

Understanding the big data of video with AI

Yan Ye

Machine Intelligence Technology Lab, DAMO Academy



Big Data of the Alibaba Ecosystem



Big data:	EBs (10^{18}) of video data
Diverse source:	e-commerce, live streaming, entertainment, sports, UGC, etc
Cloud computing:	Tens of millions of servers

OUTLINE

- ① The challenges of big data of video
- ② AI-powered video understanding
- ③ AI-powered video fingerprinting and search
- ④ AI-powered video content production



The challenges of big data of video



Big data of video...

Problem #1: the gap between how video is captured, transmitted, and stored, and how video is consumed

- Video is captured, transmitted and stored as a signal
- However, video is not (just) consumed as a signal, consumption happens at the semantics and emotional levels too
- Need to learn/understand the underlying structure in the video signal

Problem #2: managing the big data of video cost-effectively

- With an ever increasing video content database, need to increase efficiency and reduce cost
- Considering the diversity of the video source and specific applications, efficient content management must be *intelligent*

video
classification

video indexing
and search

cover image
generation

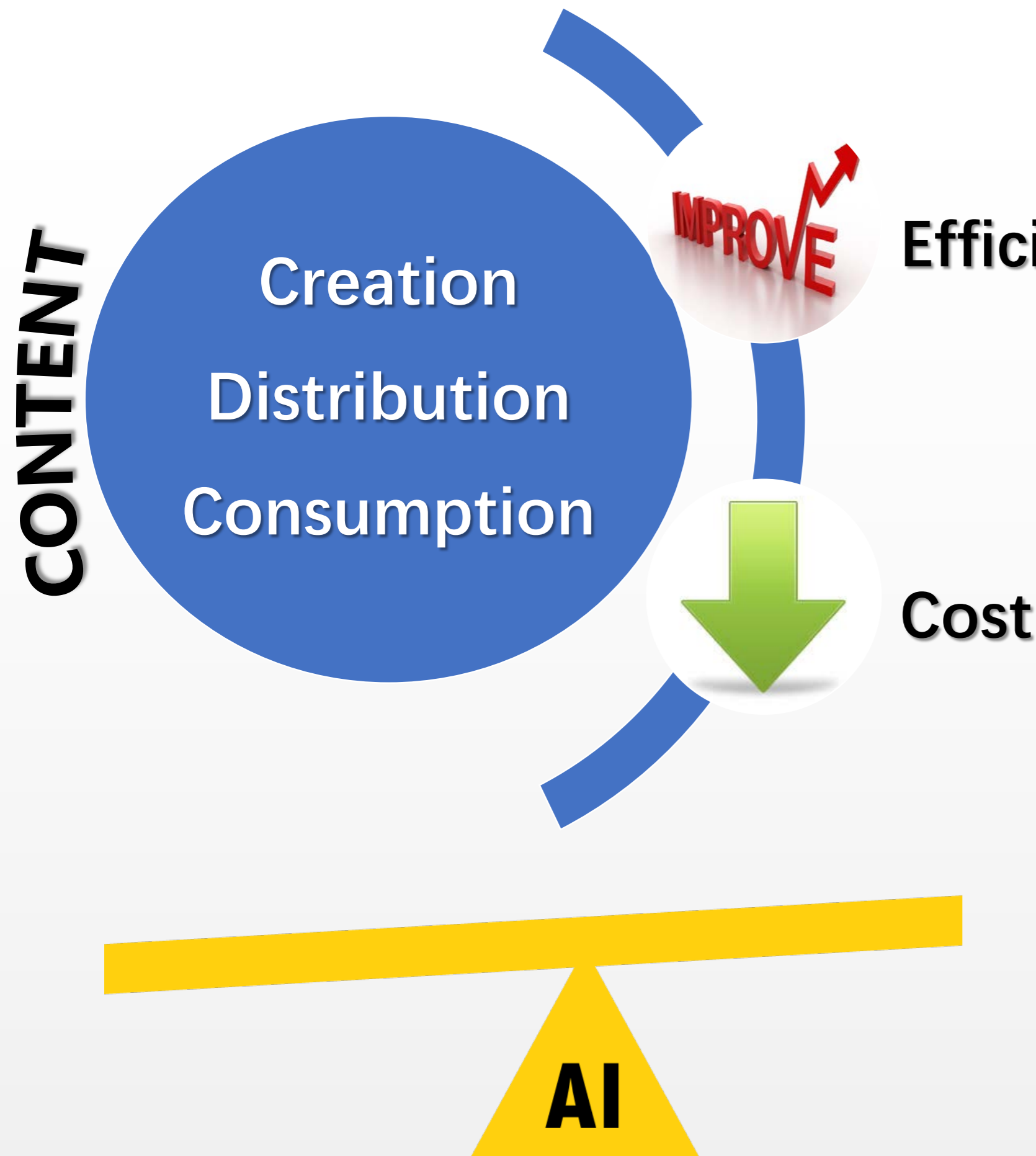
highlight video
generation

copyright
management

multi-
modality



AI Reshapes Video Content Management



AI-powered Video Understanding

- Object and scene recognition: who, what, where
- Action recognition
- Classification
- UGC labeling
- Fingerprinting & copyright

AI-powered Content Generation

- Video summarization
- Personalized cover image generation
- Audio editing
- Sports highlights
- Virtual content

AI-powered Content Distribution

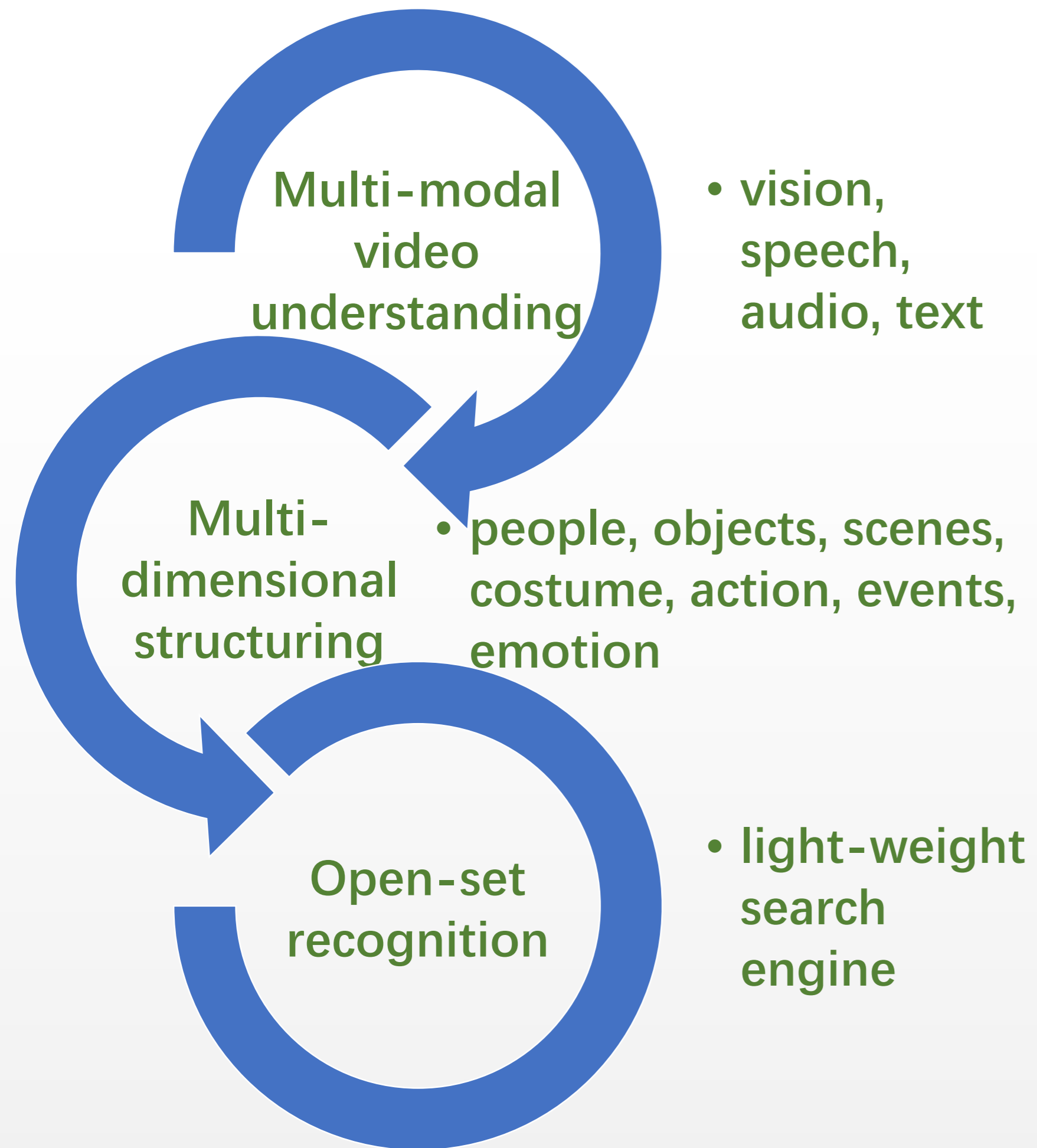
- Recommendations
- Multi-modal search
- Multi-lingual search



AI-powered Video Understanding



Multi-modal video structuring



智能标签

+ 上传内容

内容库

人脸注册

任务统计

标签统计

账户设置

视频

人物

吉杰 郭雪芙 郑京浩 朱桢 刘维

姜滋博 汪涵 钱枫 李诞 张

汪涵 - 名人

00:01:010 - 00:01:12

置信度: 87%

语音 OCR 原始文稿 翻译 审核

00:00:00: 衣服穿的单薄, 是不是冷了?

