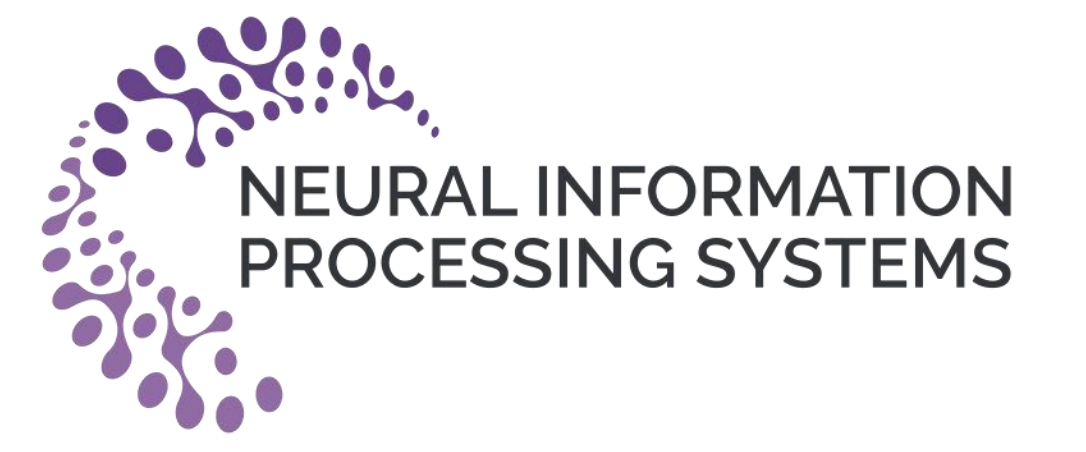


Type-to-Track: Retrieve Any Object via Prompt-based Tracking

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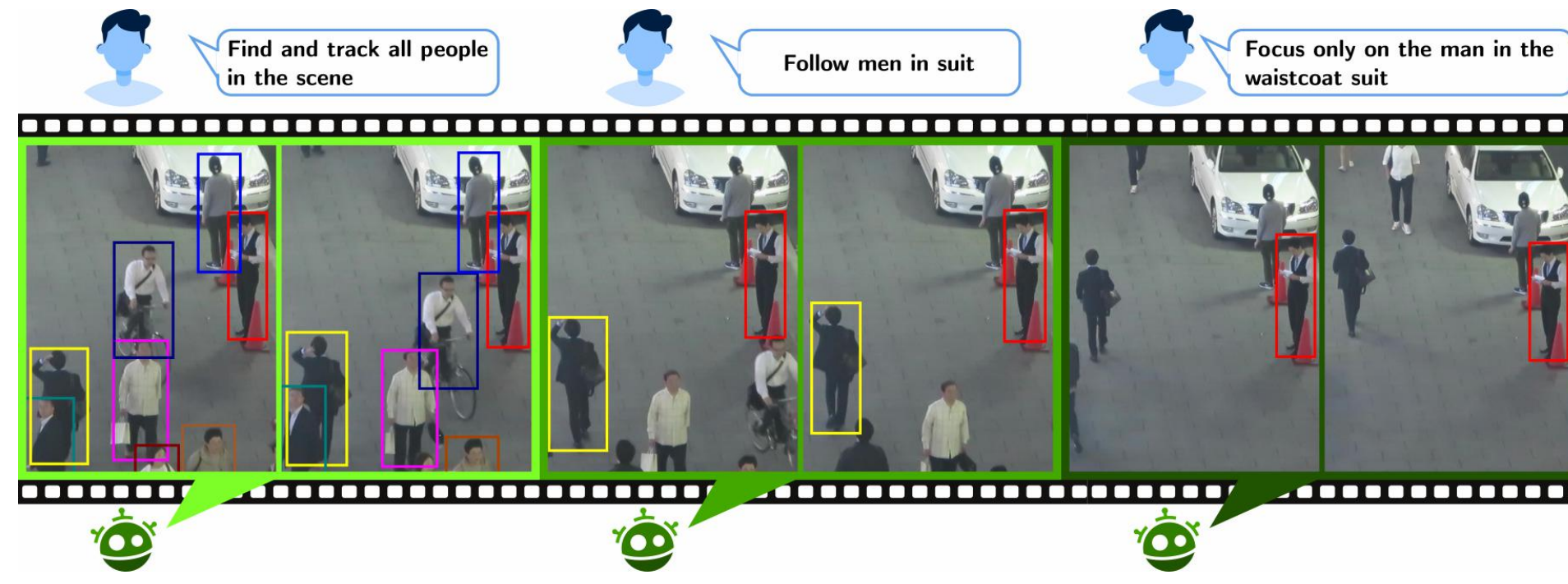
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<https://uark-cviu.github.io>



