↓

create a new reference sample

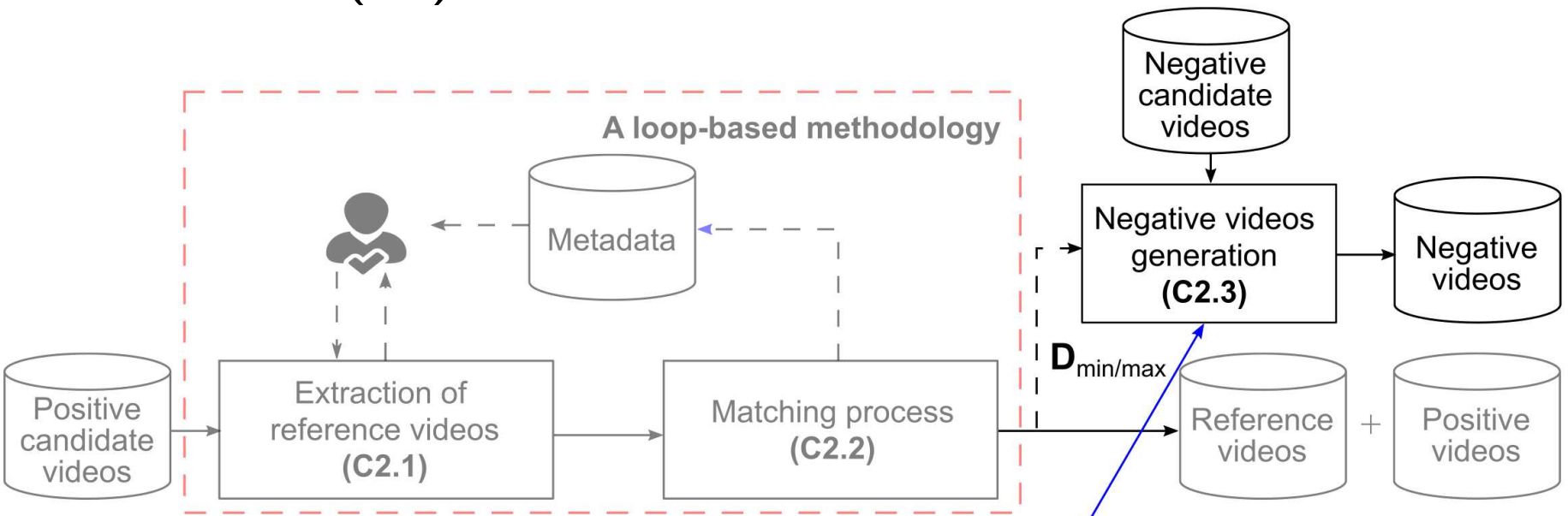
near-duplicate cases with logo change / text variation

↓

keep only one reference sample

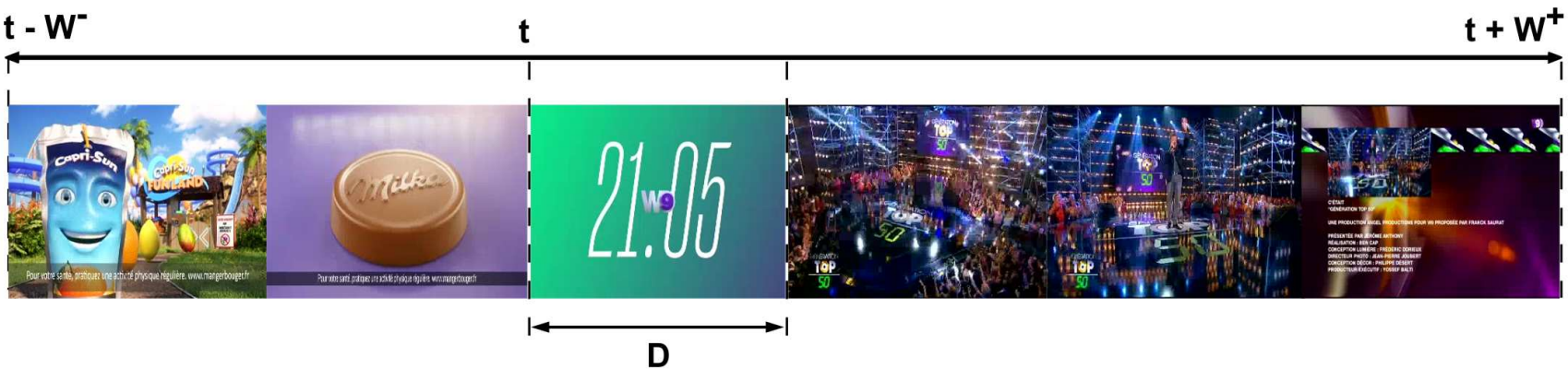
Part I: Our protocol (5/7)

Video detection **(C2)**



Generate negative videos based on the distribution of the duration of reference videos