00:00:04: 刚才都炒成了利益。

00:00:06: 还不能

00:00:08: 你要冷, 我把衣服脱下来, 给你发。

Labeling celebrities

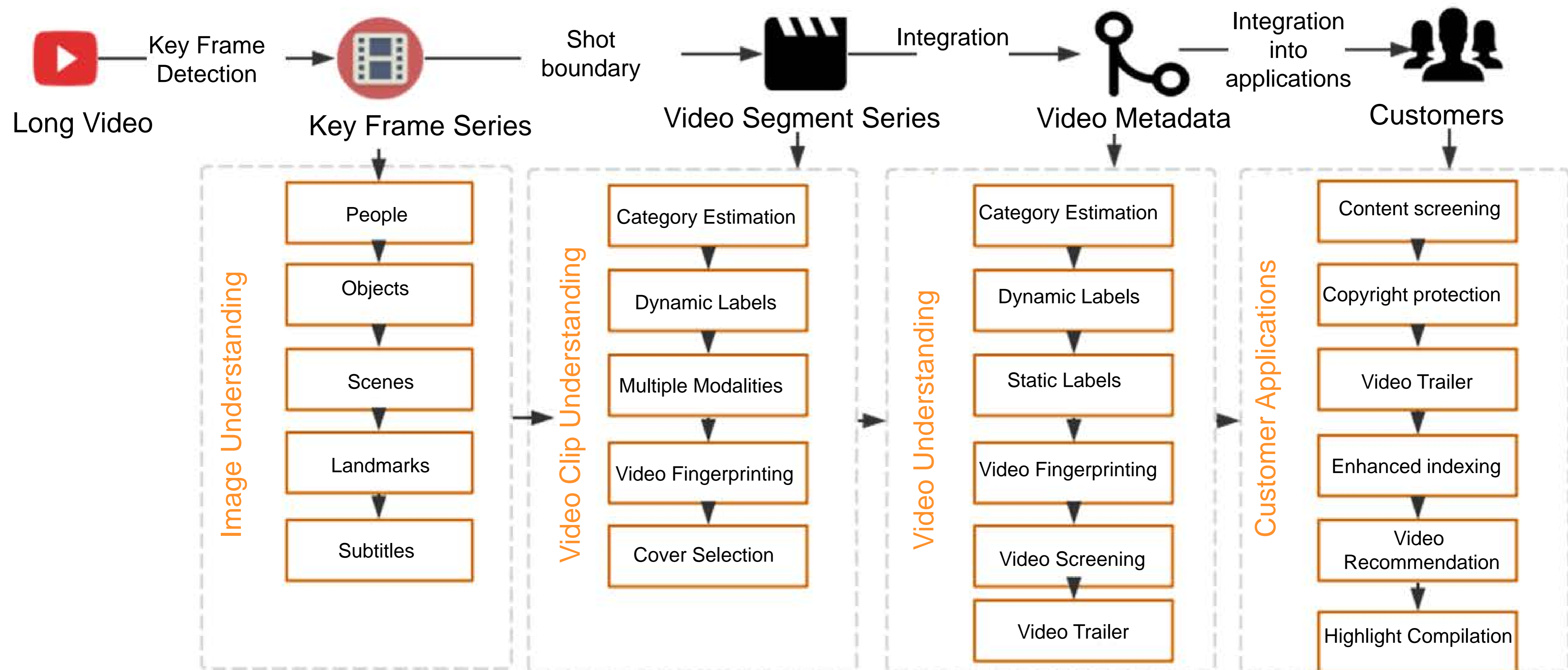
Labeling visual cues

Speech recognition

OCR

Labeling modalities

AI-powered multi-level analysis of video content



Improving Video Understanding

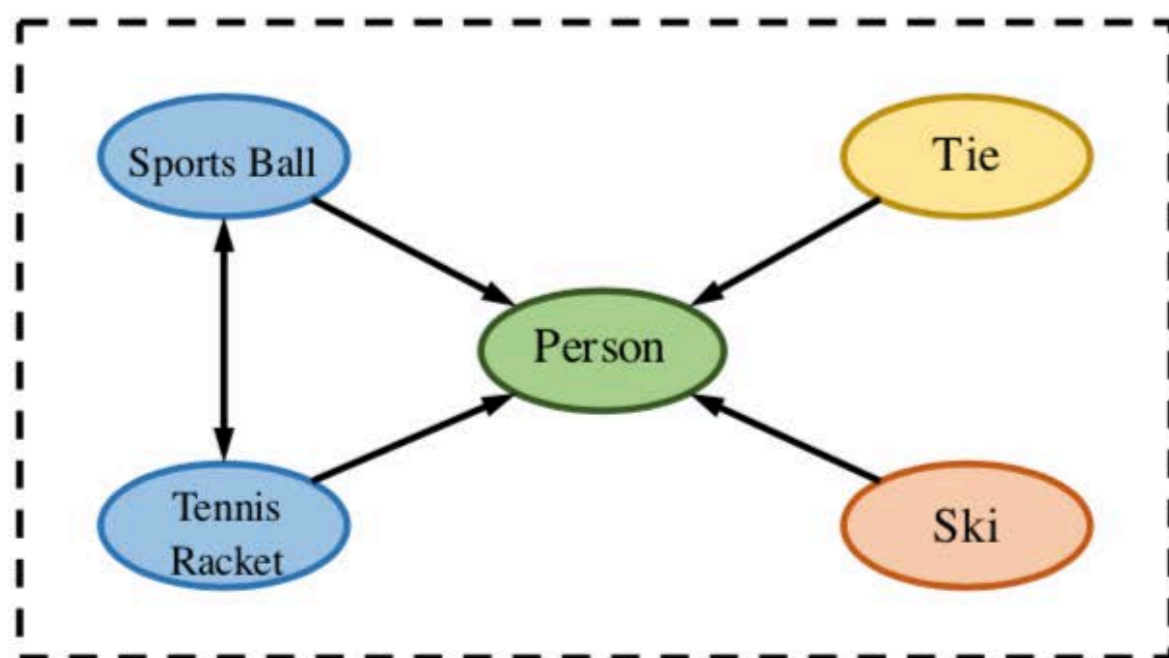
Label Correlation



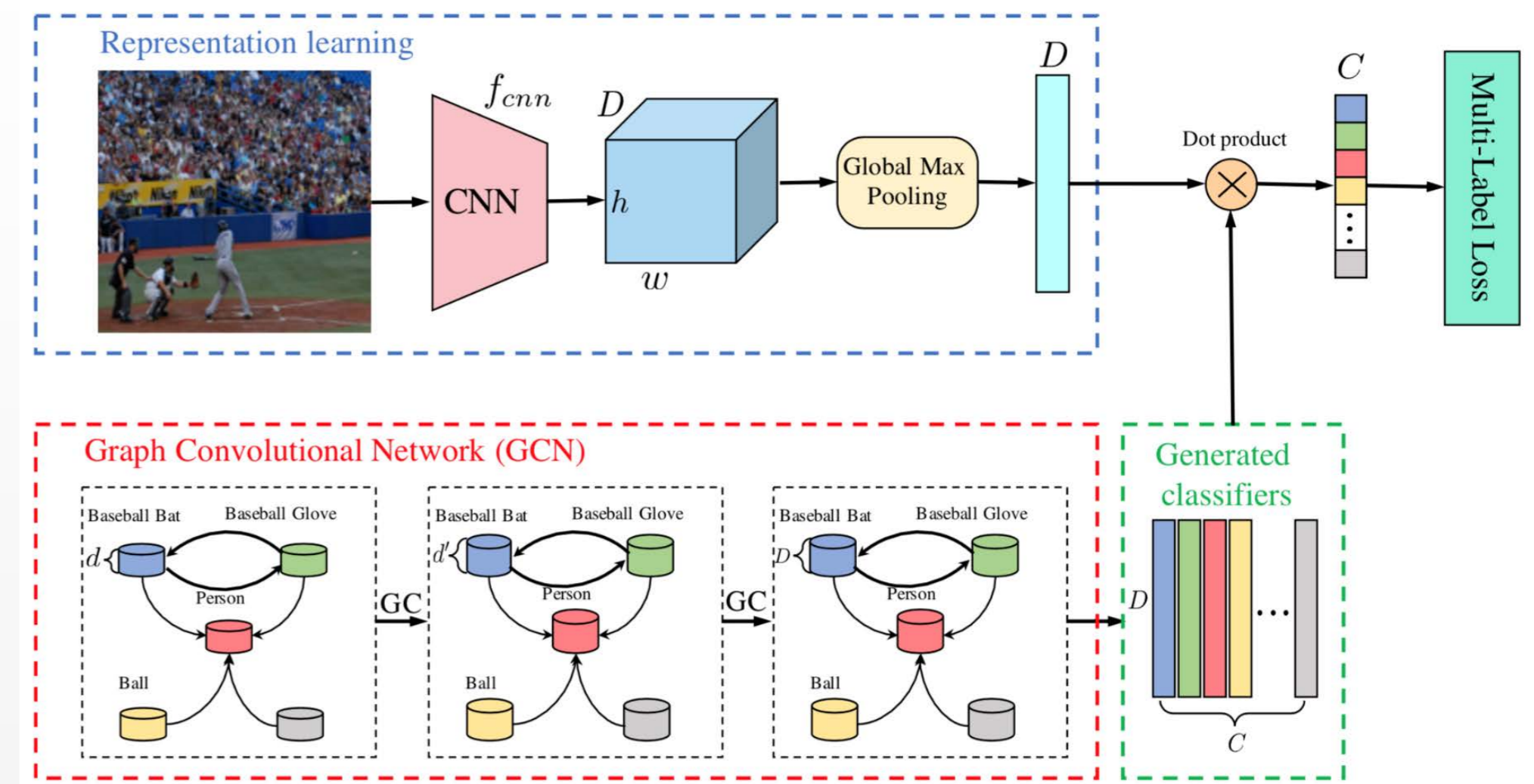
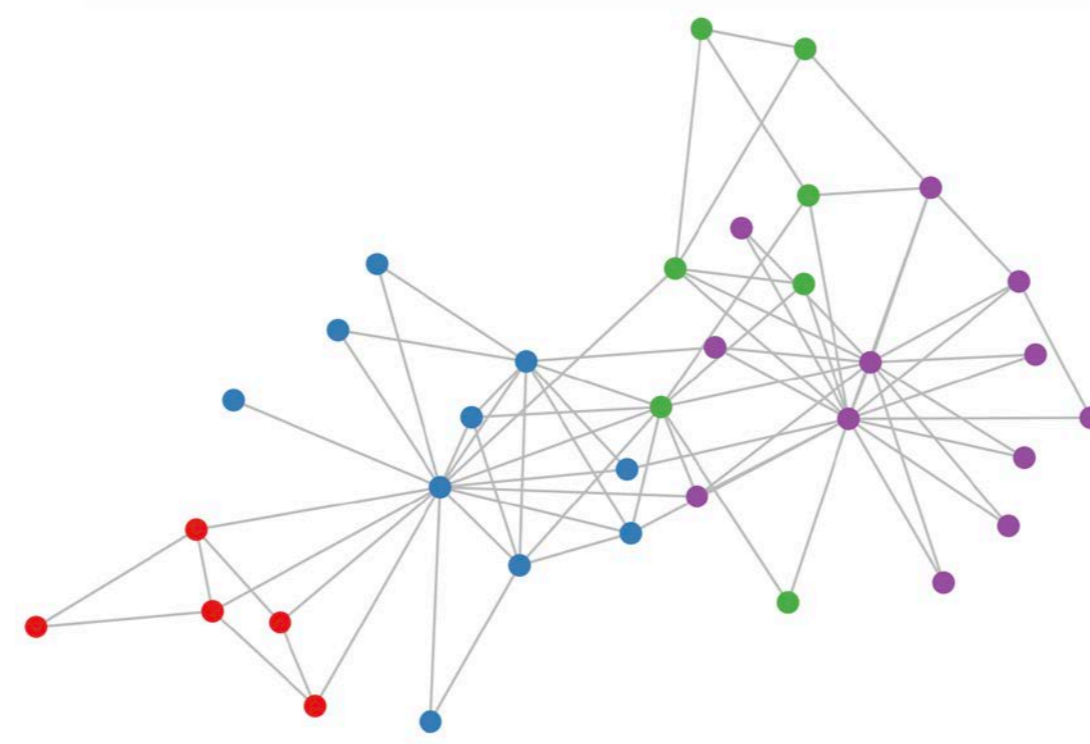
Person, Sports Ball,
Tennis Racket