NEW ORLEANS 2023

Type-to-Track Paradigm



An example of the responsive *Type-to-Track*. The user provides a video sequence and a prompting request. During tracking, the system is able to track the target subjects and iteratively responds to the request.

- New **Grounded Multiple Object Tracking** dataset named GroOT that is more advanced than existing tracking datasets.
- GroOT contains videos with **various types of multiple objects** and **detailed textual descriptions of 256K words**.
- **Five new benchmarking protocols** and **three new metrics** for prompt-based visual tracking.
- New framework **MENDER** as **the first efficient approach**.

Visual Object Tracking Benchmarks

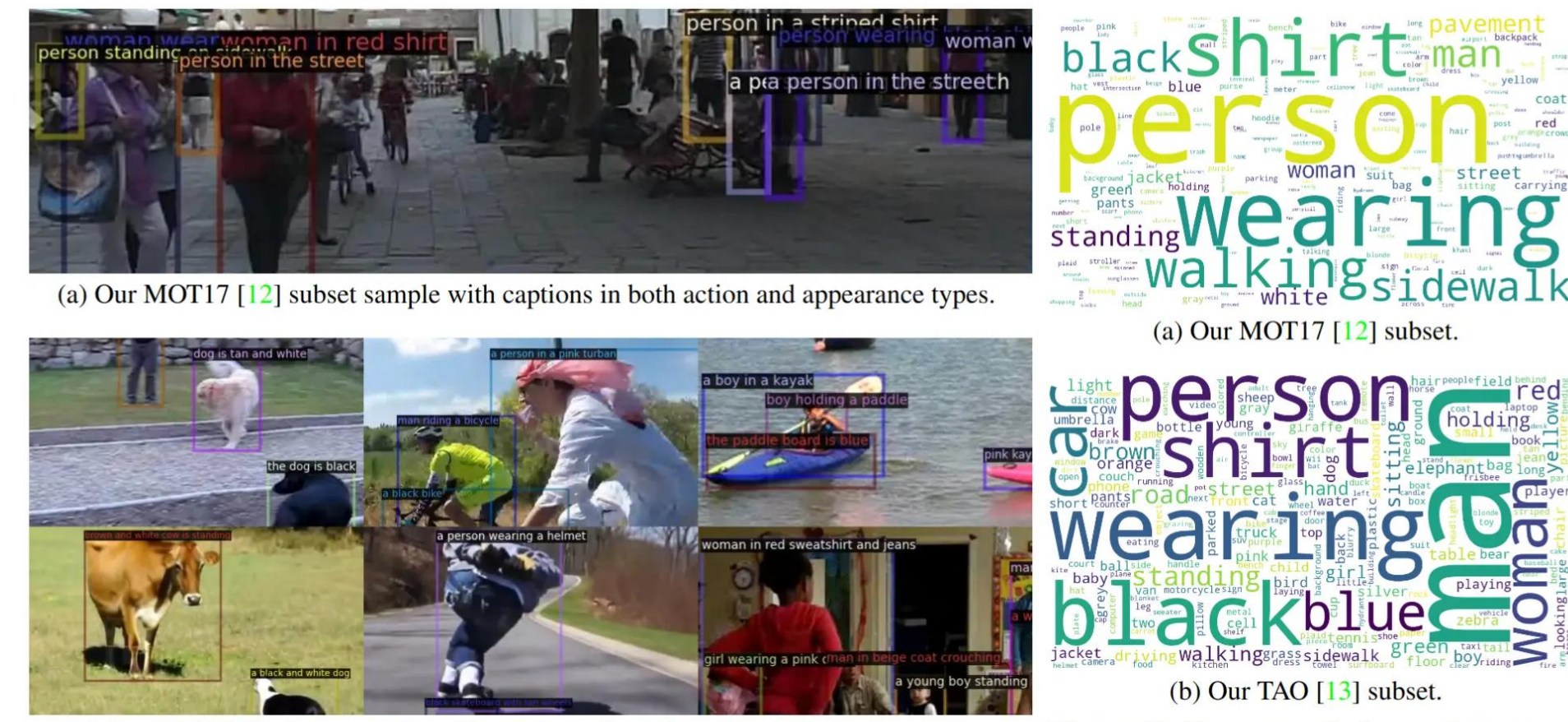
Datasets	Task	NLP	#Videos	#Frames	#Tracks	#AnnBoxes	#Words	#Settings
OTB100 [8]	SOT	✗	100	59K	100	59K	-	-
VOT-2017 [9]	SOT	✗	60	21K	60	21K	-	-
GOT-10k [10]	SOT	✗	10K	1.5M	10K	1.5M	-	-
TrackingNet [11]	SOT	✗	30K	14.43M	30K	14.43M	-	-
MOT17 [12]	MOT	✗	14	11.2K	1.3K	0.3M	-	-
TAO [13]	MOT	✗	1.5K	2.2M	8.1K	0.17M	-	-
MOT20 [14]	MOT	✗	8	13.41K	3.83K	2.1M	-	-
BDD100K [15]	MOT	✗	2K	318K	130.6K	3.3M	-	-
LaSOT [6]	SOT	✓	1.4K	3.52M	1.4K	3.52M	9.8K	1
TNL2K [7]	SOT	✓	2K	1.24M	2K	1.24M	10.8K	1
Ref-DAVIS [16]	VOS	✓	150	94K	400+	-	10.3K	2
Refer-YTVOS [17]	VOS	✓	4K	1.24M	7.4K	131K	158K	2
Ref-KITTI [18]	MOT	✓	18	6.65K	-	-	3.7K	1
GroOT (Ours)	MOT	✓	1,515	2.25M	13.3K	2.57M	256K	5

