Advancing Player Identification and Tracking with Global ID Fusion (GIF)

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WACV2026, Tucson, Arizona

Multi-perspective Broadcasting Videos

- Multi-perspective
- Clothe-changing
- Zoom-in zoom-out
- Irregular poses
- Uniform

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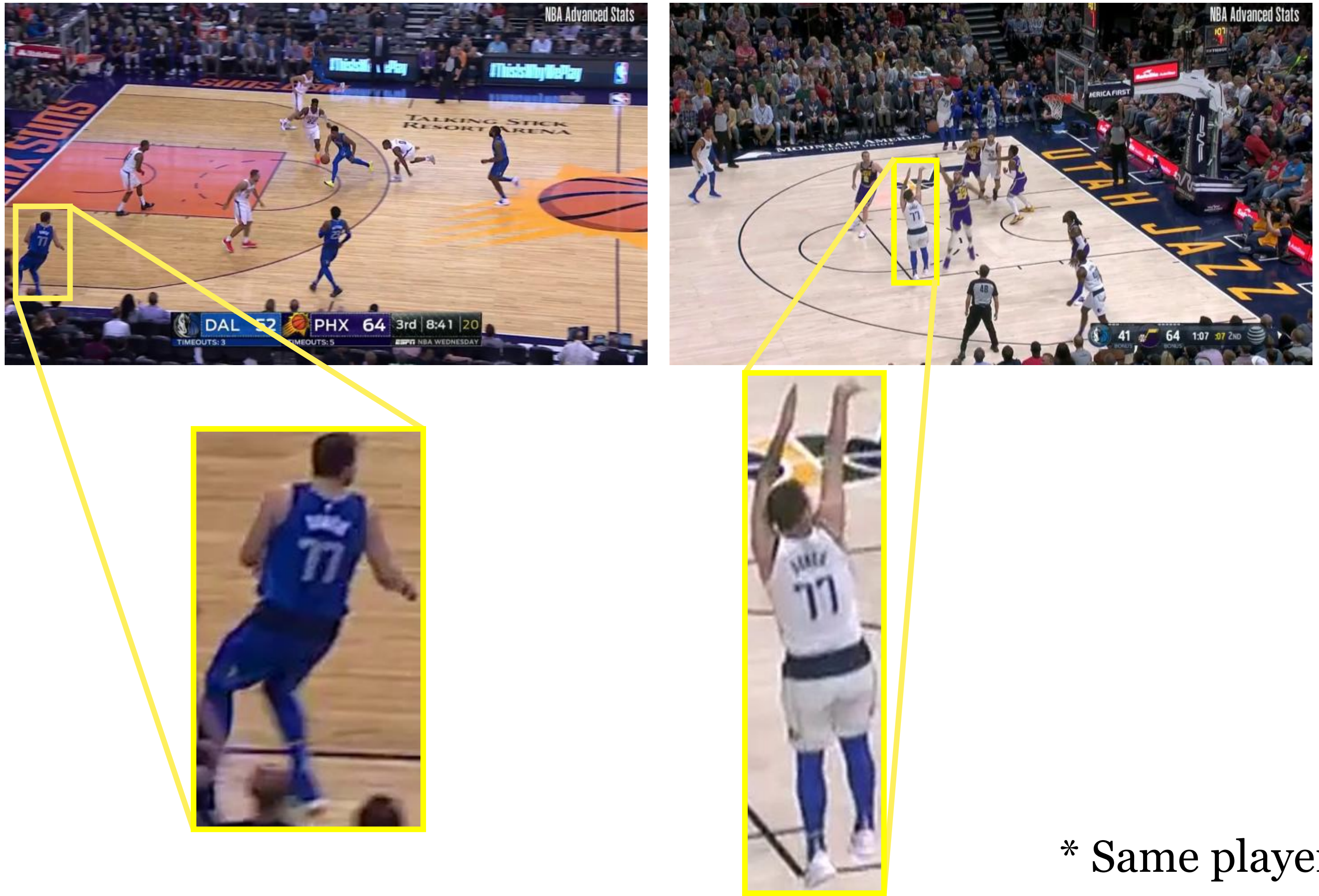

* Same player

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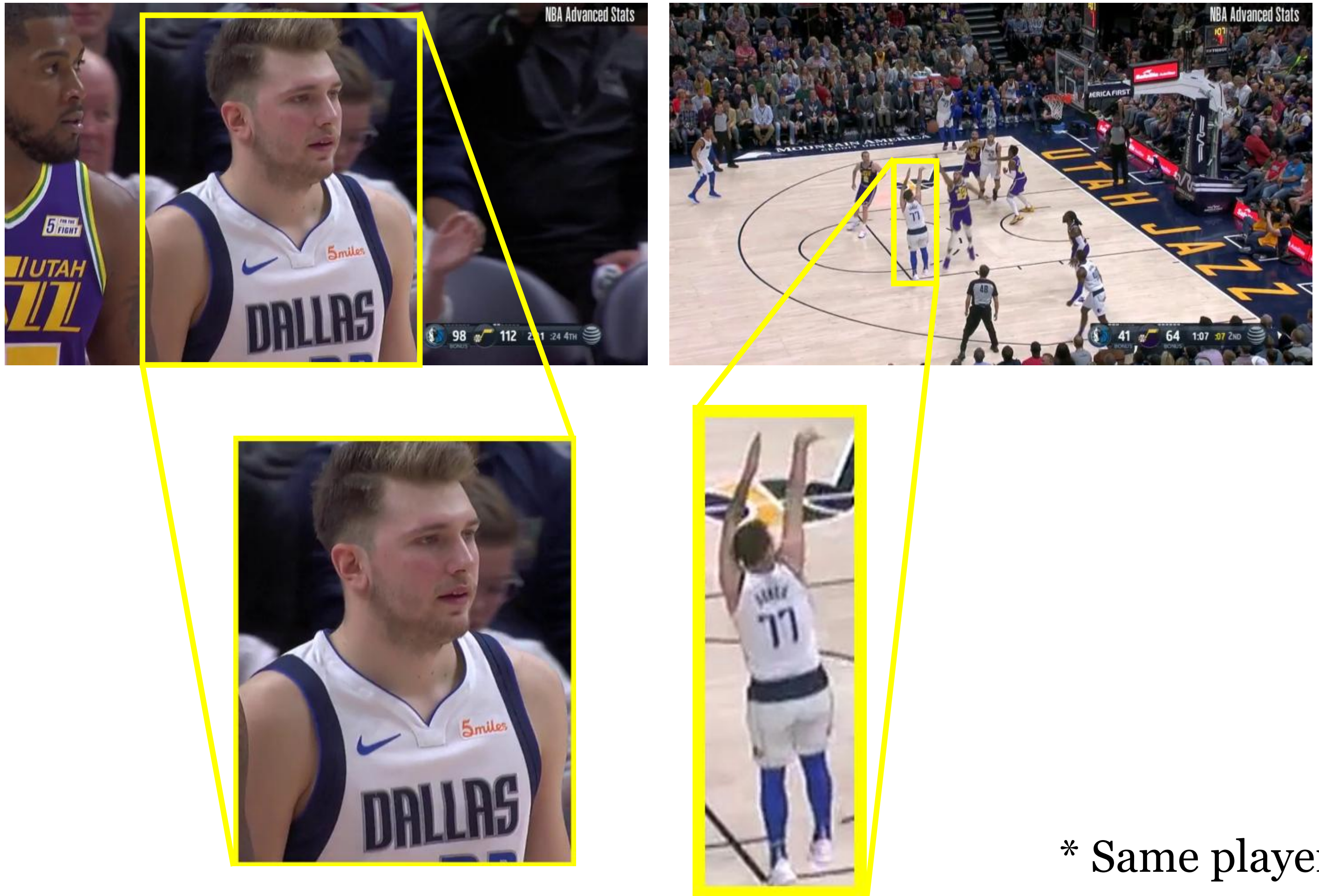

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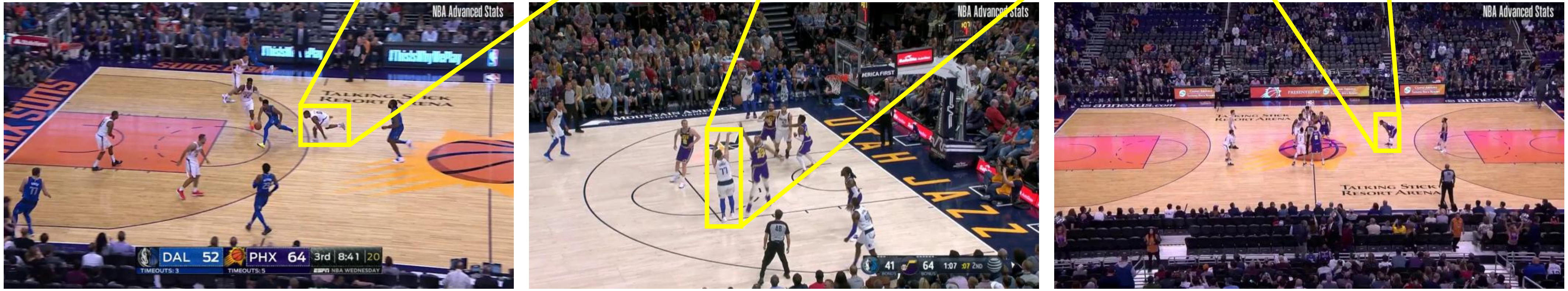