Person, Tie

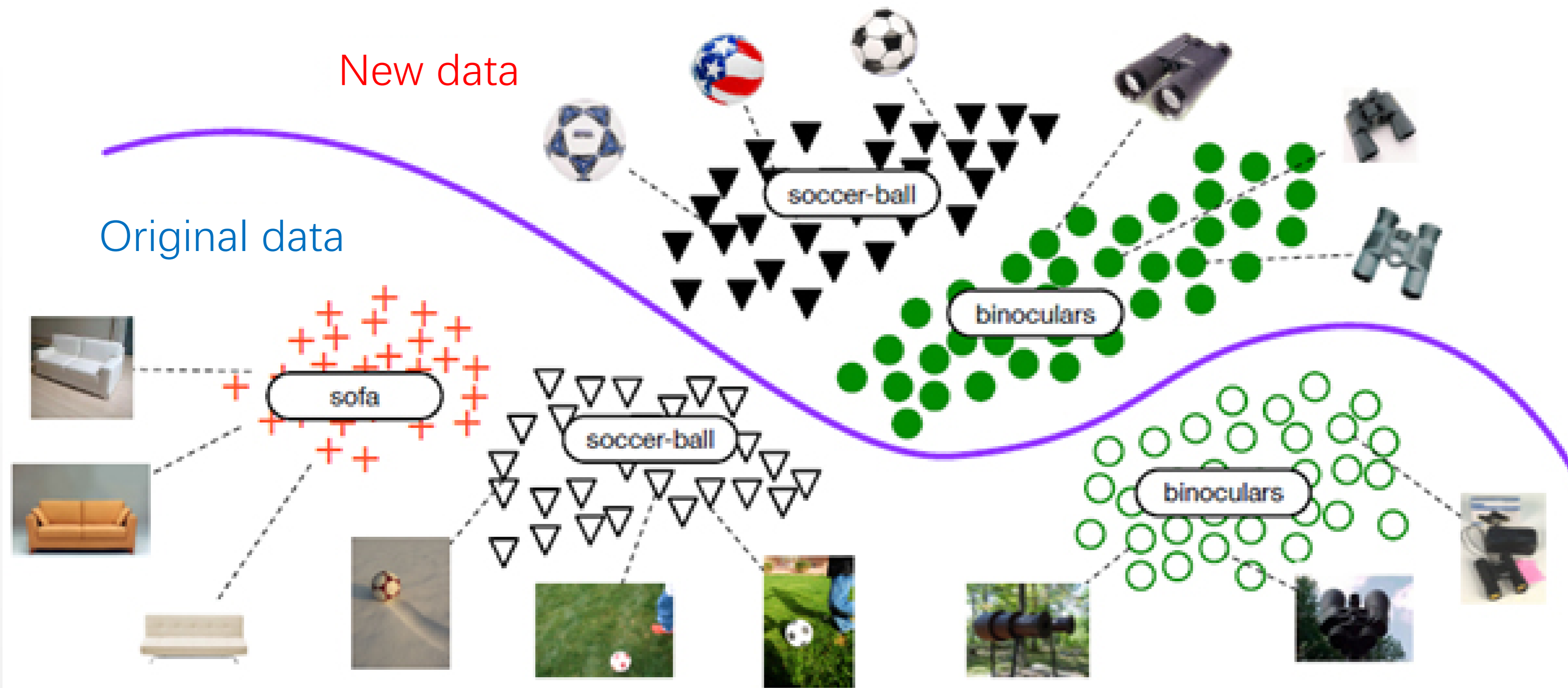
Person, Ski



Pairwise relationship modeling

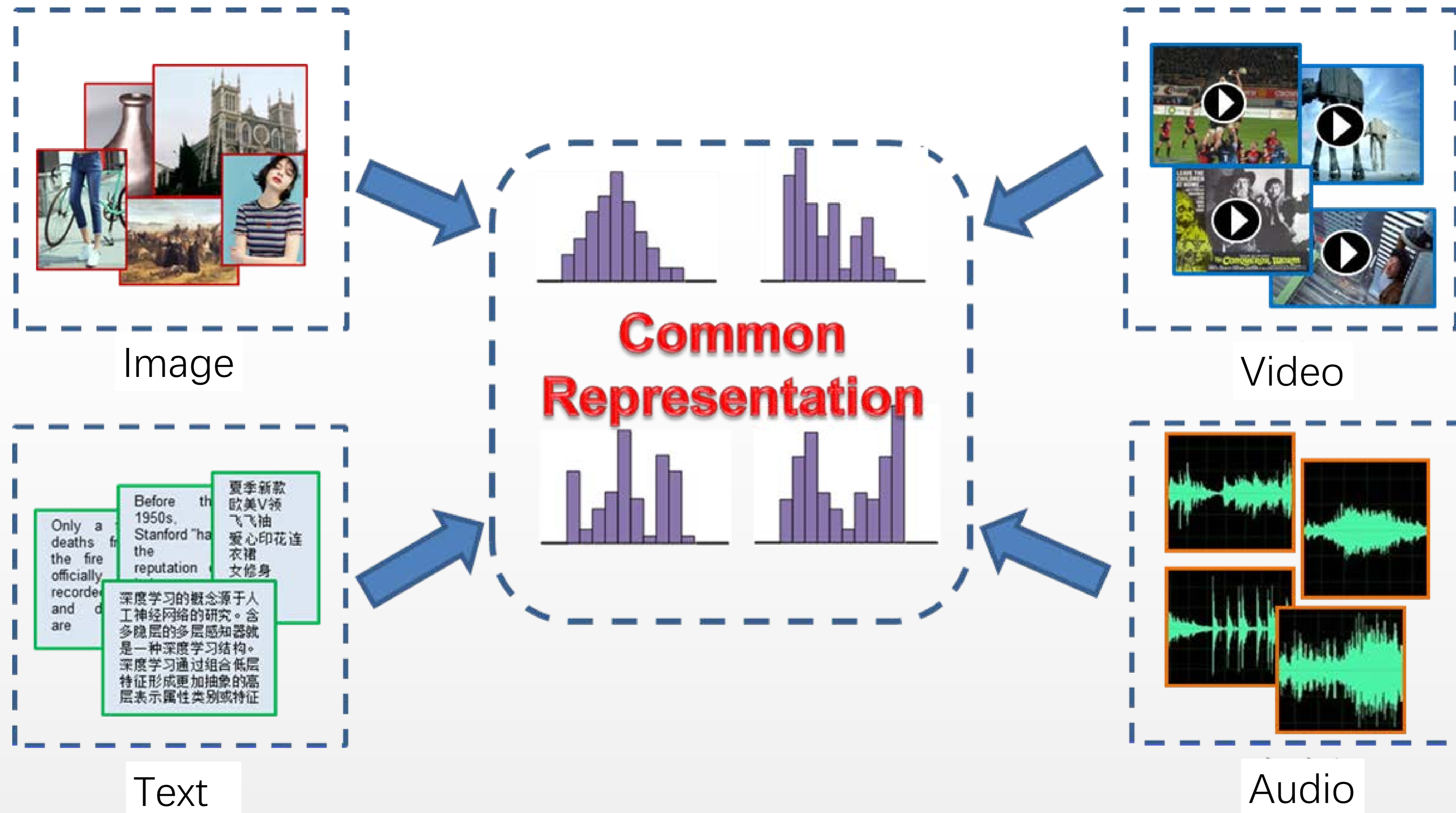


Large-scale classification with incremental learning



1. New data vs. original data: improving performance of the former while keeping the latter the same (no degradation)
2. Fast learning: no need to re-train