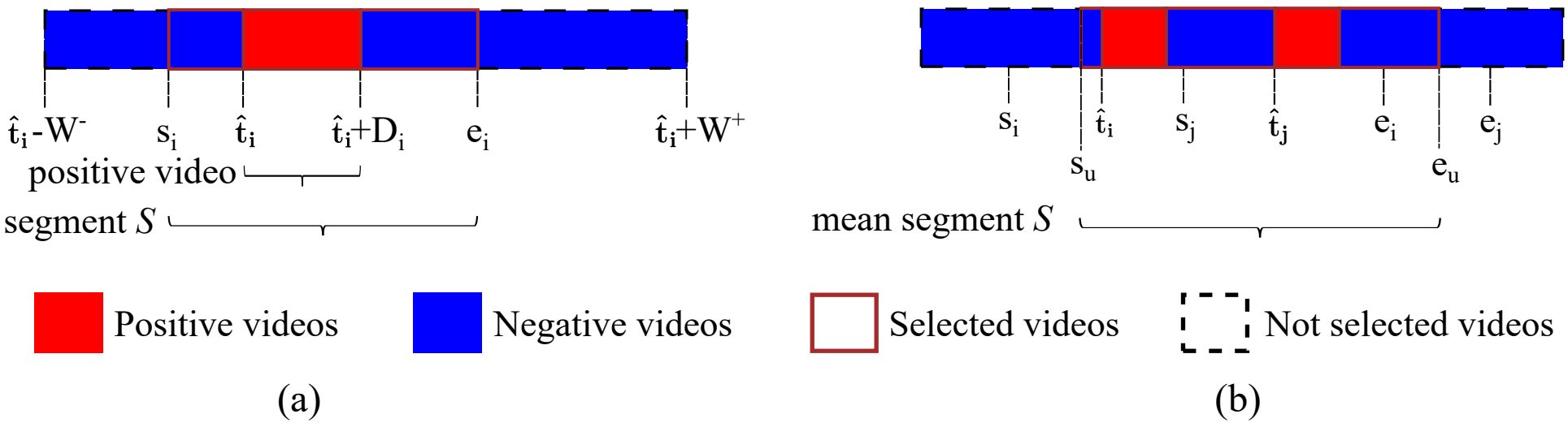
$D \in [D_{min}, D_{max}]$



Part I: Our protocol (6/7)

Video degradation **(C3)**

- **(C2)** extracts real-life partial video copies:
  - applying the latency model detected with **C2**,
  - detecting the overlapping cases for merging.



Part I: Our protocol (7/7)

Video degradation **(C3)**

- The final dataset with degradation methods: 6 sets (A-F)

	Test set	Video cut	Downscaling	Compression	Flipping	Rotating	Black-border	Video speeding
		T_0	T_1	T_2	T_3	T_4	T_5	T_6
A	Root capture	✓						
B	'Hello World'	✓	✓	✓				
C	Pixel attacks	✓	✓	✓				
D	Global transformations	✓	✓	✓	✓	✓	✓	
E	Video speeding	✓	✓	✓				✓
F	Combination	✓	✓	✓	✓	✓	✓	✓

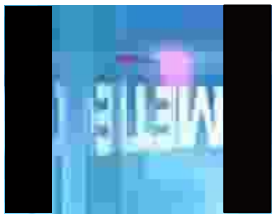
Set A

Set B

Set C


Set D


Set E


Set F

Part I: Experiments and results (1/2)

- STVD statistics: included 6 test sets in **C3**

	(C1)		(C2)		(C3)	
	Channels	Duration	Videos	Duration	Videos	Duration
Positive videos	8	4 800 h	3 780	6 h	19 280	2 515 h
Negative videos	16	9 600 h	12 165	21 h	64 040	8 145 h

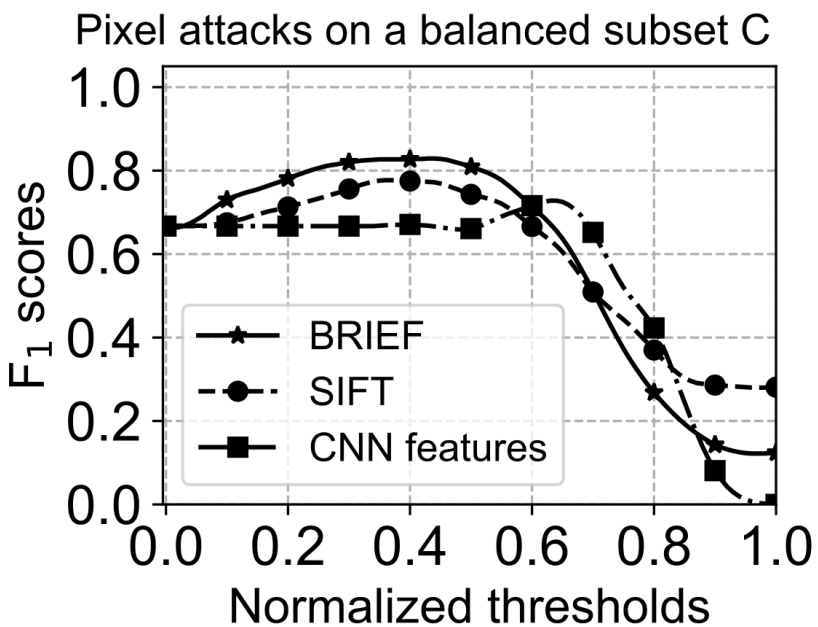
- The comparisons between STVD versus VCDB, VCSL

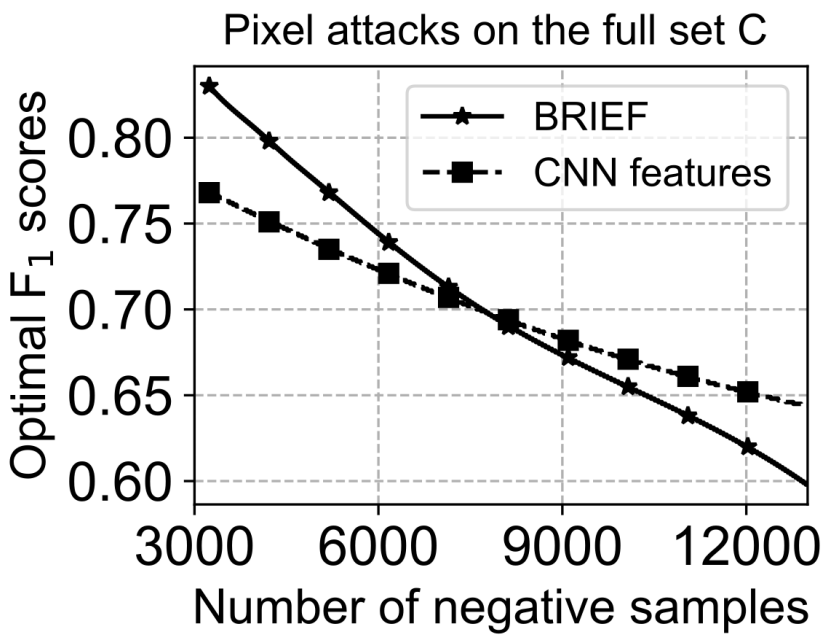
Datasets	VCDB [Jiang, 2014]	VCSL [He, 2022]	STVD Ours
Reference videos	28	122	**243**
Positive videos	528	9 207	**19 280**
Positive pairs	9 073	281 182	**1 688 225**
Negative videos	100 000	n/a	64 040
Duration (h)	2 000	n/a	**10 660**
Noise characterization	real noise	real noise	**noise-free**
Annotation cost (m-h)	700	20 000	**105**
Frame-level annotation	✗	✗	✓