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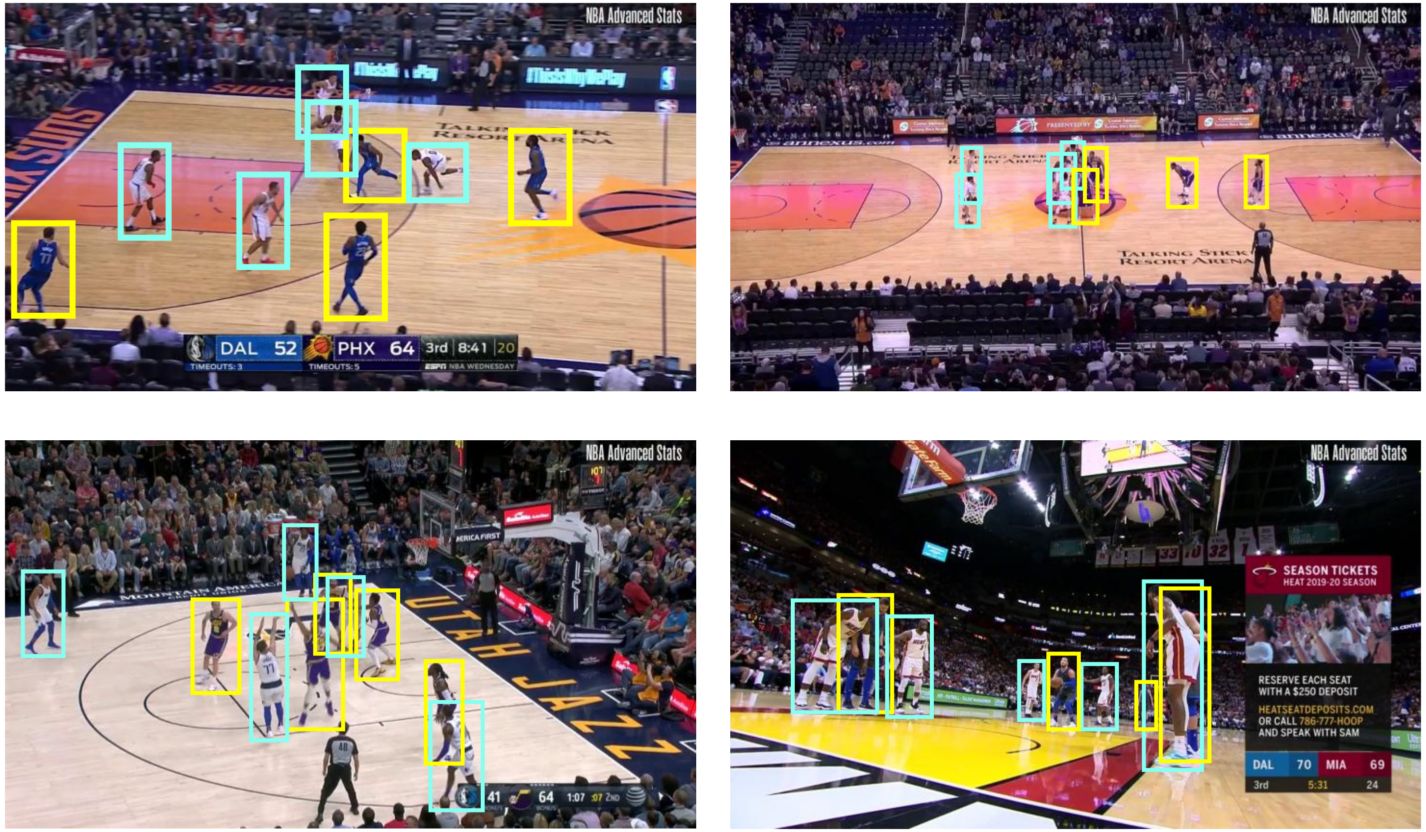


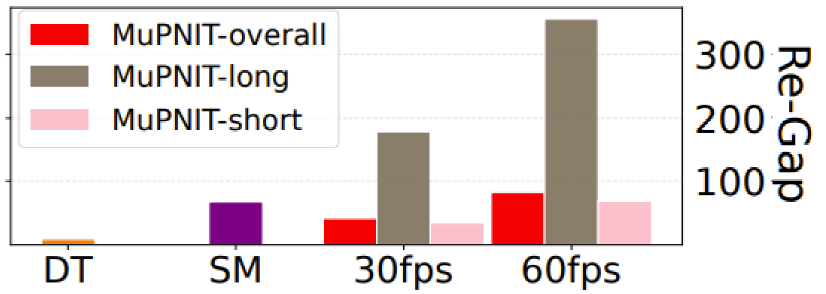
Our Contributions

- **MuPNIT & MuPNIT-ReID Datasets**: A multi-perspective benchmark for sports, featuring 2.19M boxes across 283K frames of NBA games. It addresses critical gaps in tracking across camera cuts, zooms, and cross-season appearance changes (jerseys, lighting, and poses), with a global ID feature bank
- **Global ID Fusion (GIF) Framework**: A high-performance, online fusion approach for real-time tracking and identification
- **Identity Consistency Metrics**: Introduction of five novel Global ID metrics to evaluate tracking stability and provide new insights into identity prediction tradeoffs

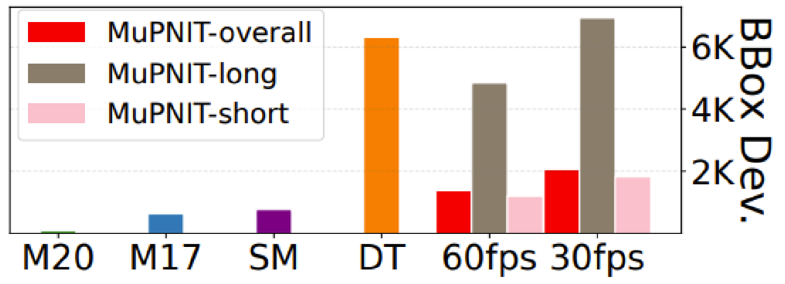
Multi-Perspective NBA Global Identity Tracking (MuPNIT) Datasets - MOT

Table 1. **Comparison of object tracking datasets.** Stats for the long and short videos are shown as long/short/overall. Colors are used to indicate largest and second-largest entry for each feature.

Dataset	MOT17 [51]	MOT20 [14]	DanceTrack [64]	SportsMOT [10]	SMOT [42]	MuPNIT 60fps	MuPNIT 30fps
Videos	14	8	100	240	**3,292**	10 / 200 / 210	
Min. Len. (s)	15.0	**17.2**	9.2	9.0	1.5	**252.4** / 5.5 / 5.5	
Avg. Len. (s)	33.0	**67.1**	52.9	24.7	22.9	**282.7** / 9.4 / 22.4	
Max. Len. (s)	85.3	**132.6**	120.1	73.0	116.0	**339.9** / 15.8 / **339.9**	
Total Len. (s)	462	536	5,292	**6,015**	**75K**	2,827 / 1,882 / 4,709	
#Tracks	796	2,332	990	3,401	**7,792**	1,661 / 2,492 / **4,153**	
#Boxes	340K	**1,699K**	574K	1,629K	335K	**2,187K**	1,094K
#Frames	11K	13K	106K	150K	**151K**	**283K**	141K
fps	**30**	25	20	25	2	**60**	**30**
multi-perspective	-	-	-	-	-	✓	✓
Global IDs	-	-	-	-	-	✓	✓



(a) Average Re-association Gap

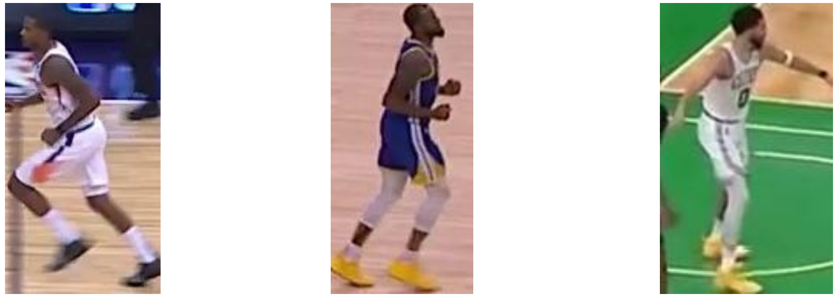


(b) Consec. BBox Size Deviation

Multi-Perspective NBA Global Identity Tracking (MuPNIT) Datasets - ReID

- MuPNIT-ReID: all player crops
- MuPNIT-ReID-light: ~200 images/player

Global ID database



In-game player crops

Table 2. **Comparison of ReID datasets.** Here + denotes image-to-image and * synthetic datasets. Acronyms: uniform (**Uni**), irregular poses (**IrP**), and number of outfits per identity (**#OpI**).