Multi-modality indexing and search



AI-powered Video Fingerprinting and Search



Video Fingerprinting and Content Search



Same Source



Similar Source

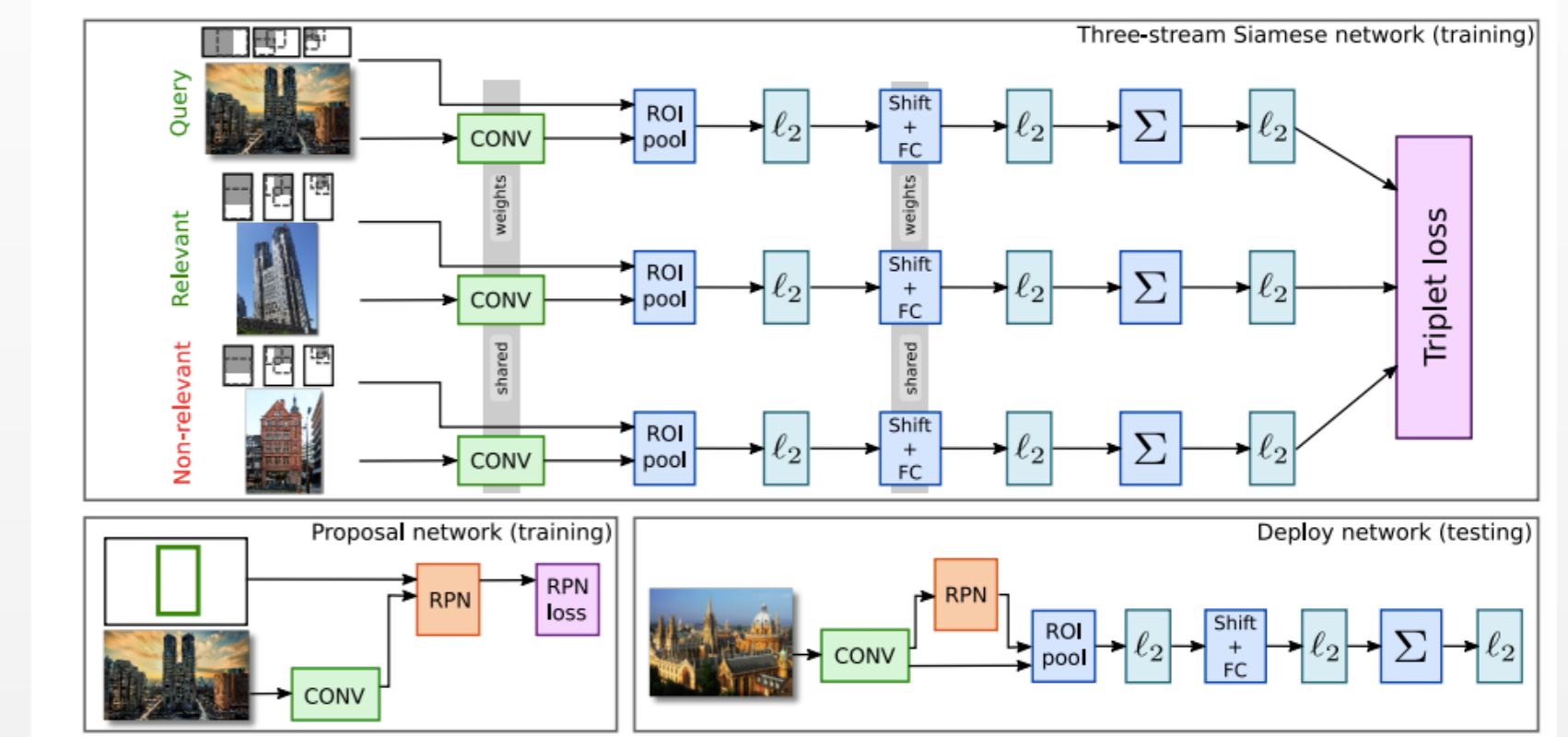
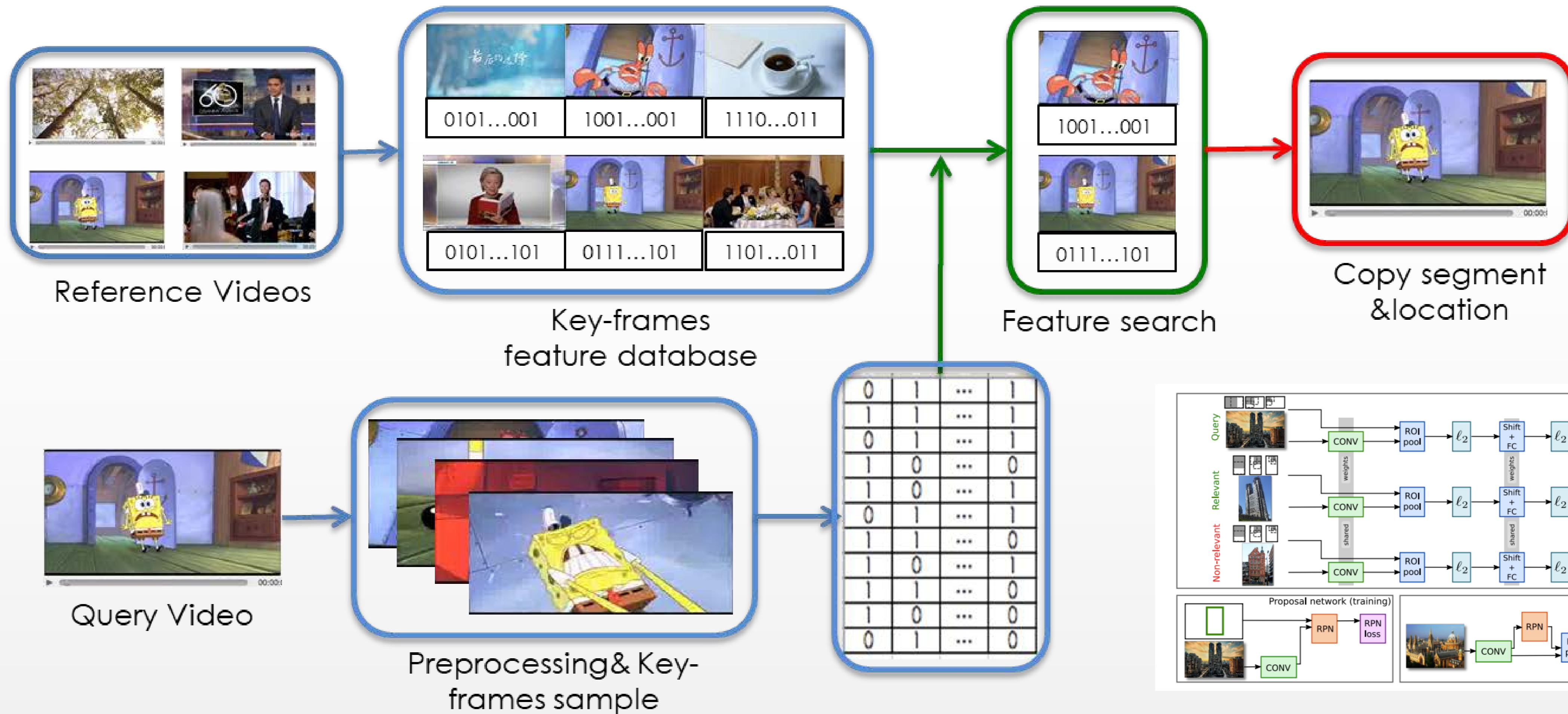


Same-source video transformations

1. Quality change: noise, contrast, blur, re-encoding ...
2. Spatial transformation: PIP, text insertion, mirroring, aspect ratio, rotation, crop, shift ...
3. Editing: timeline
4. Combination of the above



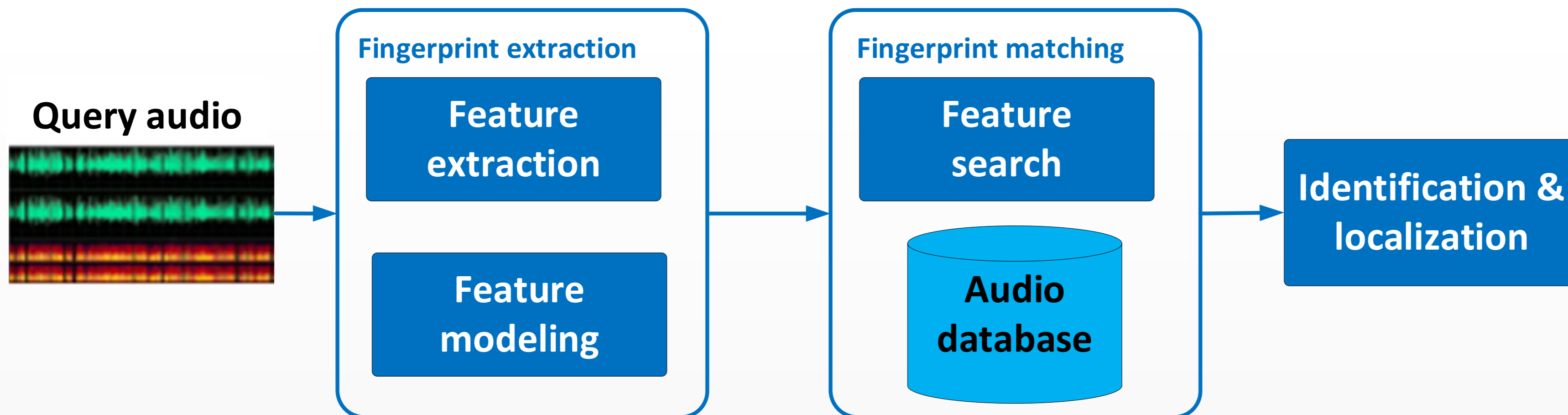
Video Fingerprinting: copyright & search