(h): hours, (m-h): man-hours, and n/a: not available

Part I: Experiments and results (2/2)

- Baseline methods for evaluation [Zhu, 2016; Zhang, 2016; Zhang, 2020]
  - Protocol: key-frame extraction & matching[4], segment-level / no-training
  - Metrics: Precision, Recall, F-measure
  - Test sets: B for a 'Hello world' ability $F_1 \simeq 0.98$, C for pixel attacks





- Local features are more effective, CNN features can deal with scalability.

[4] Correctly detected: at least one frame hits the groundtruth

Part I: Summary of results & perspectives

- We proposed a protocol to design a PVCD dataset:
  - ensuring the dataset scalability with balanced data,
  - offering a fine control of degradation,
  - and a null timing deformation with frame-level accuracy.
- We published the best PVCD dataset, named STVD that
  - includes $\simeq$**83 k** videos, **10 k** hours, **1 688 k** positive pairs,
  - evaluates baseline methods (hello-world/scalability testing),
  - is publicly available at https://dataset-stvd.univ-tours.fr/(PVCD),
  - has been promoted in the CV/ML research community[5],
  - is designed with an adaptable protocol[6].
- STVD dataset could be employed
  - for advanced performance evaluation of PVCD,
  - and to design new characterization methods.

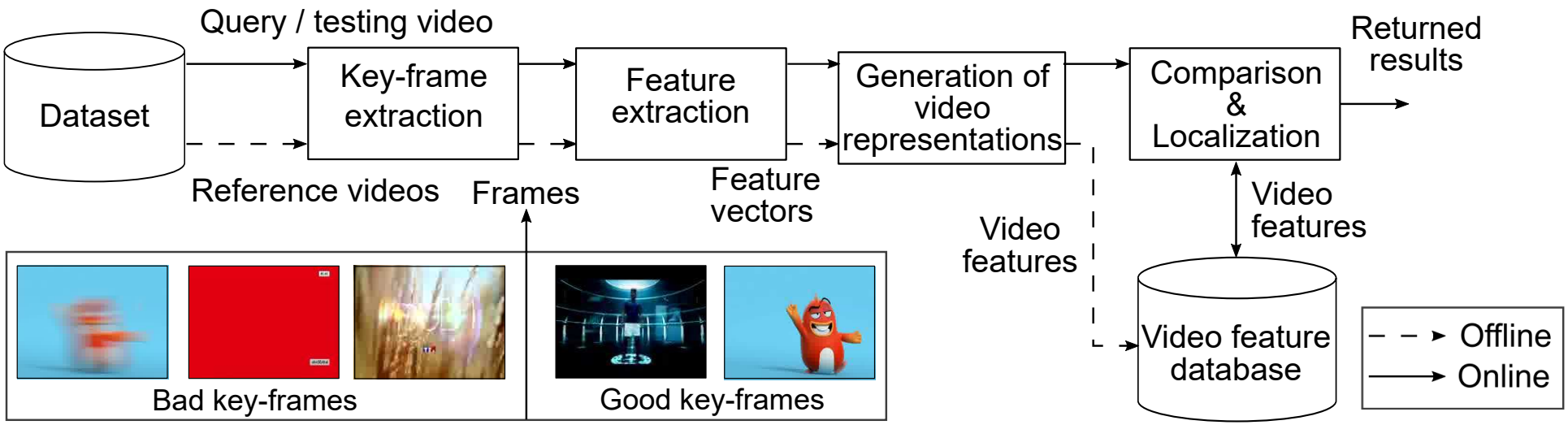
[5] cited papers: 3, CV/ML web platforms: 6, research mailings: 14, email contacts: 40.

[6] Fact checking [Rayar, 2022], operation reseach: https://dataset-stvd.univ-tours.fr/pms/

Part II: Performance evaluation for scalable PVCD

Part II: PVCD systems using 2D CNN features (1/2)

- Popularity 2D CNN features [Kordopatis, 2017; Han, 2021; Tan, 2022]