Dataset	#IDs	#Images	#Tracklets	Text	Uni	IrP	#OpI
Market1501+ [85]	751	13K	–	–	–	–	–
CUHK-SYSU+ [74]	8,432	100K	–	–	–	–	–
MARS [86]	1,261	1.19M	20K	–	–	–	1
iLIDSVID [33]	300	42K	600	–	–	–	1
PRCC+ [77]	221	34K	–	–	–	–	–
MTA* [30]	–	37.3M	2,840	–	–	–	1
P-DESTRE [31]	253	14.8M	1,894	–	–	–	–
CCVID [23]	226	348K	2,856	–	–	–	∼2
MEVID [12]	158	1.7M	8,092	–	–	–	∼4
MuPNIT-ReID-light	211	55K	2,260	✓	✓	✓	1–5
MuPNIT-ReID	211	396K	2,415	✓	✓	✓	1–5

Identity Tracking

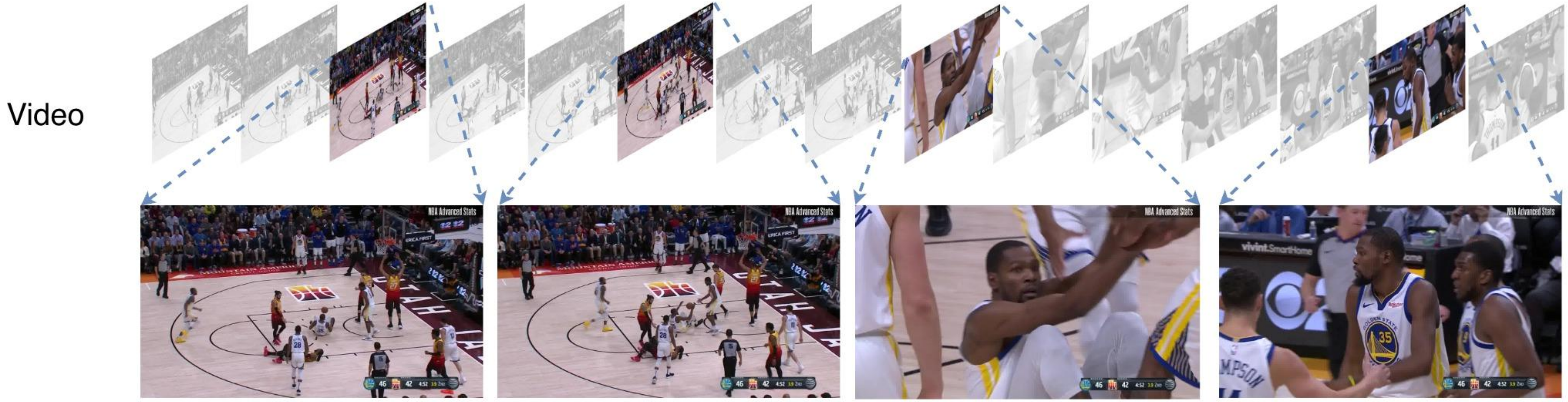


Figure 1. Visualization of GIF. Detection images are mapped against global ID representations (images and/or text) provided as context. The most frequent global ID assigned to a track is selected as its identity, enabling tracking across changes of camera perspectives.

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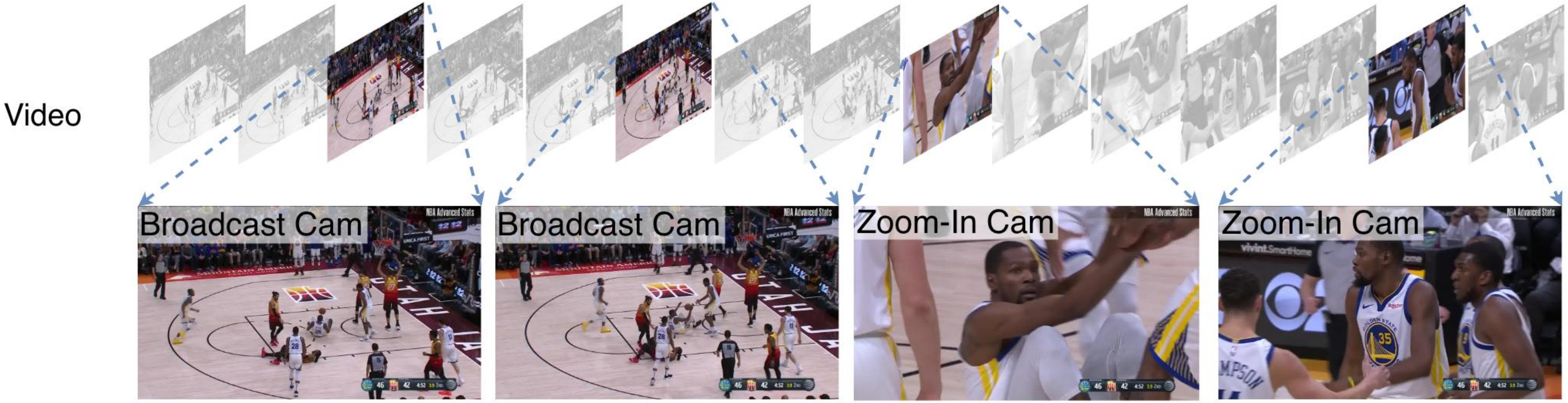

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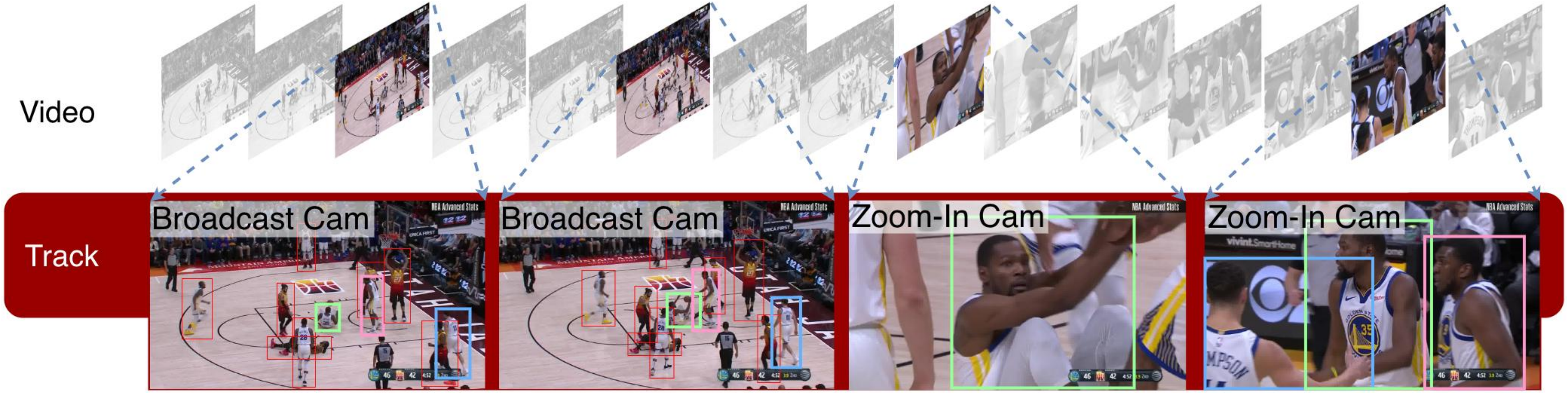

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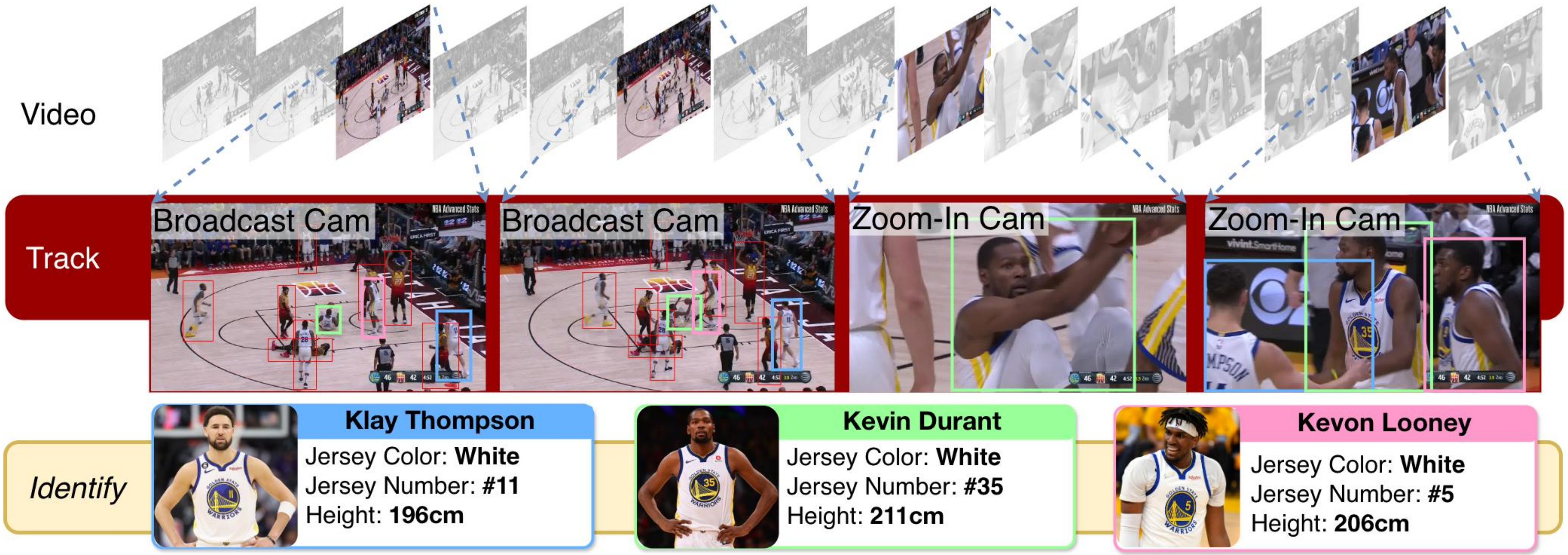