Comparison of current datasets. # denotes the number of the corresponding item. **Bold** numbers are the best number in each sub-block, while **highlighted** numbers are the best across all sub-blocks.

Most existing datasets and benchmarks for object tracking are **limited in their coverage and diversity** of language and visual concepts. Additionally, the prompts in the existing Grounded SOT benchmarks **do not contain variations in covering many objects in a single prompt**, which limits the application of existing trackers in practical scenarios.

To address this, we present **a new dataset and benchmarking metrics** to support the emerging trend of the Grounded MOT, where the goal is to **align language descriptions with fine-grained regions or objects in videos**.

Dataset Overview



Example sequences and annotations in our dataset.

Datasets		#Videos	#Frames	#Tracks	#AnnBoxes	#Words	Parts
MOT17**	Train	7	5,316	546*	112,297*	3,792	(1)
	Test	7	5,919	785*	188,076*	5,757	(2)
	Total	14	11,235	1,331*	300,373*	9,549	
TAO**	Train	500	764,526	2,645	54,639	19,222	(3)
	Val	993	1,460,666	5,485	113,112	39,149	(4)
	Test	914	2,221,846	7,972	164,650	-	
Total	2,407	4,447,038	16,089	332,401	58,371		
MOT20**	Train	4	8,931	2,332*	1,336,920*	-	(5)
	Test	4	4,479	1,501*	765,465*	-	(6)
	Total	8	13,410	3,833*	2,102,385*	-	
GroOT**	nm	1,515	2,249,837	13,294	2,570,509	21,424	all
	syn	1,515	2,249,837	13,294	2,570,509	53,540	all
	def	1,515	2,249,837	13,294	2,570,509	99,218	all
	cap	1,507	2,236,427	9,461	468,124	67,920	w/o MOT20
	retr	993	1,460,666	1,952	-	13,935	uses (4)

all uses (1, 2, 3, 4, 5, 6) and w/o MOT20 uses (1, 2, 3, 4).

* Statistics from the official site, including objects other than human.

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Statistics of GroOT's settings.

Our proposed Type-to-Track paradigm is distinct in its focus on **responsively** and **conversationally** tracking **any objects** in videos, maintaining the temporal motions of multiple objects of interest.