Training set: 10000*400 same-source transformed video

Audio Fingerprinting

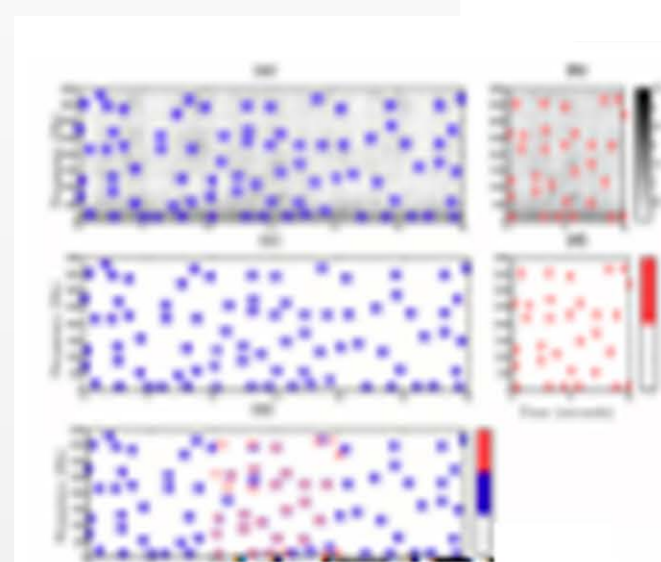
OPEN API



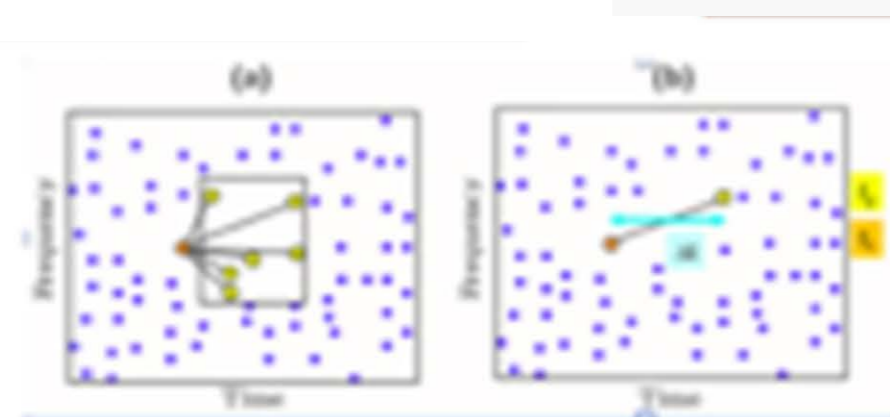
Duplication removal

Copyright protection

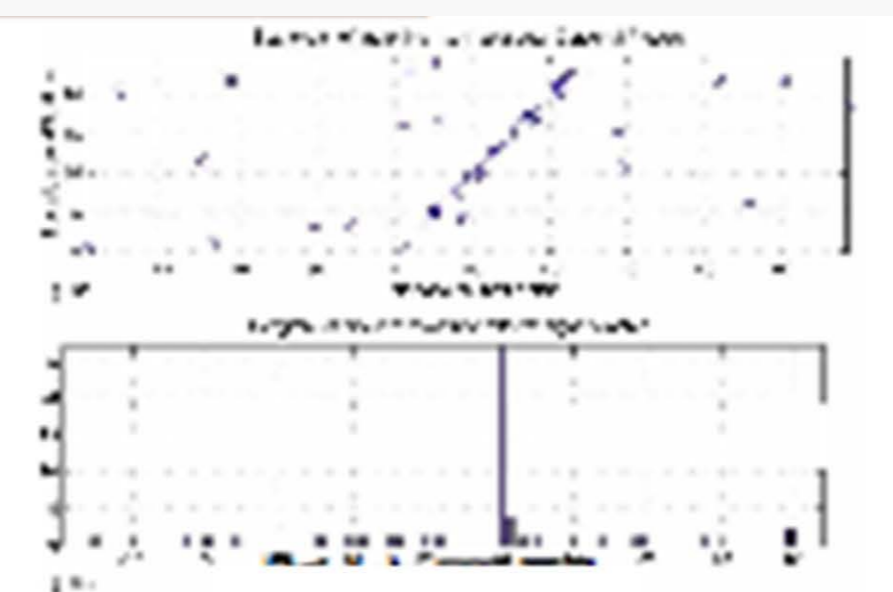
Audio search



Feature extraction



Modeling based on time-frequency analysis



Figureprint matching



AI-powered Video Content Production



Cover Image/Video Generation

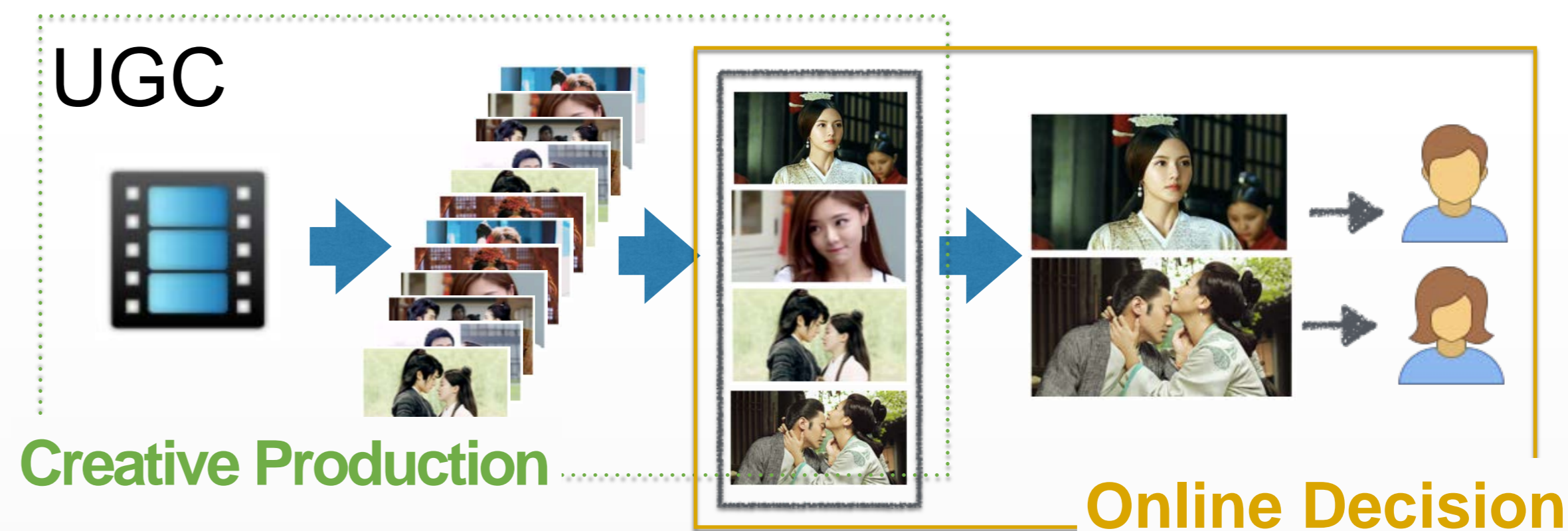
Cover image/video is directly related to user's click-through-rate (CTR)

Problem

- When we have massive amount of video from diverse sources, how do we produce the cover images/video using a general algorithm?
- How to personalize cover image/video?

Solution

- Joint video summarization + online decision optimization with bandwidth cost consideration



Results @ Youku :

CTR +15%

Dwell-Time +12%

Video Production: Sporting Event Highlights Generation



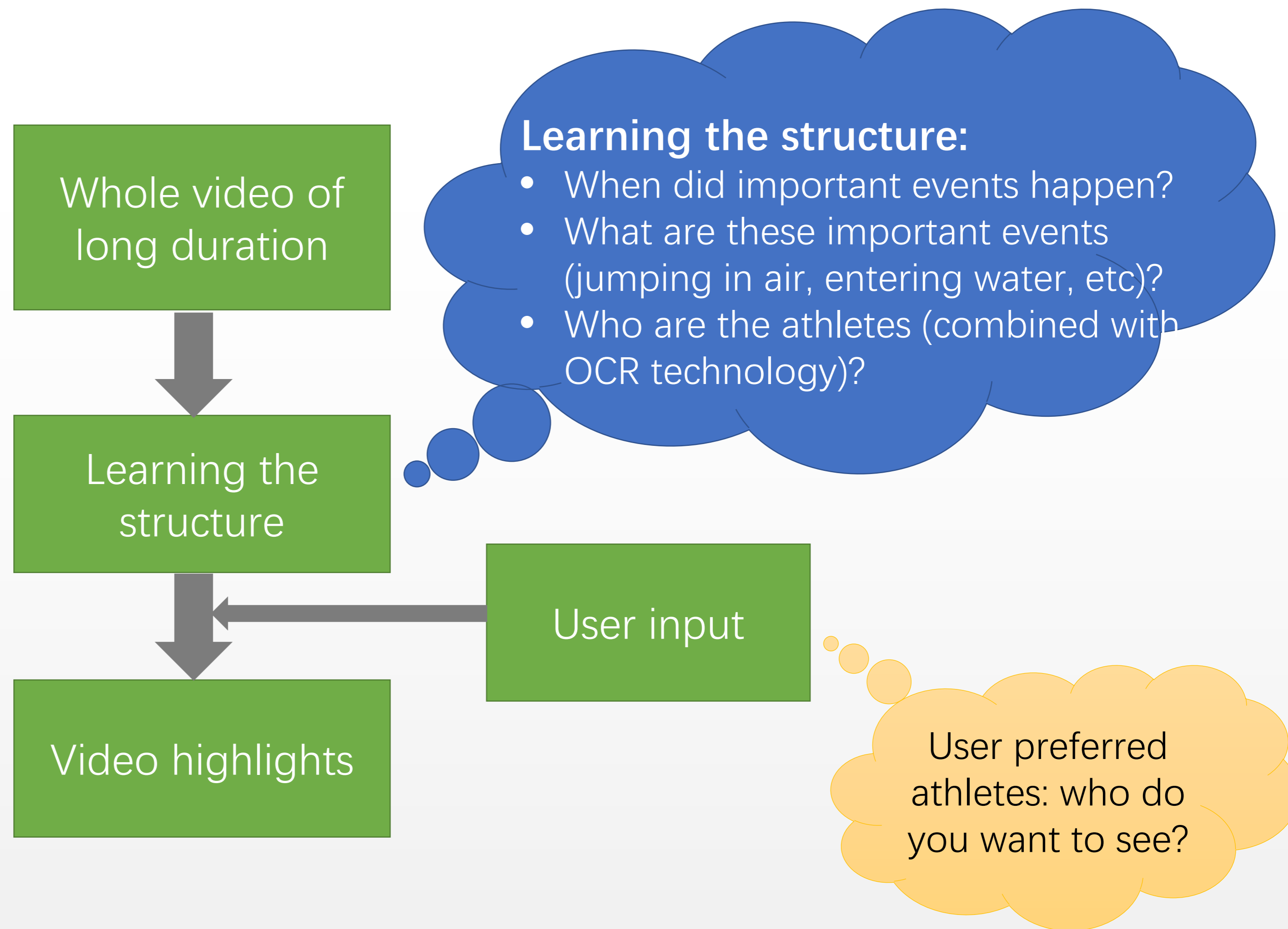
Diving highlights

❖ Why diving:

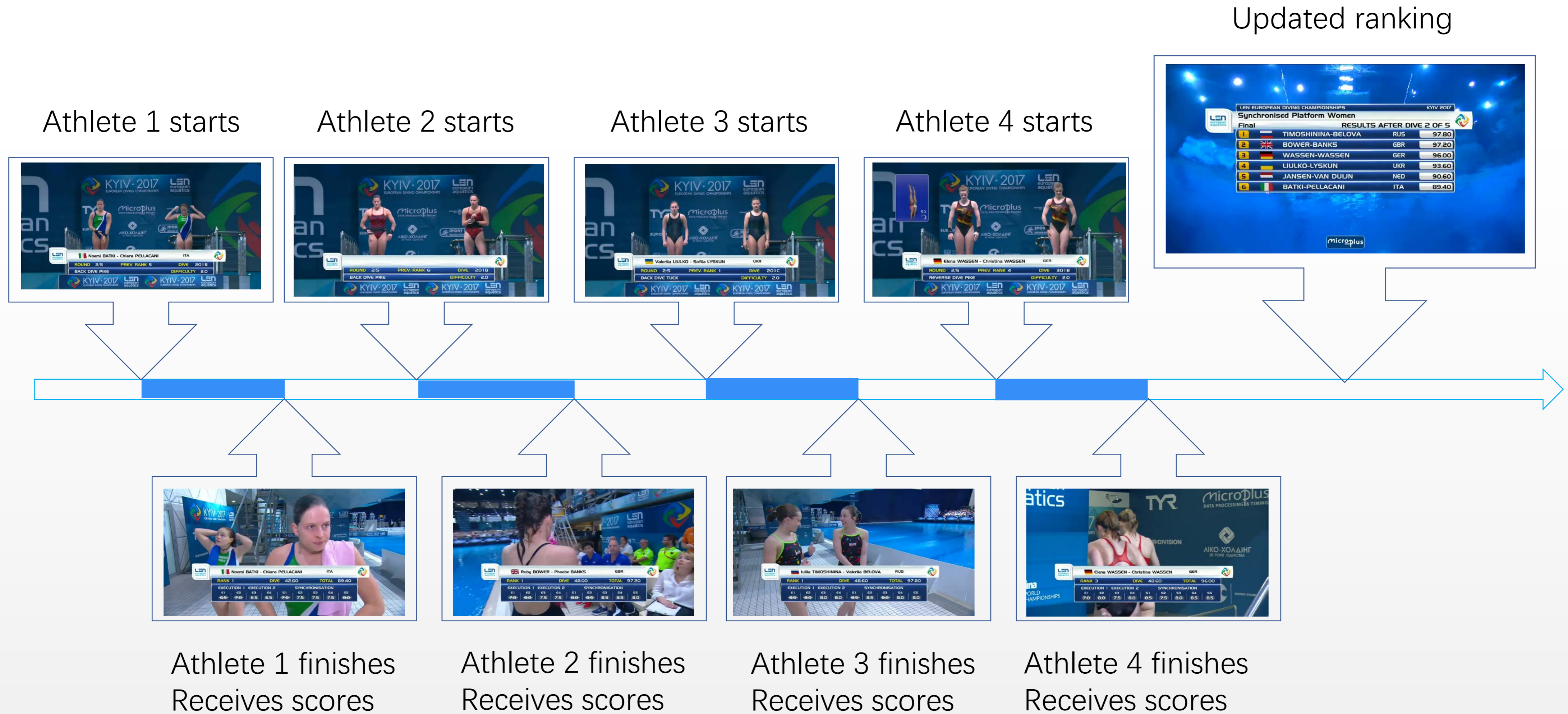
- High viewership in China
- Relatively simple video structure provides an easier starting point to deliver commercial-quality product

❖ Goal:

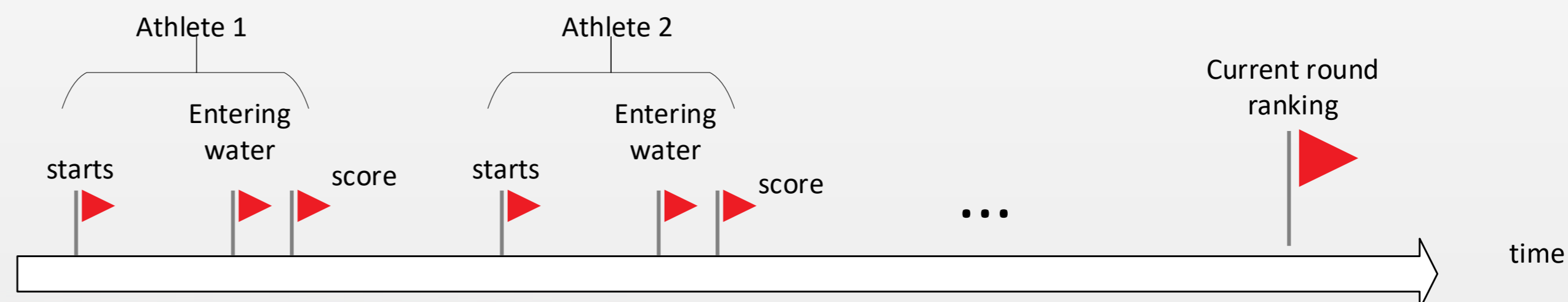
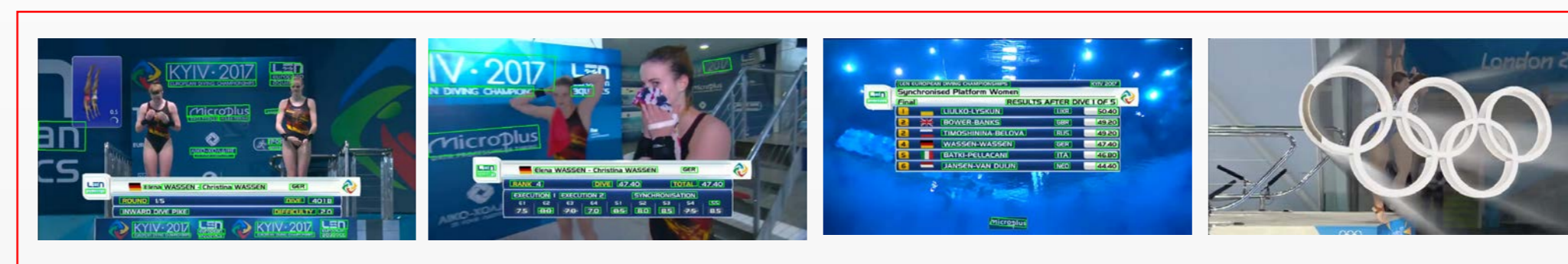
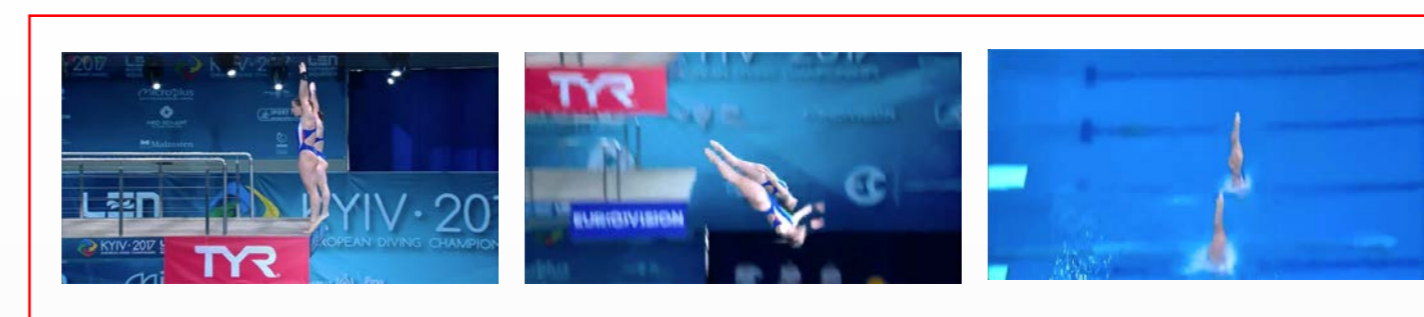
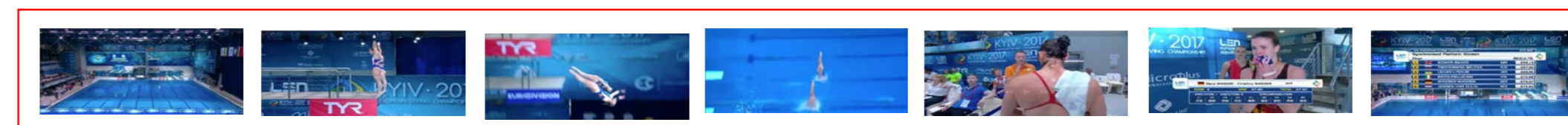
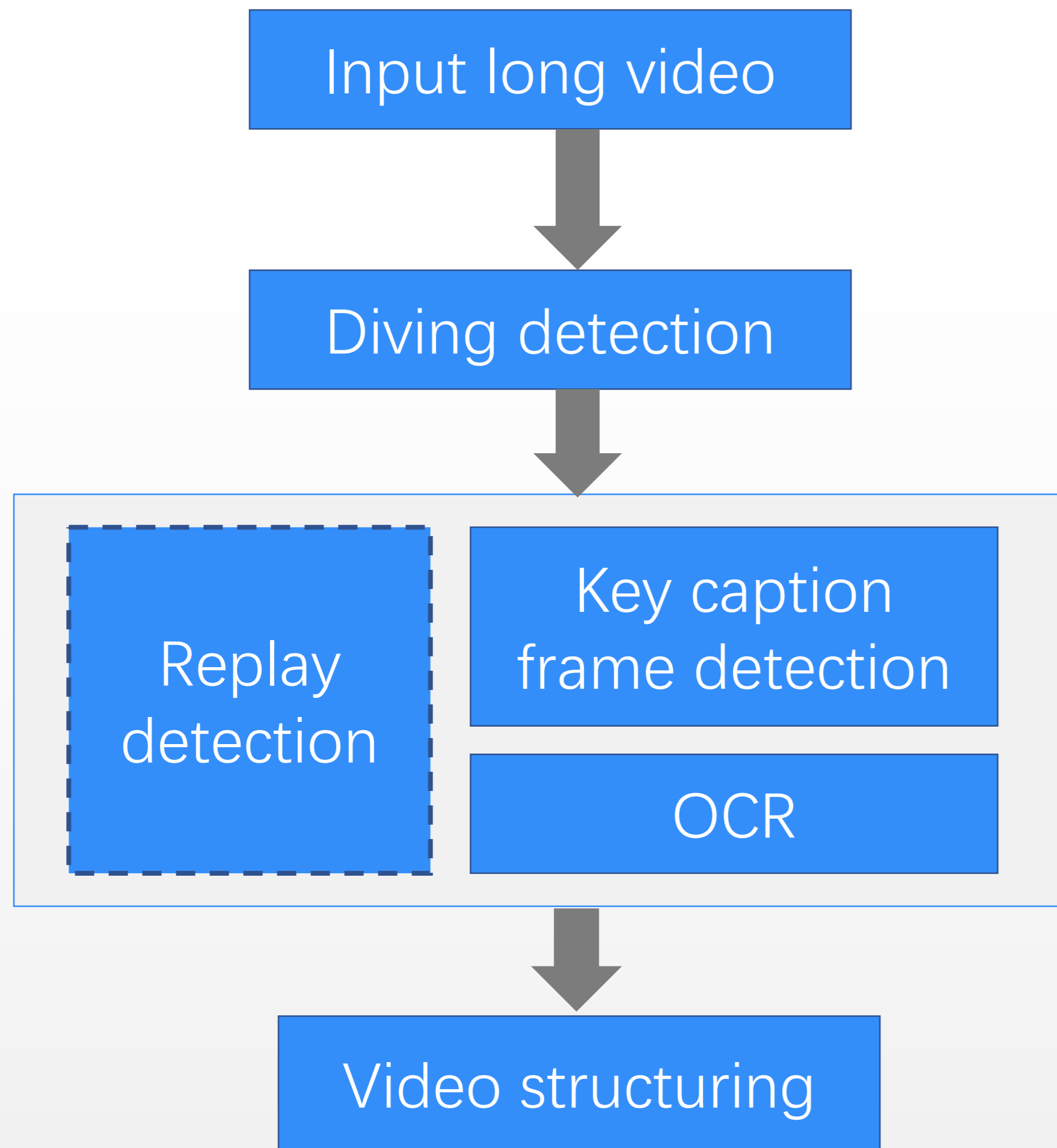
- Using DL technologies to understand the video structure
- *When, what, and who of the key events along the timeline?*
- Combine with OCR technology to allow users to create highlights of specific athletes