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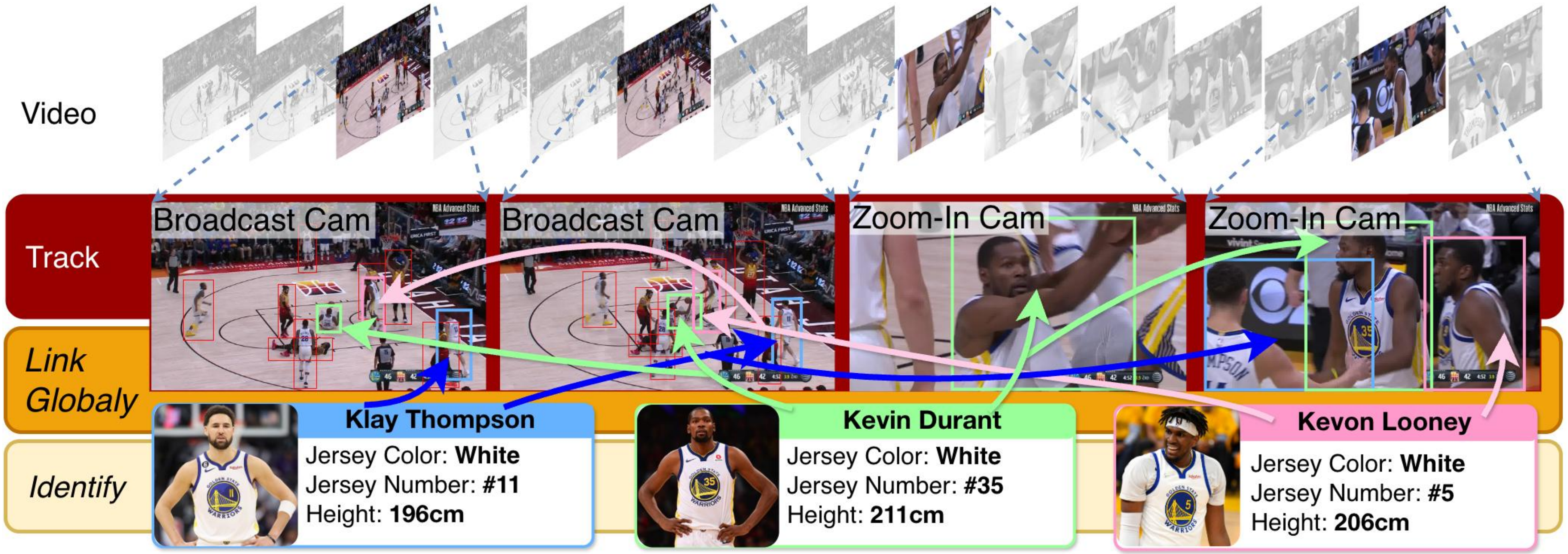

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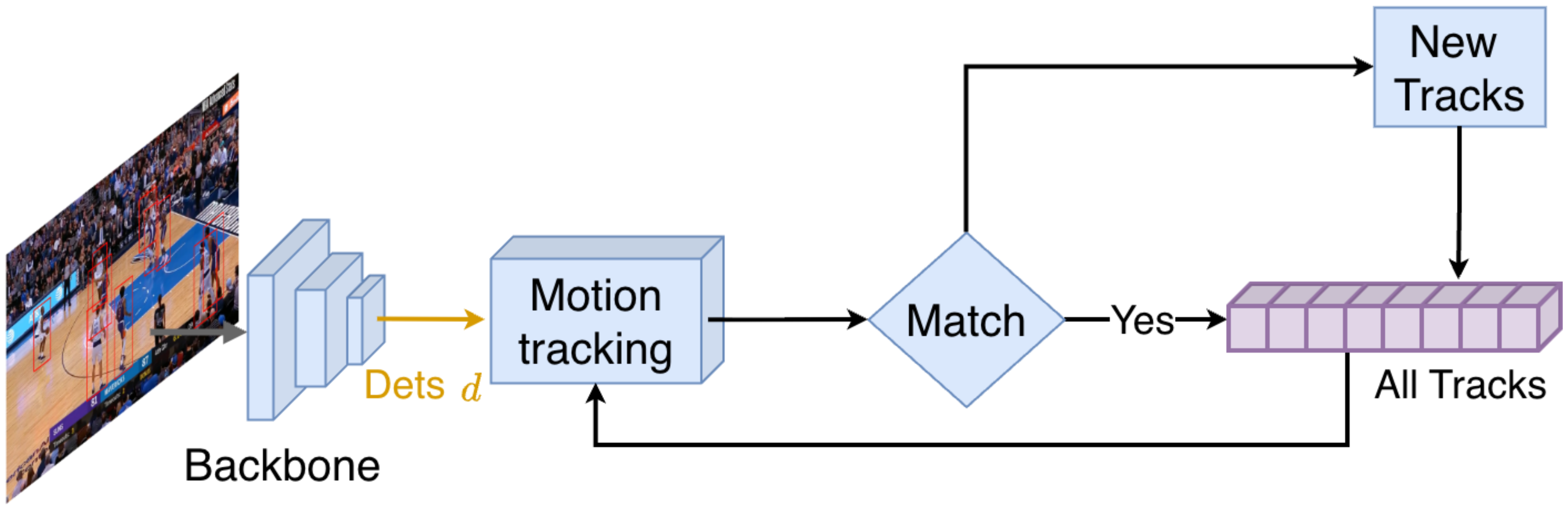

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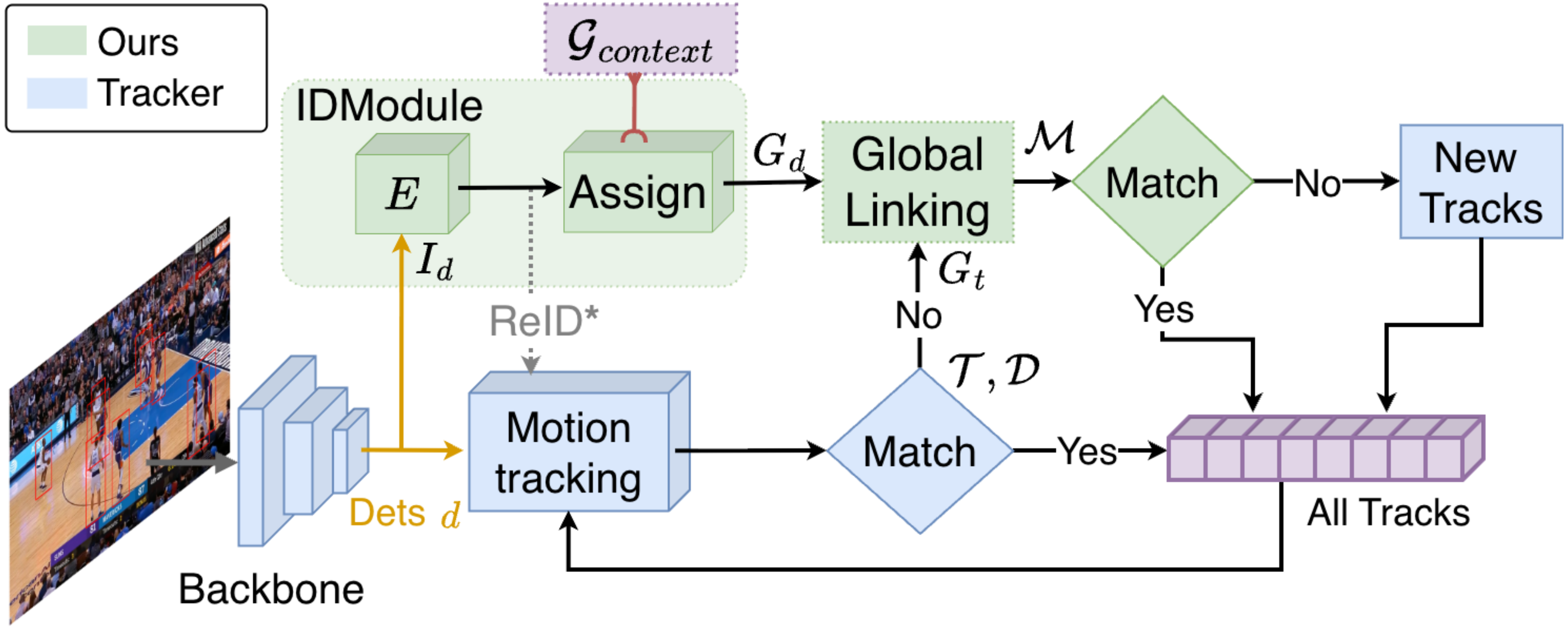