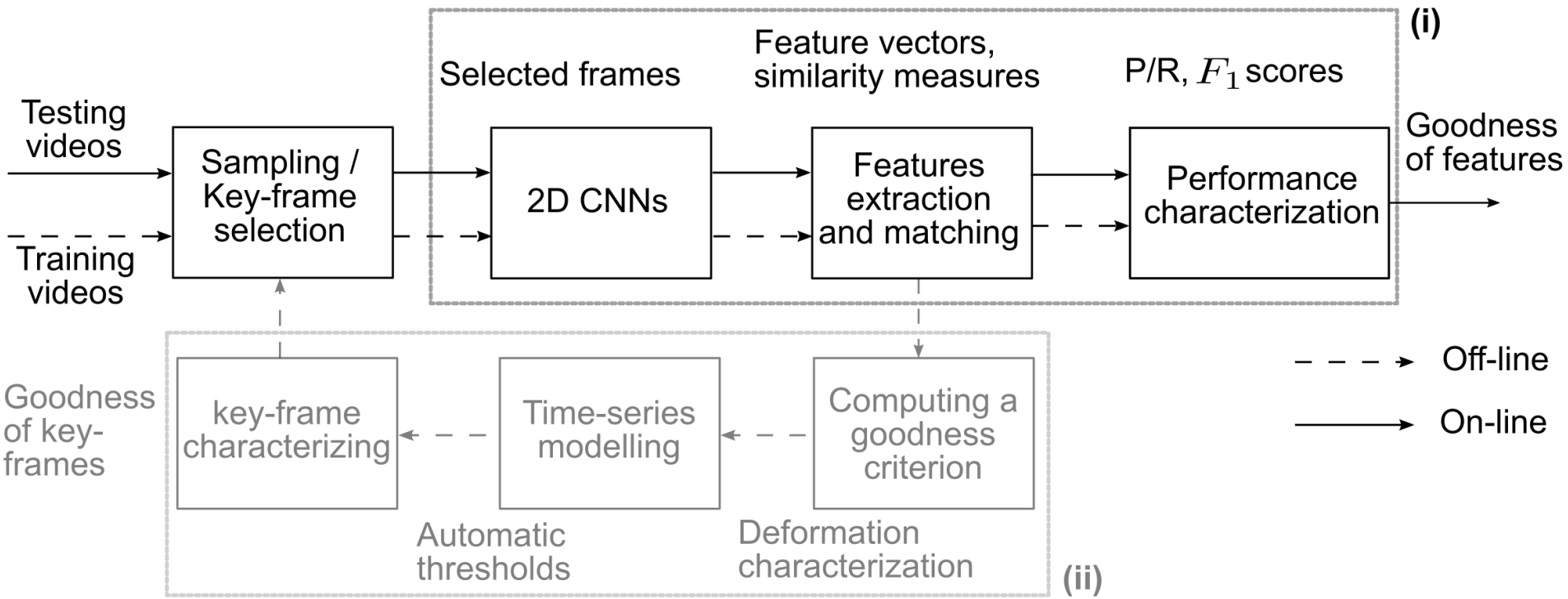


- Variety of 2D CNN features proposed [Phalke, 2020]
- 9 main pre-trained 2D CNN features are used for PVCD, based:
  - 3 CNN models (VGGNet, InceptionNet, ResNet),
  - 3 extraction techniques (Last FC, MAC, R-MAC)[7].
- Their characterization has been little discussed [Hu, 2019].

[7] Last FC: obtained from Last Fully Connected layer, MAC/R-MAC: obtained from Convolutional Layers

Part II: Our methods (1/2)

- We propose a characterization work in two steps:
  - **(i)** to evaluate the performance of popular 2D CNN features,
  - **(ii)** to characterize the goodness of key-frames with a dedicated method.



Part II: Our methods (2/2)

- Protocol: detection based on key-frames[8] [Jiang, 2016]
- Metrics: standard P/R, F_1
- Dataset: STVD[9] [Le, 2022]
  - test set D (global transformations)
  - sampling with high recommended/scalability fitting the GPU constraint
  - data split 6÷4 for training, testing

Videos	No	Duration (h)	FPS	60% training	40% testing	Total
Negative videos	12 165	1 545	0.08	259 050 f	172 700 f	431 750 f
Positive videos	3 869	415				
Copied segments	4 436	7.5	1	16 200 f	10 800 f	27 000 f
					Total[10]:	**458 750** f

[8] sampling/labeling of key-frames, matching with Cosine similarity, correctly detected: at least one key-frame shared

[9] large-scale, balanced positive/negative distribution, accurate timestamping

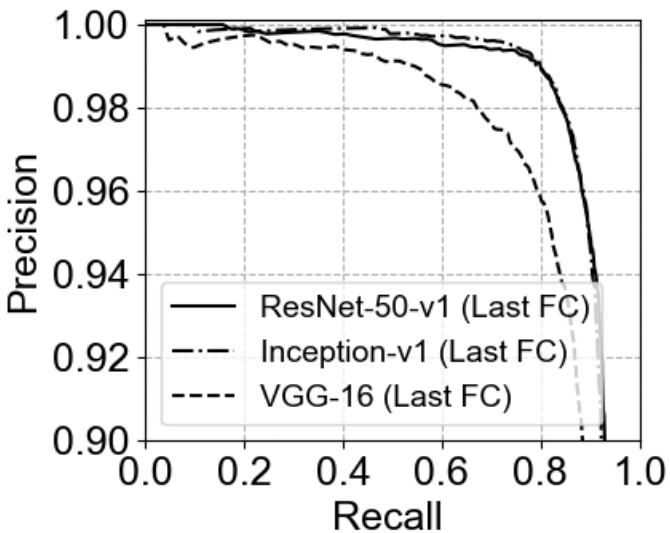
[10] Total: 458 750 f $\simeq$ 7 GiB of 4 096-F dimension

Part II: Comparison results between CNN features

- Large-scale experiments to characterize these 2D CNN features:
  - 9 CNN features (3 models $\times$ 3 methods[11]),
  - 4.4×10^6 vectors, 445×10^9 matchings, optimized implementation.
- Comparison of 2D CNN feature results

Tab. 1 Top F_1 scores

	Last FC	MAC	R-MAC
ResNet50-v1	**0.926**	0.828	0.823
Inception-v1	**0.923**	0.738	0.782
VGG-16	0.894	**0.922**	0.918