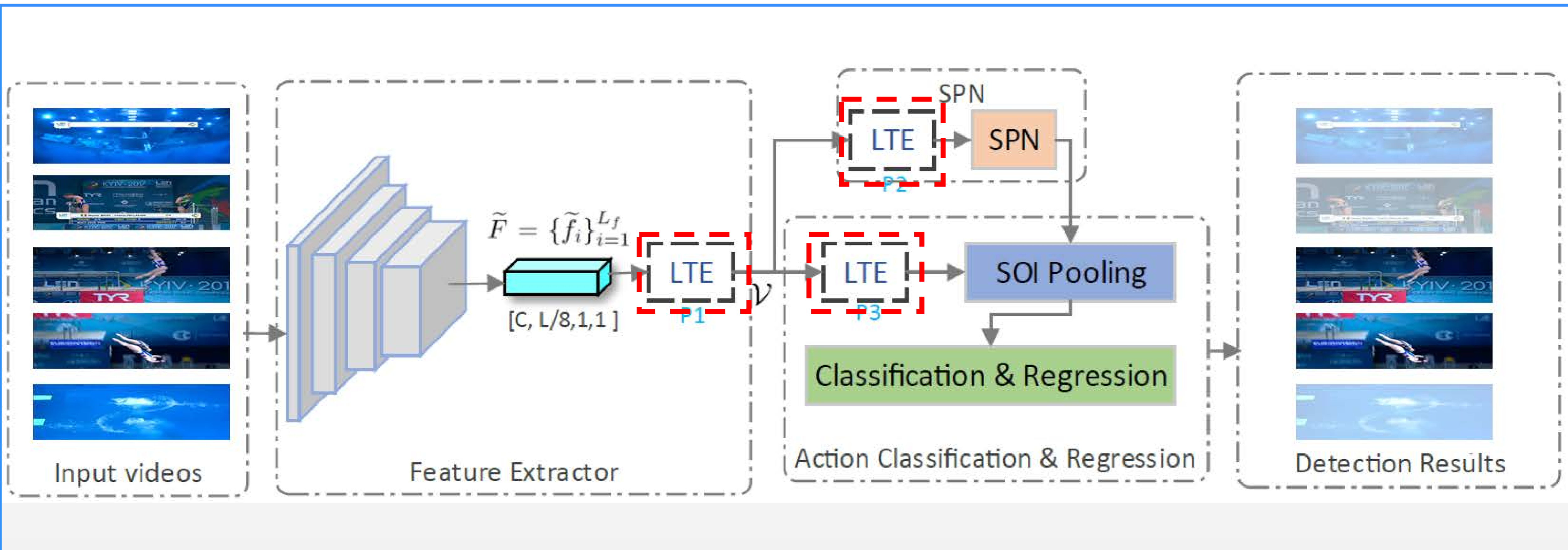
One round of diving competition



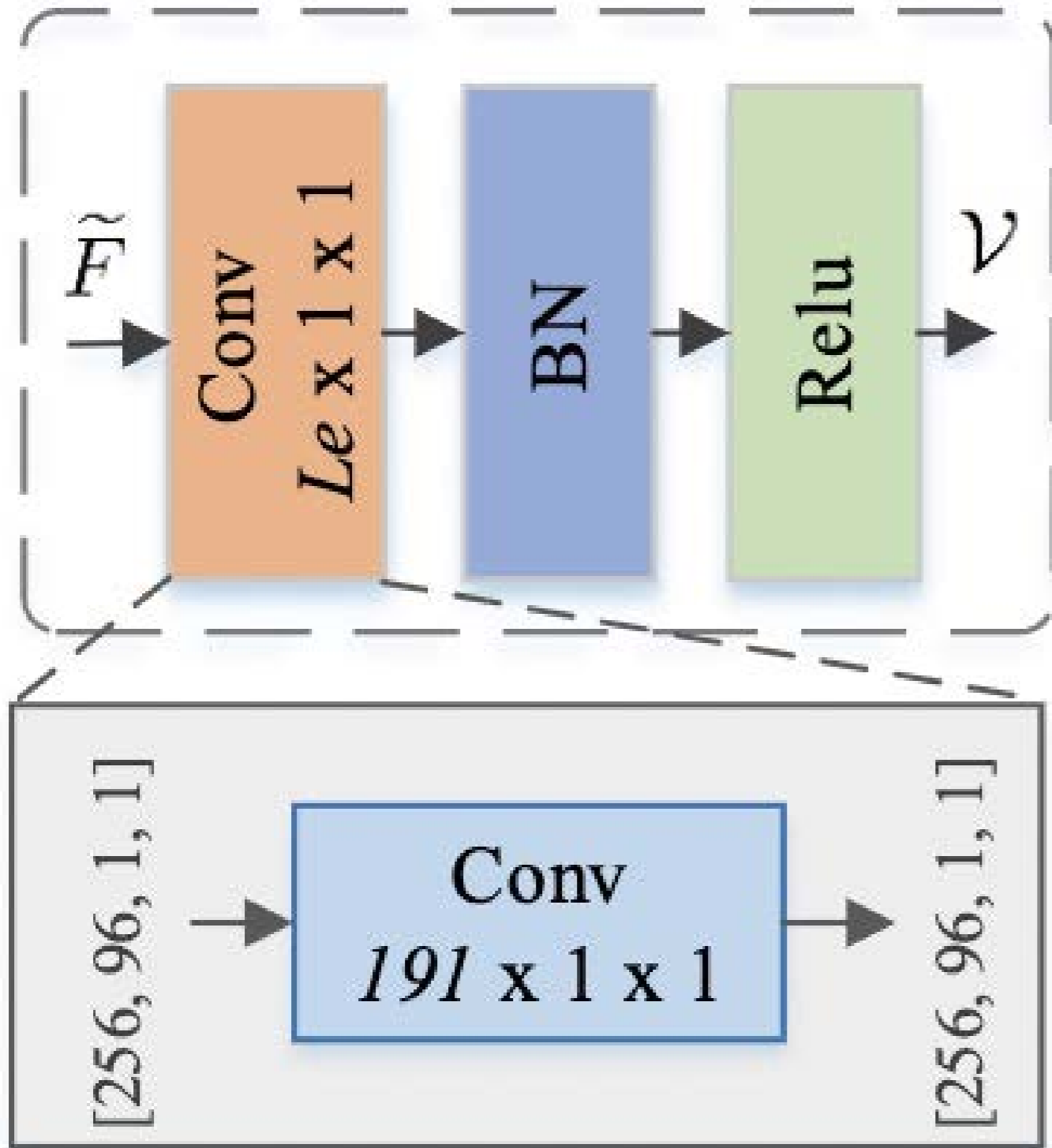
Creating Diving Highlights



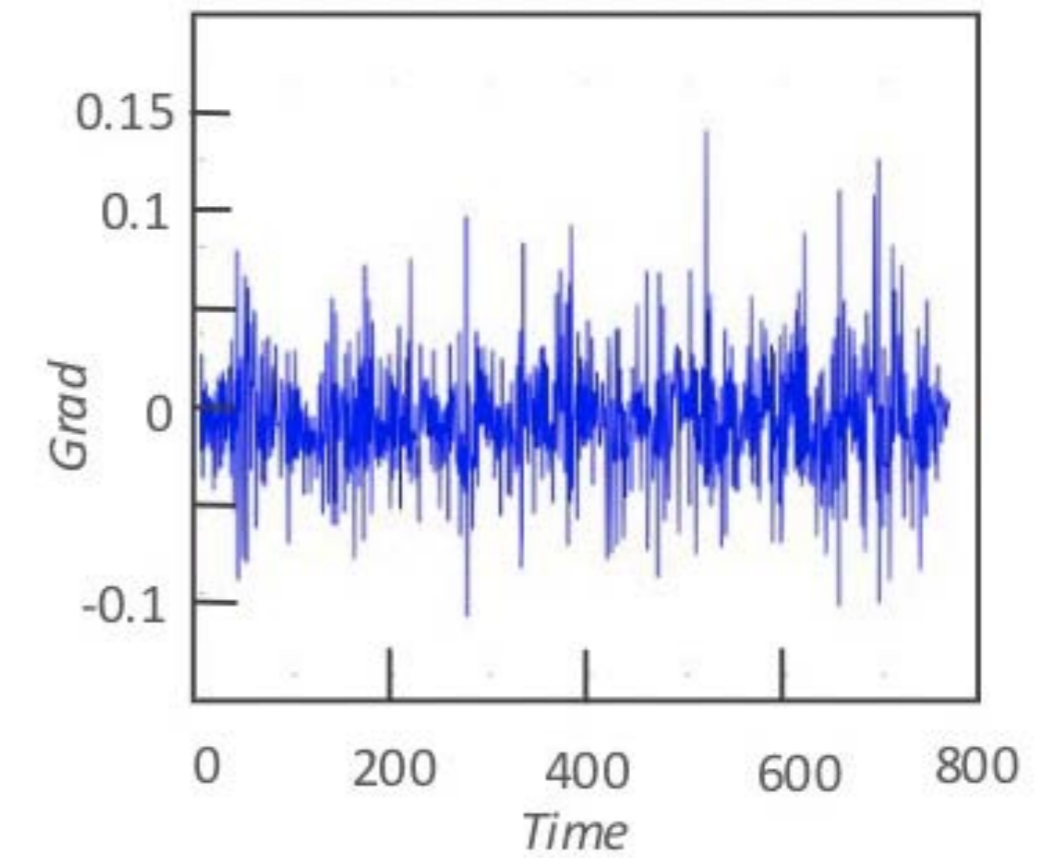
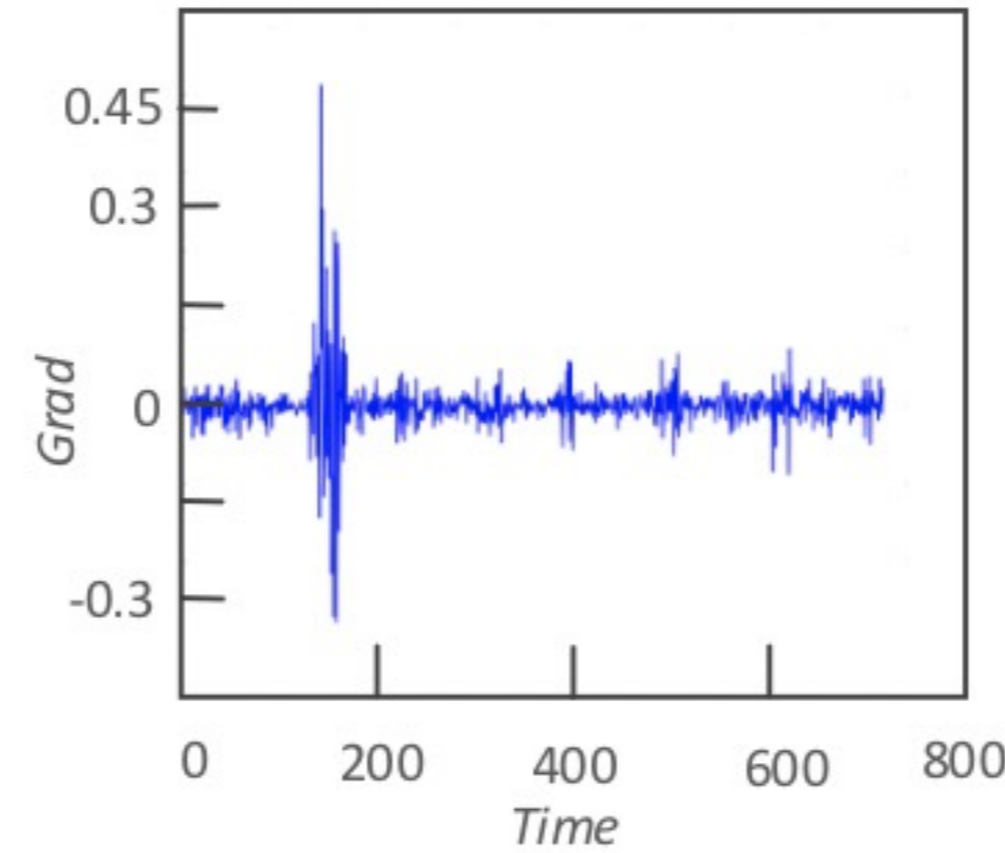
Diving detection



Long-term temporal encoding layer (LTE)



(1) Linear LTE layer



Compared to the baseline method (left), the proposed LTE layer (right) can significantly increase the effective temporal reception field (ERTF)



Detection results: public dataset

Methods requiring both RGB data and optical flow

tIoU	In ¹	0.1	0.3	0.4	0.5	0.6	0.7
Karaman <i>et al.</i> [45]	RF ²	4.6	2.4	1.4	0.9	-	-
Richard <i>et al.</i> [24]	RF	39.7	30.0	23.2	15.2	-	-
Shou <i>et al.</i> [46]	RF	47.7	36.3	28.7	19.0	10.3	5.3
Yeung <i>et al.</i> [47]	RF	48.9	36.0	26.4	17.1	-	-
Yuan <i>et al.</i> [22]	RF	51.4	33.6	26.1	18.8	-	-
Shou <i>et al.</i> [31]	RF	-	40.1	29.4	23.3	13.1	7.9
Yuan <i>et al.</i> [27]	RF	51.0	40.1	27.8	17.8	-	-
Gao <i>et al.</i> [32]	RF	60.1	50.1	41.3	31.0	19.1	9.9
Hou <i>et al.</i> [21]	RF	51.3	43.7	-	22.0	-	-
Dai <i>et al.</i> [48]	RF	-	-	33.3	25.6	15.9	9.0
Zhao <i>et al.</i> [28]	RF	66.0	51.9	41.0	29.8	-	-
Yang <i>et al.</i> [49]	RF	-	-	-	14.7	-	-
Gao <i>et al.</i> [34]	RF	54.0	44.1	34.9	25.6	-	-
Humam <i>et al.</i> [50]	RF	-	51.8	42.4	30.8	20.2	11.1
Lin <i>et al.</i> [6]	RF	-	-	45.0	36.9	28.4	20.0