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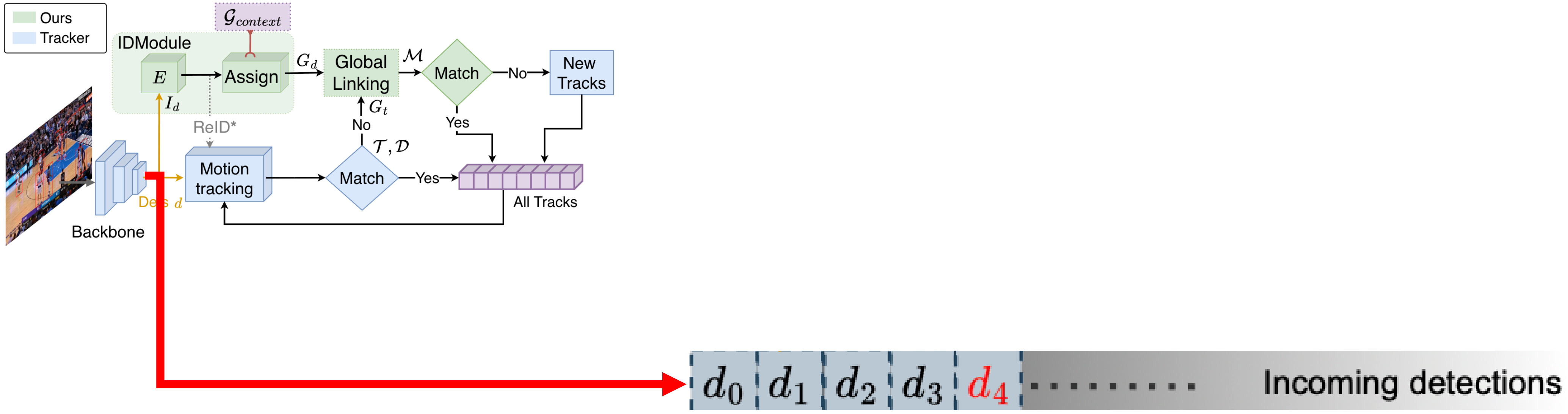

Figure 4. Visualization of successful Global Linking when the BBox assignment fails. G_{id} are global IDs assigned to the tracklet T_{id} which represents track ID, and IDM is our ID module.

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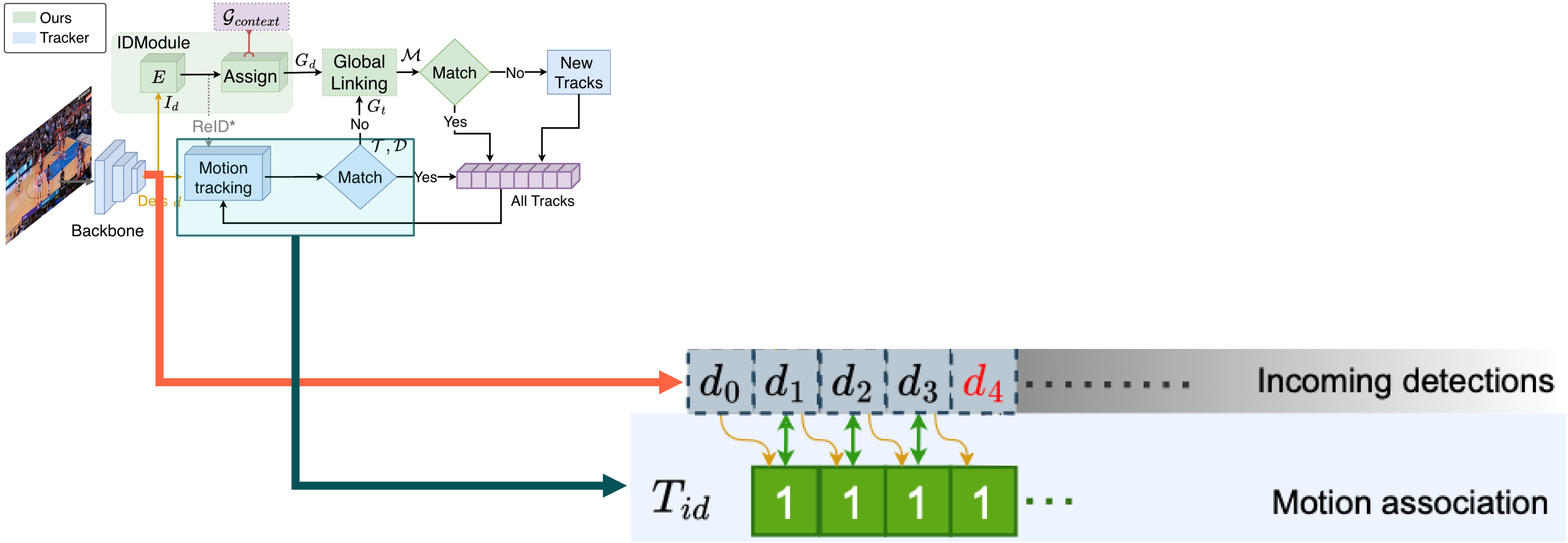

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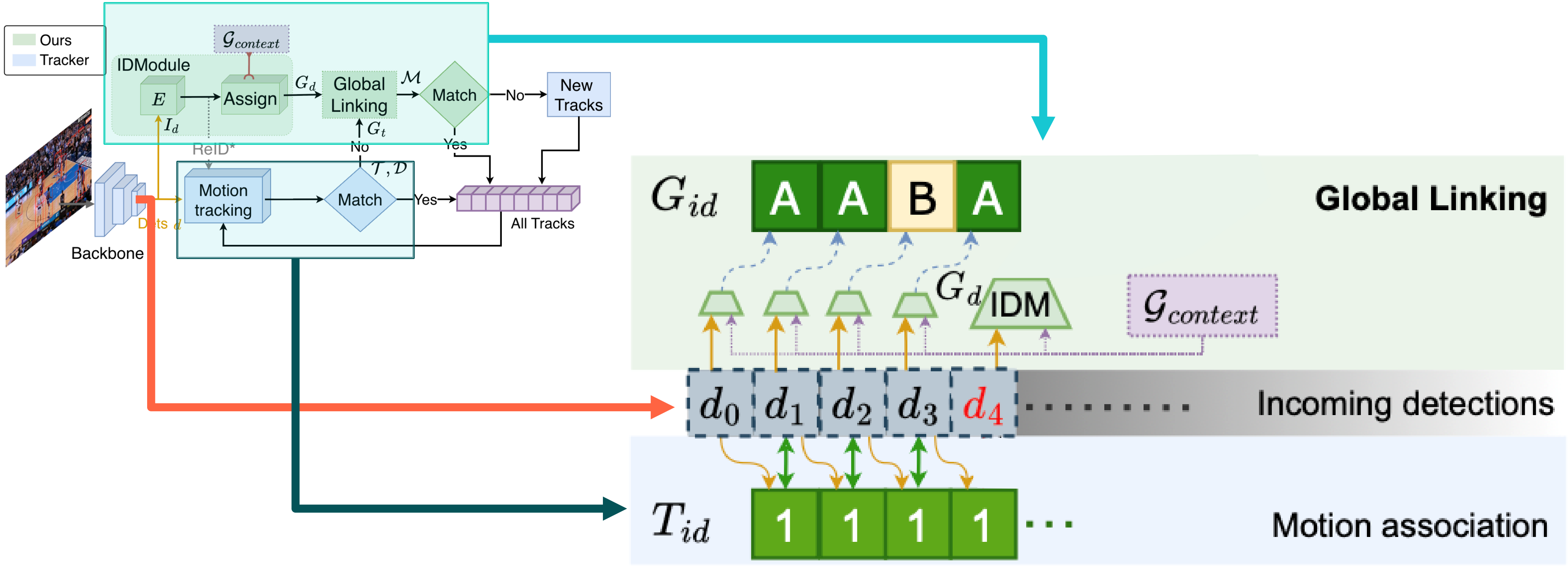