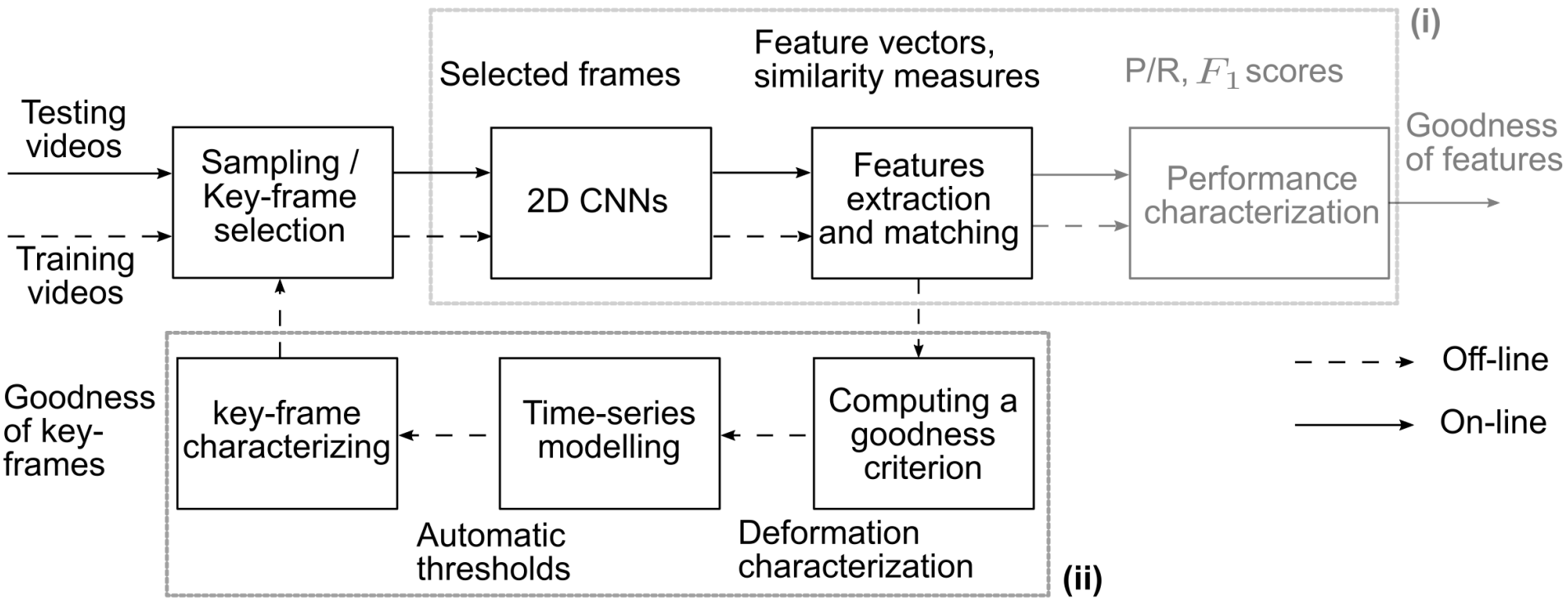


- Our results align with the state-of-the-art and highlight:
  - recent 2D CNN models (e.g., ResNet-50) outperform [He, 2016],
  - correlation between 2D CNN & methods (VGG & MAC) [Cools, 2022],
  - challenges remain in achieving full separability (even if $F_1 \simeq 0.93$).

[11] Last Fully Connected (Last FC), Maximum Activations of Convolutions (MAC), and Regional-MAC (R-MAC)

Part II: Our methods to characterize key-frames (1/4)

- We propose a characterization work in two steps:
  - **(i)** to evaluate the performance of popular 2D CNN features,
  - **(ii)** to characterize the goodness of key-frames with a dedicated method.



Part II: Our methods to characterize key-frames (2/4)

- We propose a goodness criterion $\phi(X)$ to evaluate the X separability
  - using Cosine similarity[12] (SC) $\in [0, 1]$, then $\phi(X) \in [-1, 1]$ is defined as

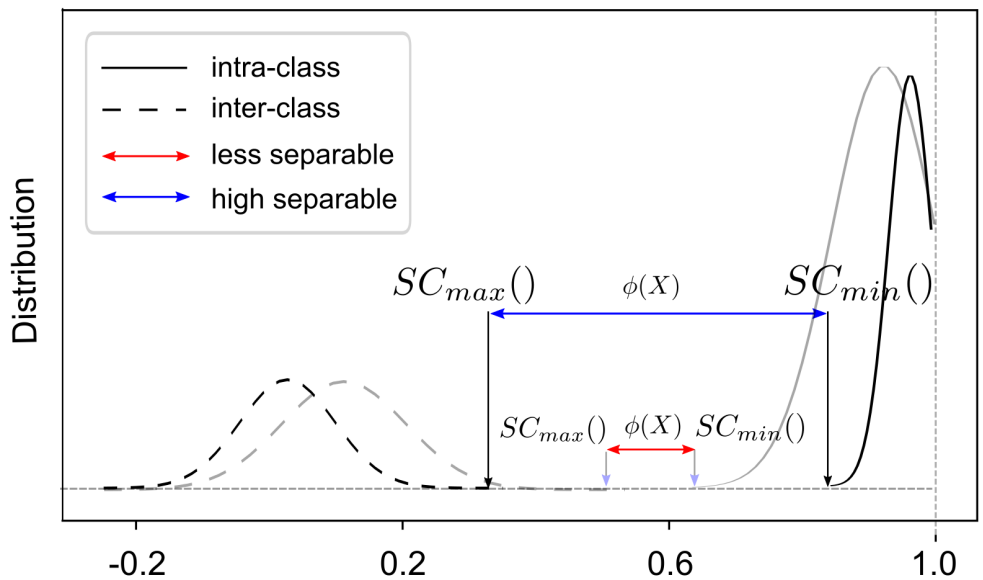
X is a feature vector

$$\phi(X) = SC_{\min}(X, \{\tilde{X}_1, \ldots, \tilde{X}_m\}) - SC_{\max}(X, \{Y_1, \ldots, Y_{n_1}\}, \{X_1^*, \ldots, X_{n_2}^*\})$$

$\tilde{X}$ are near-duplicates of X

Y are negatives,
$X^* \neq X$ are different references

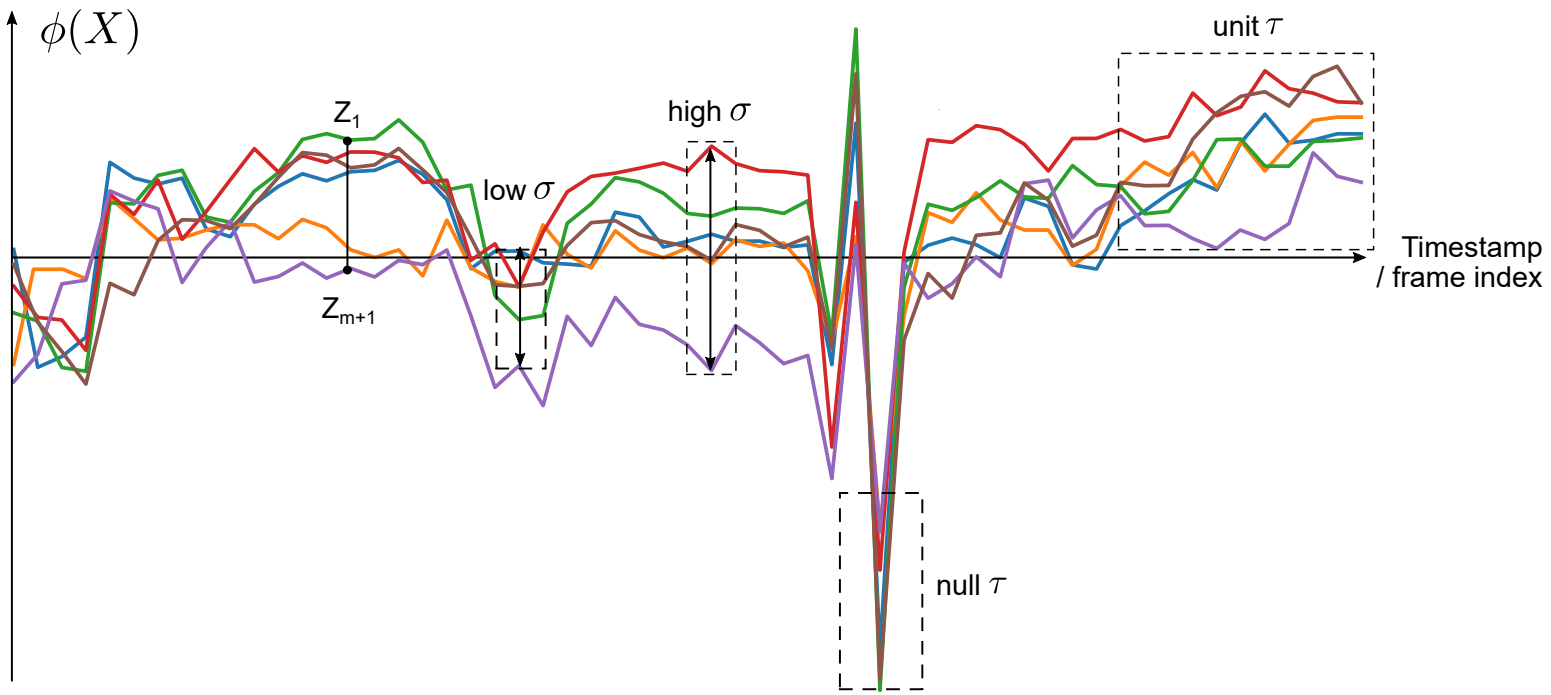
- Good key-frames support to maximize 'intra' & minimize 'inter'.



[12] SC(X,Y) $\in [0, 1]$ (non-negative vectors: ReLU, unit scale: L_2-norm) between vectors X, Y where SC(X,X) = 1

Part II: Our methods to characterize key-frames (3/4)

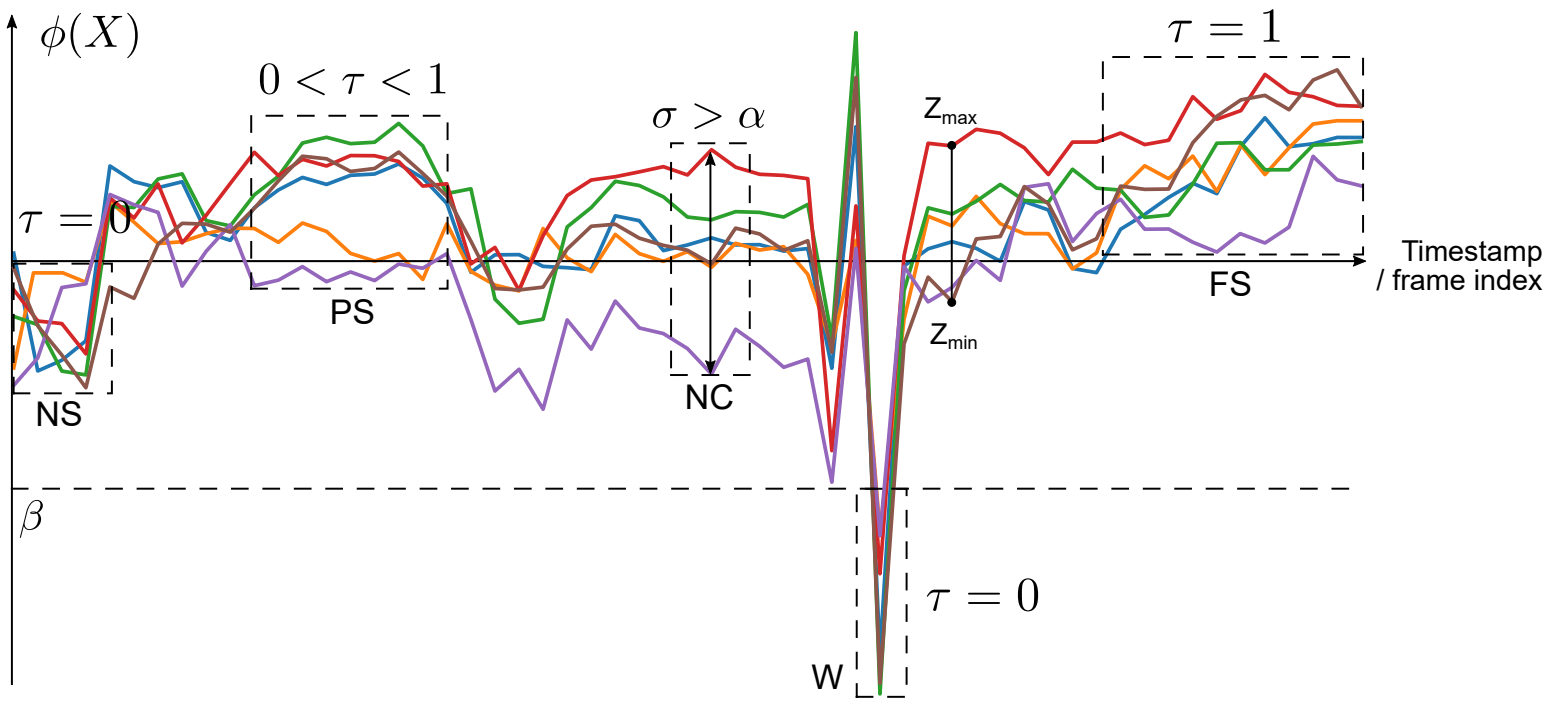
- The characterization of key-frames is done with time series:
  - modeling the criterion in the video collection and timing domains,
  - $z_1, \ldots, z_{m+1}$ values at t give the $\phi(X)$, $\phi(\tilde{X}_1)$, $\ldots$, $\phi(\tilde{X}_m)$ criteria,
  - feature vector X and its near-duplicates $\{\tilde{X}_1, \cdots, \tilde{X}_m\}$.