Shou <i>et al.</i> [51]	RF	-	35.8	29.0	21.2	13.4	5.8
Liu <i>et al.</i> [8]	RF	-	53.9	46.8	37.4	29.5	21.3

Methods requiring only RGB data

		End-to-end Method					
Xu <i>et al.</i> [11]	R ³	54.5	44.8	35.6	28.9	-	-
Yu <i>et al.</i> [12]	R	49.3	42.6	-	31.9	-	14.2
LTENet	R	59.0	53.2	48.1	41.1	32.2	22.1

The proposed method only needs the RGB input, achieves the best action recognition results: For IoU = 0.5, 41% MAP



Detection results: private dataset

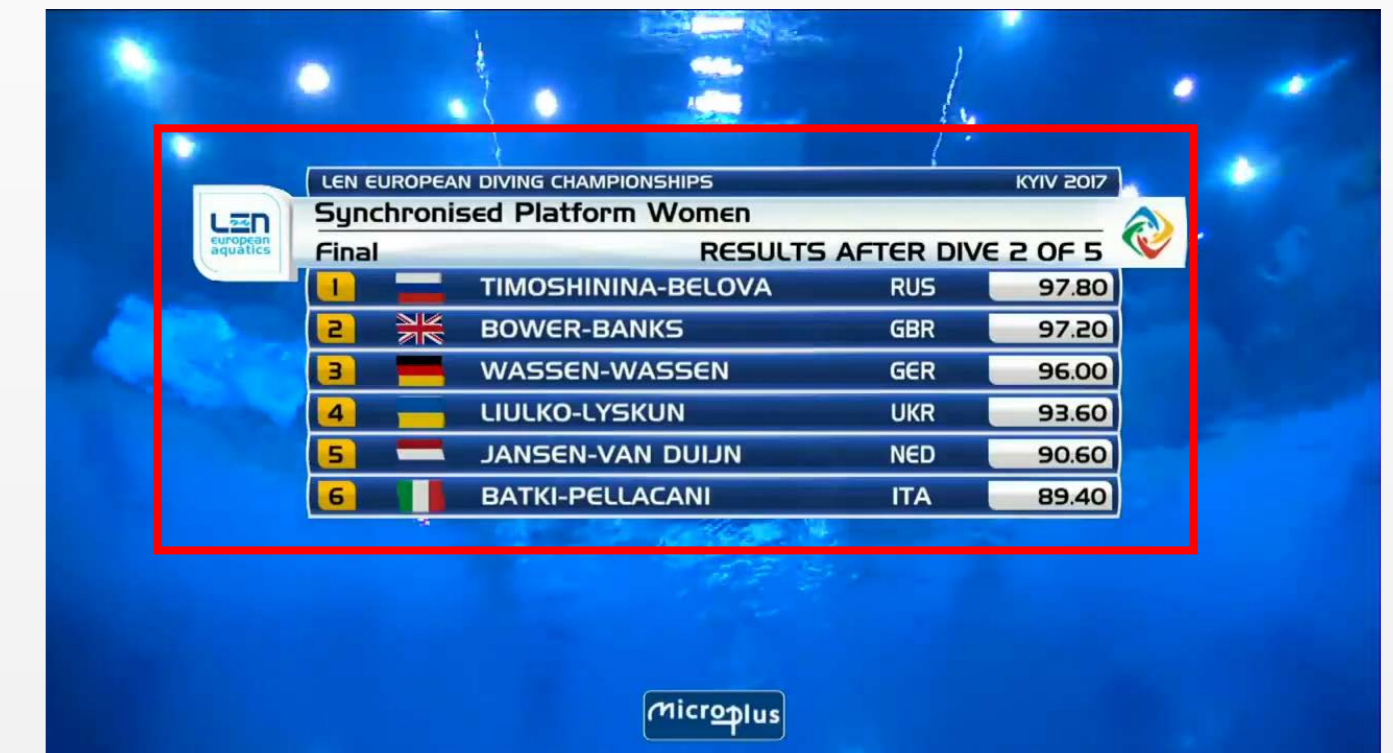
Dataset: 1.1k diving video including world tournament and Olympic games since 2010

tIoU	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	mMAP
mAP	0.955	0.944	0.937	0.914	0.881	0.856	0.763	0.554	0.229	0.011	0.7044



Caption Frame Detection

- What is a **Caption Frame**? The frame containing information about the athlete(s), scores, ranking, etc.
- Caption frame detection, combined with OCR technologies, can be used to generate diving highlight of specific athletes



Demo: diving highlights of specific athletes



Original video 39 minutes: http://publicvideos.oss-cn-hangzhou-zmf.aliyuncs.com/d_Q3PH8jsD0.mp4



Concluding remarks

- Video is much more difficult than images
- Processing efficiency can be significantly increased if learning can be conducted in the compressed domain
- Can compression technologies be adapted to assist with AI-based video learning?