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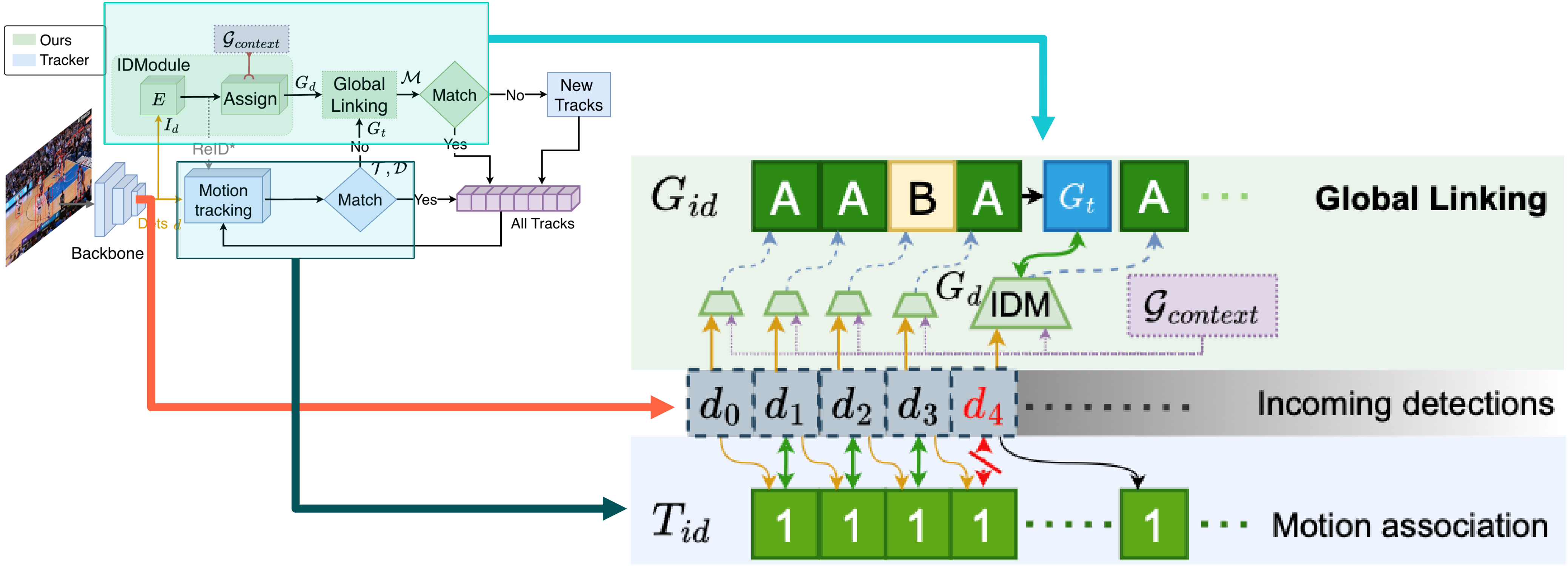

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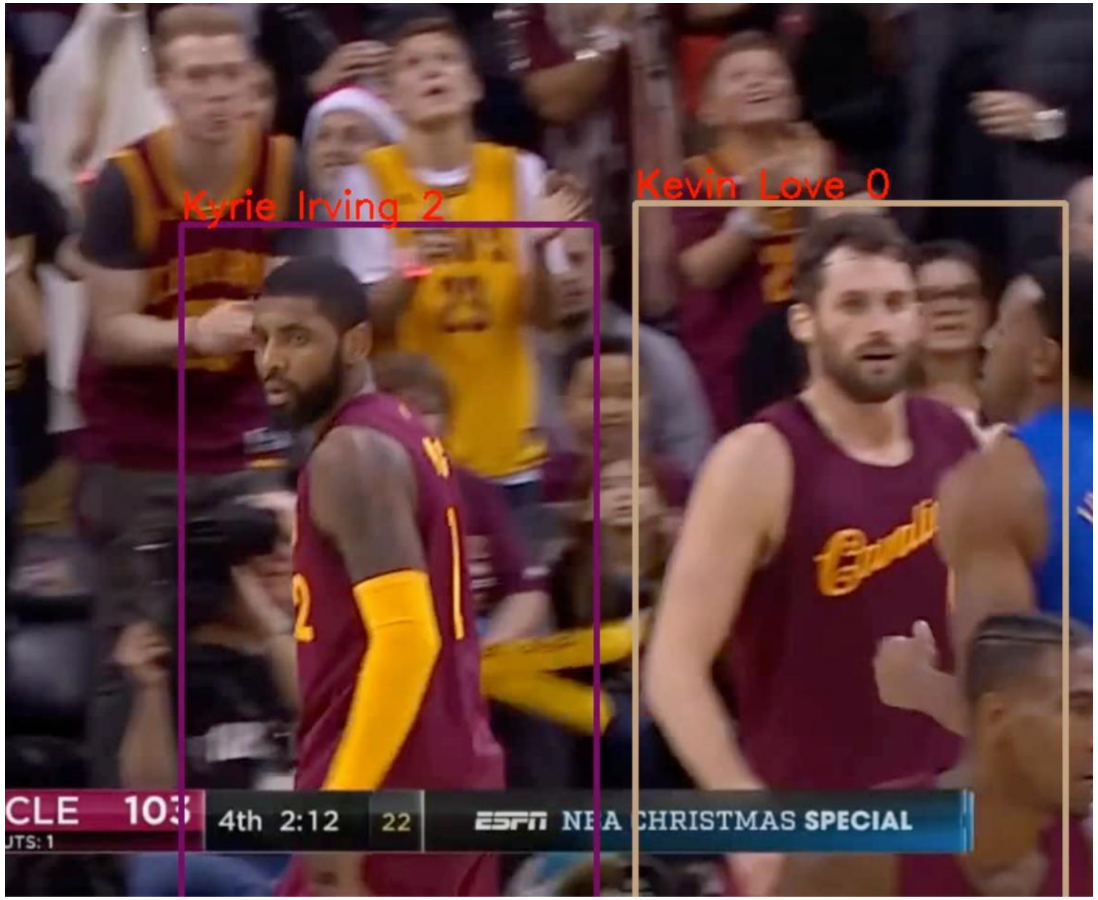
Global ID Metrics

- **Frames to First ID (FTFI):**
- The average time to first classify all tracklets
- **Frames to First Correct ID (FTFIc):**
- The average time to correctly classify IDs
- **Average Class Switches (IDsw):**
- The average number of tracklets' ID switches
- **Mean Correct Ratio (MCorr):**
- The ratio of correct ID-tracklet matches over time
- **Mean Average Precision (mAP):**
- The precision of ID classification for a tracklet



Results: ReID

- CLIP family and AP3D stand out, motivating our MOT+ReID selection

Table 4. ReID models comparison on MuPNIT-ReID-light. *proj* and *txt* represent extra projection layer and additional textual features respectively. *Facial features only.

Method	mAP↑	Top-1↑	Top-5↑	Top-10↑	Top-20↑
PCB [66]	11.0%	16.3%	39.6%	52.5%	72.4%
InsightFace* [2]	16.0%	16.1%	27.3%	36.7%	50.0%
MGN [69]	17.1%	18.6%	41.0%	53.2%	73.8%
IANet [27]	17.5%	26.3%	54.5%	66.3%	79.2%
PSTA [70]	17.5%	26.6%	51.1%	64.7%	79.5%
RGA-SC [83]	17.6%	25.9%	54.5%	69.2%	81.6%
ReIDCaps [28]	18.0%	29.8%	51.6%	64.7%	80.0%
CAL [23]	18.4%	26.7%	50.4%	63.7%	78.4%
TransReID [26]	30.4%	46.7%	71.4%	82.7%	93.1%
CLIP [56]	13.5%	18.6%	38.0%	50.0%	58.8%
CLIP_{proj} [56]	25.3%	32.2%	59.6%	69.8%	81.8%
$\text{CLIP}_{proj,txt}$ [56]	33.6%	**46.8%**	70.2%	80.9%	89.6%
AP3D [22]	**48.1%**	30.3%	**71.6%**	**88.1%**	**98.2%**

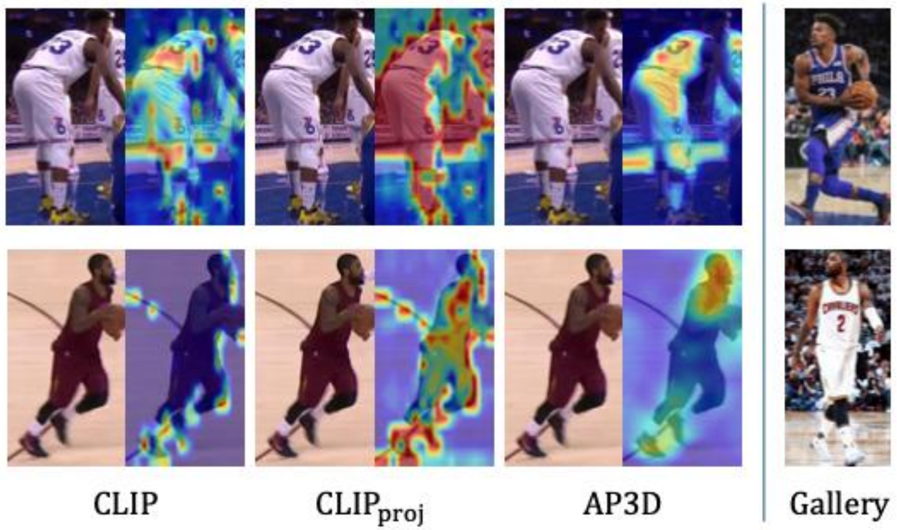
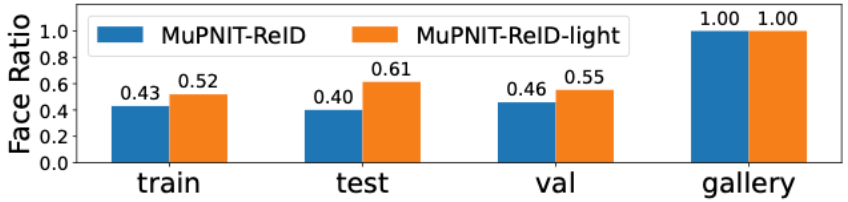


Figure 6. Activation maps on query images (left), when matching with gallery images containing different jersey colors (right).

Results: ReID

- Low face visibility makes face-based ReID fail



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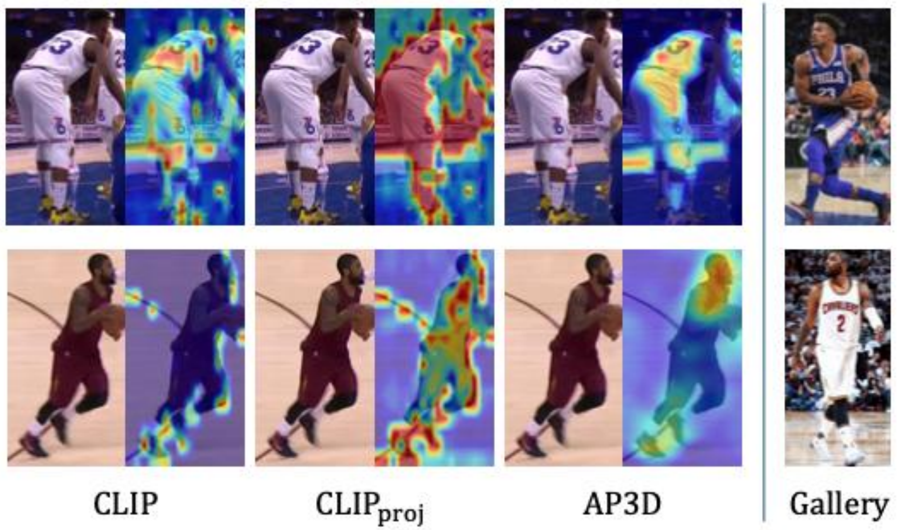

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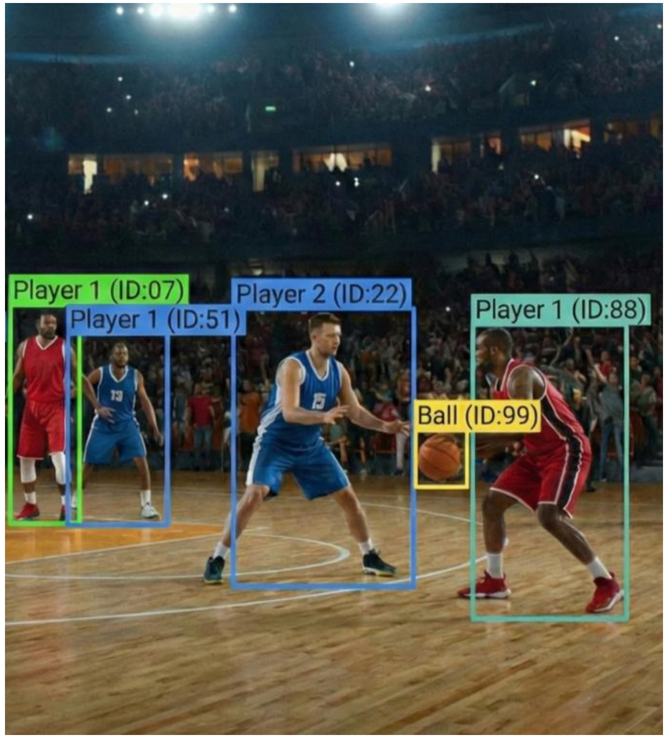
Results: Object Tracking

Table 3. Results of tracking models on MuPNIT. SORT models use YoloX-X weights trained on *train* (*t*) and *trainval* (*tv*) splits.

Model	HOTA↑	DetA↑	AssA↑	MOTA↑	IDF1↑	IDs↓
MASA [39] (RN50)	27.39	48.764	15.825	40.78	20.467	1946
MASA (GDINO)	27.638	48.765	16.11	40.758	20.594	2045
MOTRv1 [80]	30.338	72.676	12.88	87.728	20.46	1579
GTR [88]	31.614	73.618	13.723	88.739	22.36	1088
ByteTrack$_t$ [81]	31.539	73.809	13.574	90.677	22.916	1122
SORT$_t$ [5]	32.118	75.191	13.84	90.729	22.856	1221
MOTRv2 [82]	32.32	73.245	14.393	86.783	23.704	**850**
HybridSORT$_t$ [76]	32.518	75.284	14.208	90.711	23.033	1138
ByteTrack$_{tv}$	32.859	77.208	14.046	**93.925**	24.138	958
SORT$_{tv}$	32.994	78.261	13.975	93.236	23.375	1057
OC-SORT$_t$ [6]	33.349	78.725	14.231	93.248	23.621	1001
HybridSORT$_{tv}$	33.451	78.522	14.363	93.218	23.533	1009
OC-SORT$_{tv}$ (OC)	33.496	78.761	14.359	93.263	23.669	1002
OC$_{tv}$+CLIP	33.536	78.742	14.395	93.286	23.712	998
OC$_{tv}$+AP3D	**33.943**	**78.769**	**14.741**	93.286	**24.140**	997

- Both CLIP family and AP3D help the strongest baseline, OC-SORT



Results: Object Tracking

- GL significantly improves ID tracking

Table 5. Identity-aware tracking results with various ID modules, with/without global linking, across temporal windows (1, 60, 240).

Model	HOTA↑	DetA↑	AssA↑	MOTA↑	IDF1↑	FTFI↓	FTFIc↓	IDsw↓	MCorr↑	mAP↑
Baseline [6]	33.496	78.761	14.359	93.263	23.669	-	-	-	-	-
Global **context (All players in the test set)**										
GL$_{CLIP}$	35.642	78.403	16.309	93.369	31.241	**42.097**	**92.783**	123.180	34.7	19.0
GL$_{AP3D}$	**38.384**	**78.404**	**18.900**	93.395	**35.512**	72.147	105.145	142.688	41.0	23.8
CLIP+GL$_{60}$	36.616	78.284	17.235	93.396	32.973	101.174	182.076	14.500	56.2	23.5
AP3D+GL$_{60}$	38.035	78.394	18.559	93.403	34.088	101.887	152.601	11.883	61.7	30.6
AP3D+GL$_{240}$	38.310	78.314	18.845	**93.418**	34.890	116.199	180.034	**7.151**	**72.8**	**31.0**
Game **context (Only players in the game)**										
GL$_{CLIP}$	34.419	78.672	15.166	93.295	26.36	**16.264**	29.808	118.825	40.6	30.2
GL$_{AP3D}$	34.577	**78.719**	15.298	93.311	26.598	17.152	**28.935**	88.740	52.4	39.5
CLIP+GL$_{60}$	38.729	78.134	19.298	93.414	37.106	117.046	177.122	19.101	60.1	38.0
AP3D+GL$_{240}$	40.703	78.205	21.282	**93.463**	41.019	101.472	159.487	**9.994**	**77.7**	46.0
AP3D+GL$_{60}$	**41.959**	78.032	**22.655**	93.452	**42.489**	85.004	133.528	15.416	68.8	**46.1**

Results: Object Tracking

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- Performance is relatively insensitive to window size

Results: Object Tracking

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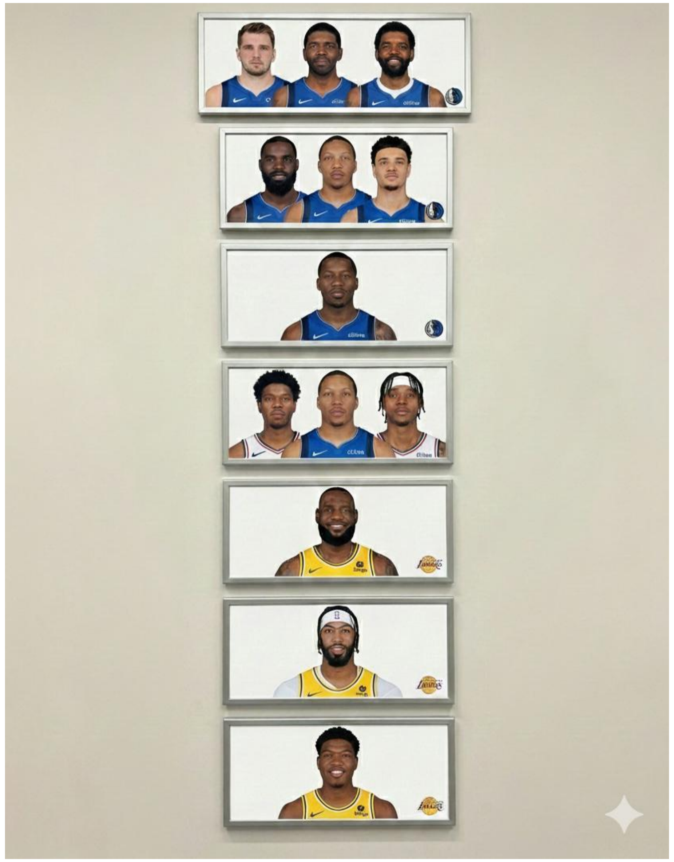
GL_{AP3D}	34.577	**78.719**	15.298	93.311	26.598	17.152	**28.935**	88.740	52.4	39.5
CLIP+GL_{60}	38.729	78.134	19.298	93.414	37.106	117.046	177.122	19.101	60.1	38.0
AP3D+GL_{240}	40.703	78.205	21.282	**93.463**	41.019	101.472	159.487	**9.994**	**77.7**	46.0
AP3D+GL_{60}	**41.959**	78.032	**22.655**	93.452	**42.489**	85.004	133.528	15.416	68.8	**46.1**

Local (Game)

- The benefit of increasing window size is non-monotonic



Results: Object Tracking

Table 5. Identity-aware tracking results with various ID modules, with/without global linking, across temporal windows (1, 60, 240).

Model	HOTA↑	DetA↑	AssA↑	MOTA↑	IDF1↑	FTFI↓	FTFIc↓	IDsw↓	MCorr↑	mAP↑
Baseline [6]	33.496	78.761	14.359	93.263	23.669	-	-	-	-	-
Global context (All players in the test set)										
GL$_{CLIP}$	35.642	78.403	16.309	93.369	31.241	**42.097**	**92.783**	123.180	34.7	19.0
GL$_{AP3D}$	**38.384**	**78.404**	**18.900**	93.395	**35.512**	72.147	105.145	142.688	41.0	23.8
CLIP+GL$_{60}$	36.616	78.284	17.235	93.396	32.973	101.174	182.076	14.500	56.2	23.5
AP3D+GL$_{60}$	38.035	78.394	18.559	93.403	34.088	101.887	152.601	11.883	61.7	30.6
AP3D+GL$_{240}$	38.310	78.314	18.845	**93.418**	34.890	116.199	180.034	**7.151**	**72.8**	**31.0**
Game context (Only players in the game)										
GL$_{CLIP}$	34.419	78.672	15.166	93.295	26.36	**16.264**	29.808	118.825	40.6	30.2
GL$_{AP3D}$	34.577	**78.719**	15.298	93.311	26.598	17.152	**28.935**	88.740	52.4	39.5
CLIP+GL$_{60}$	38.729	78.134	19.298	93.414	37.106	117.046	177.122	19.101	60.1	38.0
AP3D+GL$_{240}$	40.703	78.205	21.282	**93.463**	41.019	101.472	159.487	**9.994**	**77.7**	46.0
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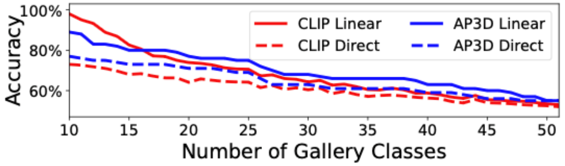
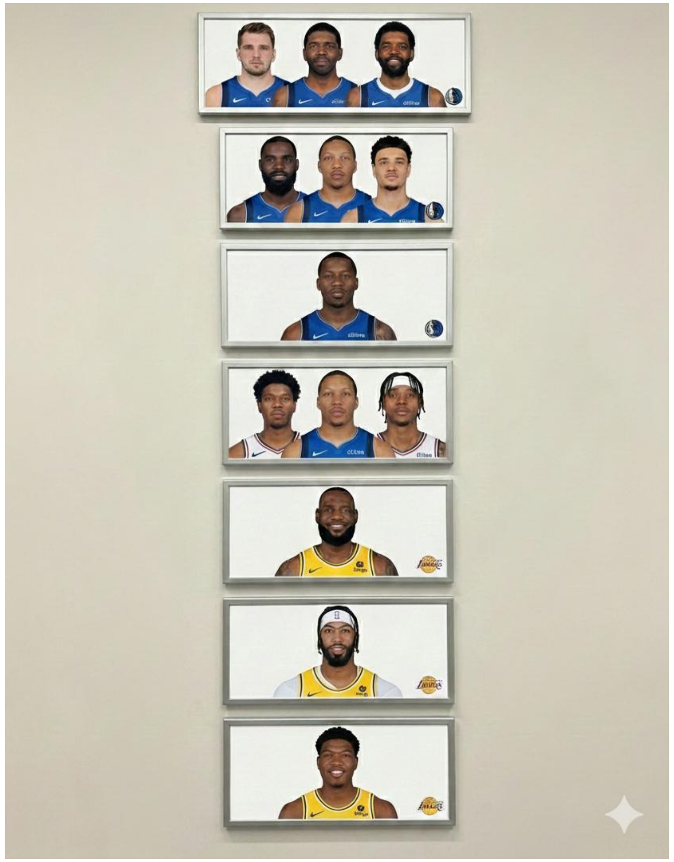


Figure 7. Classification accuracies of 10 fixed query classes vs. number of gallery classes for CLIP$_{proj}$ and AP3D models using direct and linear assignment strategies.

- Linear assignment consistently outperforms direct matching



Results: Generalization

Table 9. Generalization performance on MuPNIT, SportsMOT, and SoccerNet datasets using 500 general text embeddings.

Model	HOTA↑	DetA↑	AssA↑	MOTA↑	IDF1↑	IDs↓
MuPNIT test split						
Base [6]	33.496	**78.761**	14.359	93.263	23.669	1002
Base+GL	**35.053**	78.618	**15.742**	**93.334**	**27.866**	**696**
Gain	+4.6%	-0.2%	+9.6%	+0.1%	+17.7%	-30.5%
SportsMOT val split (basketball)						
Base [6]	73.361	**89.609**	60.236	97.318	74.790	331
Base+GL	**73.502**	89.564	**60.507**	**97.319**	**75.169**	**314**
Gain	+0.2%	-0.1%	+0.4%	-	+0.5%	-5.1%
SportsMOT val split (football)						
Base [6]	67.425	84.904	54.518	90.531	65.696	1030
Base+GL	**68.243**	**85.177**	**55.666**	**90.845**	**67.816**	**830**
Gain	+1.2%	+0.3%	+2.1%	+0.4%	+3.2%	-19.4%
SportsMOT val split (volleyball)						
Base [6]	69.979	86.104	57.756	92.503	71.034	493
Base+GL	**71.104**	**86.553**	**59.366**	**92.879**	**72.943**	**416**
Gain	+1.6%	+0.5%	+2.8%	+0.4%	+2.7%	-15.6%
SoccerNet test split						
Base [6]	**52.864**	**71.909**	**39.034**	**85.908**	55.432	5932
Base+GL	51.917	71.700	37.746	85.209	**56.171**	**3823**
Gain	-1.8%	-0.3%	-3.3%	-0.8%	+1.3%	-35.6%

- We report the generalizability of GL on multiple benchmarks

A player with yellow jersey and number 30
A player with white jersey and number 07
A player with red jersey and number 77
A player with blue jersey and number 24
A player with green jersey and number 55
A player with yellow jersey and number 01
A player with white jersey and number 68
A player with red jersey and number 19
A player with blue jersey and number 33
A player with green jersey and number 91
A player with yellow jersey and number 15
A player with white jersey and number 42

Results: Generalization

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- GL consistently improves ID tracking in MuPNIT and SportsMOT

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Results: Generalization

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- GL yields clear gains in IDF1 and IDs for SoccerNet, despite incomplete IDs and lack of a global ID bank here

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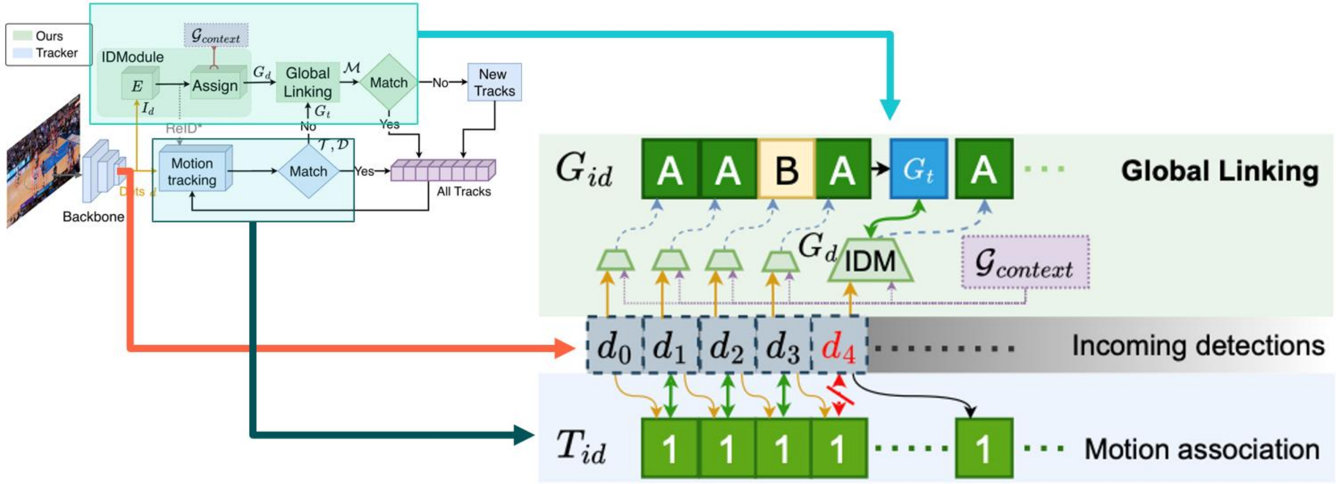
Our Contributions

- Two datasets for multi-perspective ID-aware MOT
- GIF, a generalizable, online tracking-with-ID approach
- Five novel Global ID tracking metrics evaluating ID prediction tradeoffs in multi-perspective MOT

Global ID database

In-game player crops



Advancing Player Identification and Tracking with Global ID Fusion (GIF)

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