Class-agnostic Evaluation Metrics

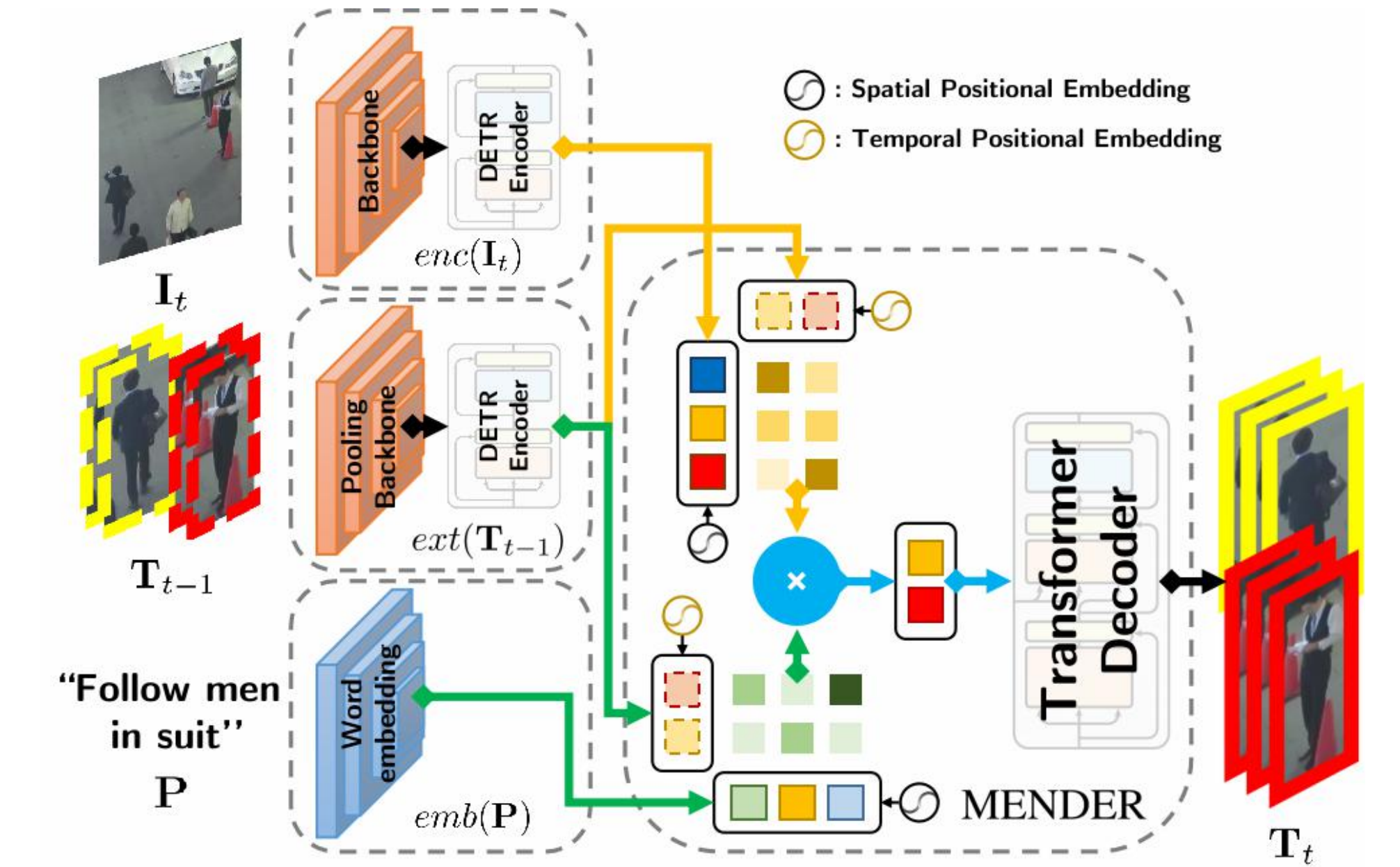
$$\text{MOTA} = \frac{1}{|CLS^n|} \sum_{cls} \left(1 - \frac{\sum_t (FN_t + FP_t + IDS_t)}{\sum_t GT_t} \right)_{cls}, \text{CA-MOTA} = 1 - \frac{\sum_t (FN_t + FP_t + IDS_t)_{CLS^1}}{\sum_t (GT_{CLS^1})_t} \quad (1)$$