- Detect consistency & separability of key-frames from $z_1, \cdots, z_{m+1}$:
  - the standard deviation σ,
  - a rate τ accounting the amount of positive criteria.

Part II: Our methods to characterize key-frames (4/4)

- We compare σ, τ to automatic thresholds α, β for categorization:
  - $\sigma > \alpha$ serves to filter Not Consistent (NC),
  - $\tau \neq 0$ serves to get Partially Separable (PS), Fully Separable (FS),
  - β is an adaptive threshold to split Not separable (NS) / Worst (W).



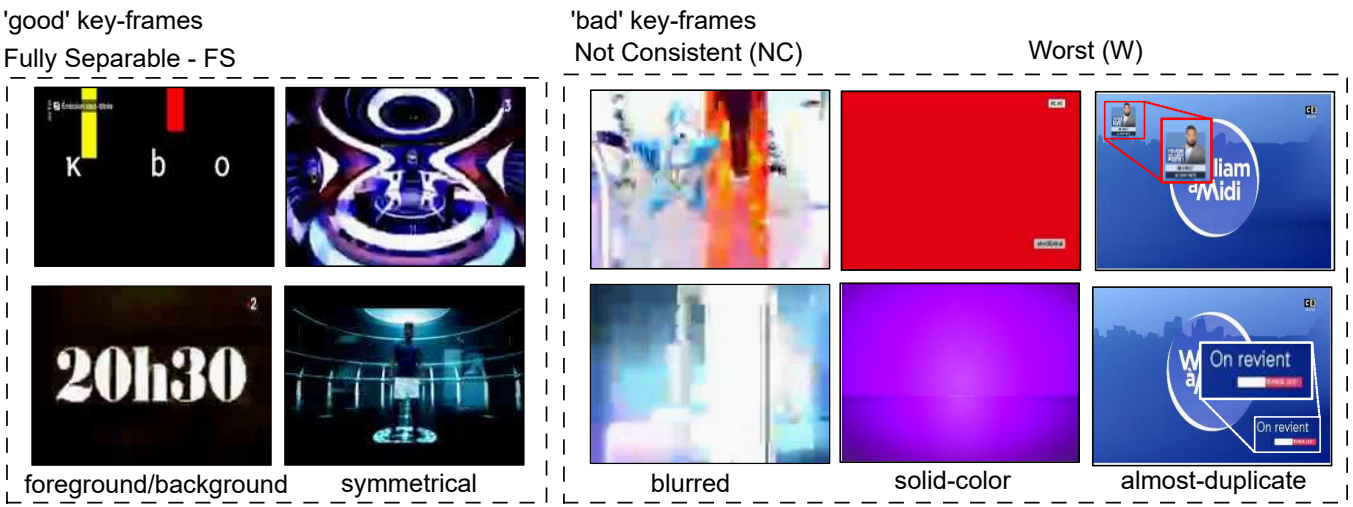
Part II: Our results & key-frame categories

- We extended **(i)** dataset for the feature VGG-16/MAC[13] at 30 FPS. (50×10^3 indices, 0.8×10^6 vectors, 244×10^9 matchings)

(NC-Not consistent, W-Worst, NS-Not separable, PS-Partially Separable, FS-Fully Separable.)

Total indices	NC	W	NS	PS	FS
50 844	6 966	4 169	33 049	4 881	1 780
100 %	13.7 %	8.2 %	65 %	9.6 %	3.5 %
		86.9 %		**13.1 %**	

- Key-frame categories:
  - $\simeq$ **4**% 'good' (FS) key-frames,
  - $\simeq$ **87**% 'hardly' separable (NC+W+NS), of which $\simeq$ **22**% 'bad' (NC, W)



[13] for a trade-off between a strong detection and the memory constraint ($F_1 = 0.922$ & 512-F dimension)

Part II: Summary of results

- We reported large-scale experiments to characterize 2D CNN features:
  - **9** CNN features, **4.4 m** vectors, **445 b** matchings,
  - ResNet-50 outperforms, correlation CNN & methods,
  - scalability challenge offered by the STVD dataset.
- We proposed a method for the characterization of key-frames:
  - goodness criterion, time-series modelling, categorization method,
  - **50 k** indices, **0.8 m** vectors, **244 b** matchings,
  - a dominant amount of key-frames is not suitable for 2D CNN features.

Conclusions & perspectives

Conclusions (1/2)

- We proposed a protocol to design a PVCD dataset offering:
  - scalability, balanced data, fine control of degradation,
  - null timing deformation with frame-level accuracy.
- We published the best PVCD dataset, named STVD that:
  - includes $\simeq$**83 k** videos, **10 k** hours, **1 688 k** positive pairs, **5** test sets,
  - is publicly available and promoted in the CV/ML research community.

Conclusions (2/2)

- We conducted extensive experiments for performance evaluation.
  - Protocol: key-frame extraction and matching
  - Metrics: P, R, F_1
- We draw several key conclusions:
  - ability of our dataset for PVCD,
  - hand-crafted features process well on standard tasks,
  - characterization of PVCD 2D CNN features.
- We provided a fine characterization of key-frames:
  - goodness criterion, time-series modeling, and automatic thresholding,
  - a dominant amount of key-frames is not suitable for 2D CNN features.

Our perspectives

- Perspectives on our dataset:
  - promote (contest online / conference, communication),
  - generate new test sets for specific challenges,
  - provide more scalability[14],
  - adapt our protocol to new research problems,
  - address a non-rigid PVCD problem.
- Perspectives on PVCD performance evaluation:
  - very large scalability / brute-force (cluster of GPU),
  - re-training for CNNs [He, 2022],
  - other recent deep learning models (2D, 3D),
  - key-frame classification / selection for video representations.

[14] Two strategies for collaborative and user interaction optimization / fully automatic annotation.

List of publications

1. **V.H. Le**, M. Delalandre and H. Cardot, *Performance Characterization of 2D CNN Features for Partial Video Copy Detection*, Conference on Computer Analysis of Images and Patterns (CAIP), pp. 205-215, 2023.
2. F. Rayar, M. Delalandre and **V.H. Le**. *A large-scale TV video and metadata database for French political content analysis and fact-checking*. Conference on Content-Based Multimedia Indexing (CBMI), pp. 181-185, 2022.
3. **V.H. Le**, M. Delalandre and D. Conte. *A large-Scale TV Dataset for partial video copy detection*. International Conference on Image Analysis and Processing (ICIAP), Lecture Notes in Computer Science (LNCS), vol 13233, pp. 388-399, 2022.
4. **V.H. Le**, M. Delalandre and D. Conte. *Une large base de données pour la détection de segments de vidéos TV*. Journées Francophones des Jeunes Chercheurs en Vision par Ordinateur (ORASIS), 2021.
5. **V.H. Le**, M. Delalandre and D. Conte. *Real-time detection of partial video copy on TV workstation*. (CBMI), pp. 1-4, 2021.

Thank you for your attention !

References I

Cools, A., M.A. Belarbi, and S.A. Mahmoudi (2022). "A Comparative Study of Reduction Methods Applied on a Convolutional Neural Network". In: *Electronics* 11, p. 1422.

Guzman, Z.Z.J et al (2019). "Partial-copy detection of non-simulated videos using learning at decision level". In: *Multimedia Tools and Applications*.

Han, Z. et al (2021). "Video similarity and alignment learning on partial video copy detection". In: *ACM International Conference on Multimedia*.

He, K. (2016). "Deep residual learning for image recognition". In: *Conference on computer vision and pattern recognition (CVPR)*, pp. 770–778.

He, S. et al (2022). "A Large-scale Comprehensive Dataset and Copy-overlap Aware Evaluation Protocol for Segment-level Video Copy Detection". In: *Computer Vision and Pattern Recognition (CVPR)*.

Hu, Y. et al (2019). "STRNN: End-to-end deep learning framework for video partial copy detection". In: *Journal of Physics: Conference Series*.

Jiang, Y.G. and J. Wang (2016). "Partial copy detection in videos: A benchmark and an evaluation of popular methods". In: *IEEE Transactions on Big Data* 2.1, pp. 32–42.

Jiang, Y.G. et al (2014). "VCDB: a large-scale database for partial copy detection in videos". In: *European Conference on Computer Vision (ECCV)*.

Joly, A. et al (2007). "Content-based copy retrieval using distortion-based probabilistic similarity search". In: *Transactions on Multimedia*.

References II

Kordopatis, Z.G. et al (2017). "Near-duplicate video retrieval by aggregating intermediate cnn layers". In: *International conference on Multimedia Modeling (MMM)*.

Kordopatis-Zilos, G. (2017). "Near-duplicate video retrieval with deep metric learning". In: *International Conference on Computer Vision Workshops (ICCV)*, pp. 347–356.

Law-To, J. et al (2007). "Video copy detection: a comparative study". In: *International Conference on Image and Video Retrieval (CIVR)*.

Le, V.H., M. Delalandre, and D. Conte (2022). "A large-Scale TV Dataset for partial video copy detection". In: *International Conference on Image Analysis and Processing (ICIAP)*. Vol. 13233. Lecture Notes in Computer Science (LNCS), pp. 388–399.

Liu, X. et al (2021). "GANN: A Graph alignment neural network for video partial copy detection". In: *Conference on Big Data Security on Cloud (BigDataSecurity)*.

Phalke, D. A. and S. Jahirabadkar (2020). "A survey on near duplicate video retrieval using deep learning techniques and framework". In: *Pune Section International Conference (PuneCon)*. IEEE, pp. 124–128.

Rayar, F., M. Delalandre, and V.H. Le (2022). "A large-scale TV video and metadata database for French political content analysis and fact-checking". In: *International Conference on Content-based Multimedia Indexing (CBMI)*, pp. 181–185.

Shen, L. et al (2020). "Advance on large scale near-duplicate video retrieval". In: *Frontiers of Computer Science (Front. Comput. Sci.)* 14.5, pp. 1–24.

References III

Tan, W. et al (2022). "A Fast Partial Video Copy Detection Using KNN and Global Feature Database". In: *Winter Conference on Applications of Computer Vision (WACV)*.

Tolias, G., R. Sicre, and H. Jégou (2016). "Particular Object Retrieval With Integral Max-Pooling of CNN Activations". In: *International Conference on Learning Representations (ICLR)*, pp. 1–12.

Zhang, C. et al (2020). "Large-scale video retrieval via deep local convolutional features". In: *Advances in Multimedia*.

Zhang, Y. et al (2016). "Effective real-scenario video copy detection". In: *International Conference on Pattern Recognition (ICPR)*.

Zhu, Y. et al (2016). "Large-scale video copy retrieval with temporal-concentration sift". In: *Neurocomputing*.