$$\text{IDF1} = \frac{1}{|CLS^n|} \sum_{cls} \left(\frac{2 \times \text{IDTP}}{2 \times \text{IDTP} + \text{IDFP} + \text{IDFN}} \right)_{cls}, \text{CA-IDF1} = \frac{(2 \times \text{IDTP})_{CLS^1}}{(2 \times \text{IDTP} + \text{IDFP} + \text{IDFN})_{CLS^1}} \quad (2)$$

$$\text{HOTA} = \frac{1}{|CLS^n|} \sum_{cls} \left(\sqrt{\text{DetA} \cdot \text{AssA}} \right)_{cls}, \text{CA-HOTA} = \sqrt{(\text{DetA}_{CLS^1}) \cdot (\text{AssA}_{CLS^1})} \quad (3)$$

where CLS^n is the category, set size n is reduced to 1 by combining all elements: $CLS^n \rightarrow CLS^1$.

MENDER for MOT by Prompts



The structure of our proposed *MENDER*. It employs a visual backbone to extract visual features and a word embedding to extract textual features. We model the tracklet-prompt correlation instead of the region-prompt to avoid unnecessary computation caused by no-object tokens.

Quantitative Results

P	sim	CA-MOTA	CA-IDF1	MT	IDs	mAP	FPS	Approach	CA-MOTA	CA-IDF1	MT	IDs	mAP	FPS
GroOT - MOT17 Subset														
nm	✓	67.00	71.20	544	1352	0.876	10.3	MDETR + TFm	62.60	64.70	519	1382	0.793	2.2
syn	✓	65.10	71.10	554	1348	0.874	10.3	MENDER	65.10	71.10	554	1348	0.874	10.3
def	✗	67.00	72.10	556	1343	0.876	5.8	MDETR + TFm	62.60	64.70	519	1382	0.793	2.2
	✓	67.30	72.40	568	1322	0.877	10.3	MENDER	67.30	72.40	568	1322	0.877	10.3
cap	✗	58.20	53.20	289	1751	0.674	3.4	MDETR + TFm	44.80	45.20	193	1945	0.619	2.1
	✓	59.50	54.80	201	1734	0.688	7.8	MENDER	59.50	54.80	201	1734	0.688	7.8
GroOT - TAO Subset														
nm	✓	27.30	37.20	3523	4284	0.212	11.2	MDETR + TFm	21.30	33.20	2945	5834	0.184	3.1
syn	✓	25.70	36.10	3212	5048	0.198	11.2	MENDER	25.70	36.10	3212	5048	0.198	11.2
def	✗	15.20	27.30	2452	6253	0.154	6.2	MDETR + TFm	14.60	21.40	1944	6493	0.137	3.1
	✓	16.80	27.70	2547	6118	0.158	10.5	MENDER	16.80	27.70	2547	6118	0.158	10.5
cap	✗	20.30	31.80	2943	5242	0.188	4.3	MDETR + TFm	15.30	23.60	2132	6354	0.156	3.0
	✓	20.70	32.00	3103	5192	0.184	8.7	MENDER	20.70	32.00	3103	5192	0.182	8.7
retr	✗	32.40	38.40	630	3238	0.423	7.6	MDETR + TFm	25.70	26.40	513	3993	0.387	3.1
	✓	32.90	39.30	645	3194	0.430	11.5	MENDER	32.90	39.30	645	3194	0.430	11.5
GroOT - MOT20 Subset														
nm	✓	72.40	67.50	823	2498	0.826	7.6	MDETR + TFm	61.20	60.40	784	2824	0.732	1.9
syn	✓	70.90	65.30	809	2509	0.823	7.6	MENDER	70.90	65.30	809	2509	0.823	7.6
def	✗	72.90	67.70	823	2489	0.826	4.3	MDETR + TFm	68.00	66.30	763	2975	0.783	1.9
	✓	72.10	67.10	812	2503	0.825	7.6	MENDER	72.10	67.10	812	2503	0.825	7.6

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Project page:

