

Confidence intervals for tracking performance scores

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Annotations for multi-object tracking



Tracking evaluation

\mathbb{Z} : Annotation

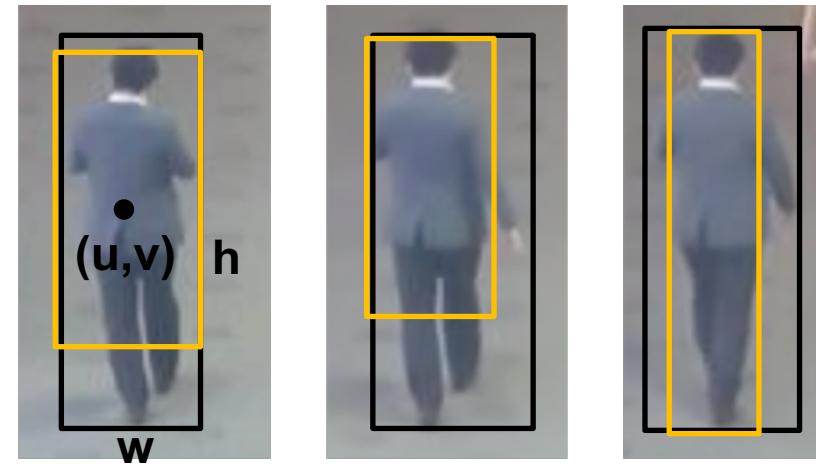
$$\mathbb{Z} = \{\mathbf{z}_k^\lambda : \lambda = 1 \dots \Lambda; k = 0 \dots K_\lambda - 1\}$$

$$\mathbf{z}_k^\lambda = (u, v, w, h)$$

λ : target identity

k : time

\mathbb{X} : Estimated object



Tracking score:

$$s = f(\mathbb{Z}, \mathbb{X})$$

Ranking via direct score comparison

MOTB15/16/17

Tracker	Avg Rank	↑MOTA	IDF1	MT	ML	FP	FN	ID Sw.
DH_TRK	16.0	54.1 ±13.0	49.2	21.6%	28.4%	36,196	216,670	5,918 (96.1)
1. ✓								
HIK_MOT17	11.3	53.9 ±13.7	54.3	23.7%	32.0%	27,656	230,042	2,386 (40.3)
2. ✓								
NOTBD	18.2	53.9 ±12.7	51.2	21.5%	35.6%	28,912	228,356	2,964 (49.8)
3. ✓								
IOUT_Re	18.6	52.7 ±13.0	43.3	20.1%	32.6%	16,529	243,226	6,946 (122.1)
4. ⚡ ✓								
yt_face	15.2	52.6 ±13.1	51.5	23.0%	35.9%	23,894	241,489	2,047 (36.8)
5. ⚡ ✓								

KITTI

	Method	Setting	Code	Out-Noc	Out-All	Avg-Noc	Avg-All
1	M2S_CSPN			1.19 %	1.53 %	0.4 px	0.5 px
2	MS_CSPN			1.25 %	1.61 %	0.4 px	0.5 px
3	DM-Net-Pretrained-30			1.28 %	1.68 %	0.5 px	0.5 px
4	NCA-Net			1.28 %	1.68 %	0.5 px	0.5 px
5	Samsung_System_LSI			1.38 %	1.79 %	0.5 px	0.5 px

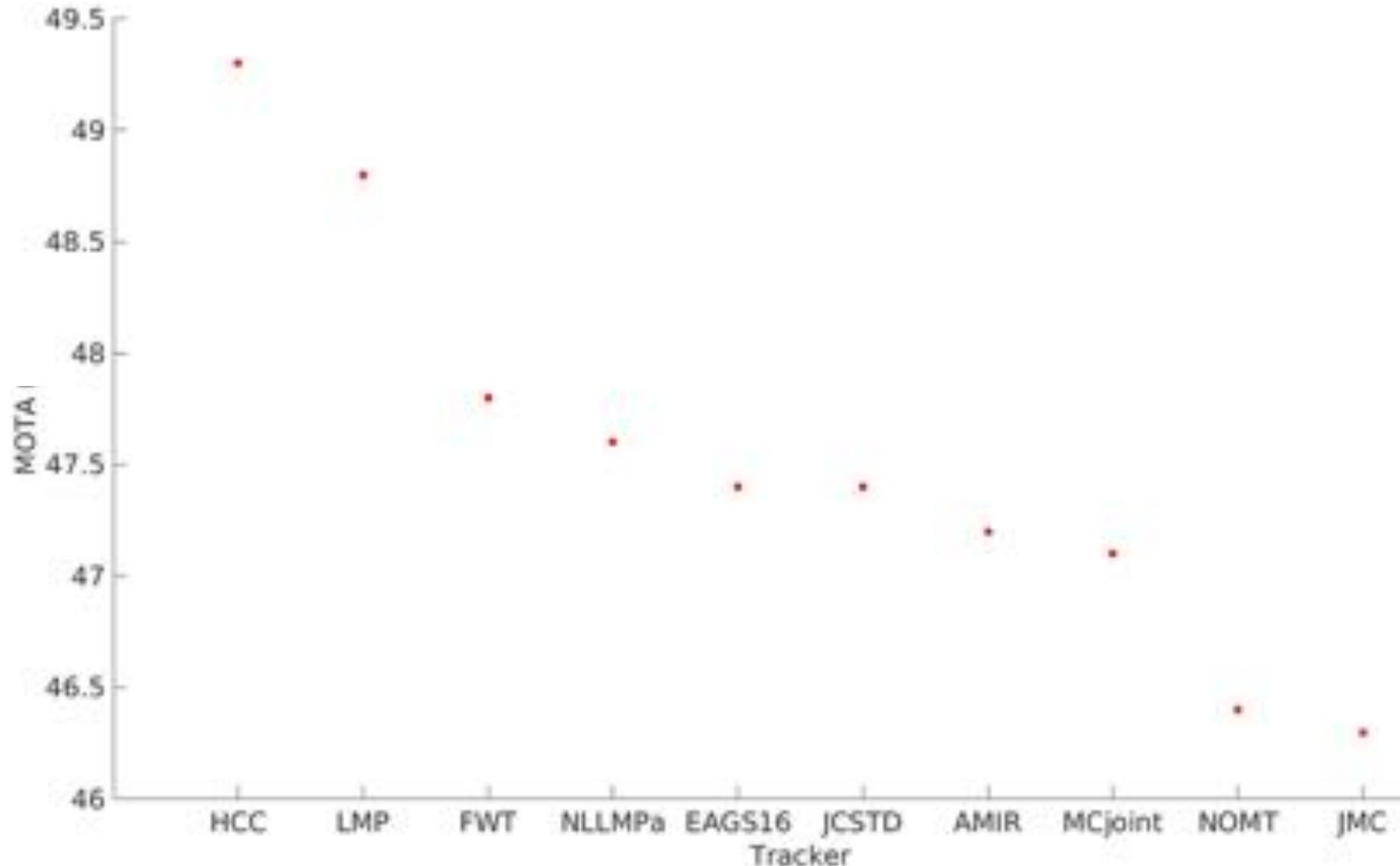
VOT17

	Tracker	baseline		
		EAO	A	R
1.	○ LSART	0.323 ①	0.493	0.218 ①
2.	✗ CFWCR	0.303 ②	0.484	0.267 ②
3.	* CFCF	0.286 ③	0.509	0.281
4.	▽ ECO	0.280	0.483	0.276 ③
5.	◇ Gnet	0.274	0.502	0.276 ③

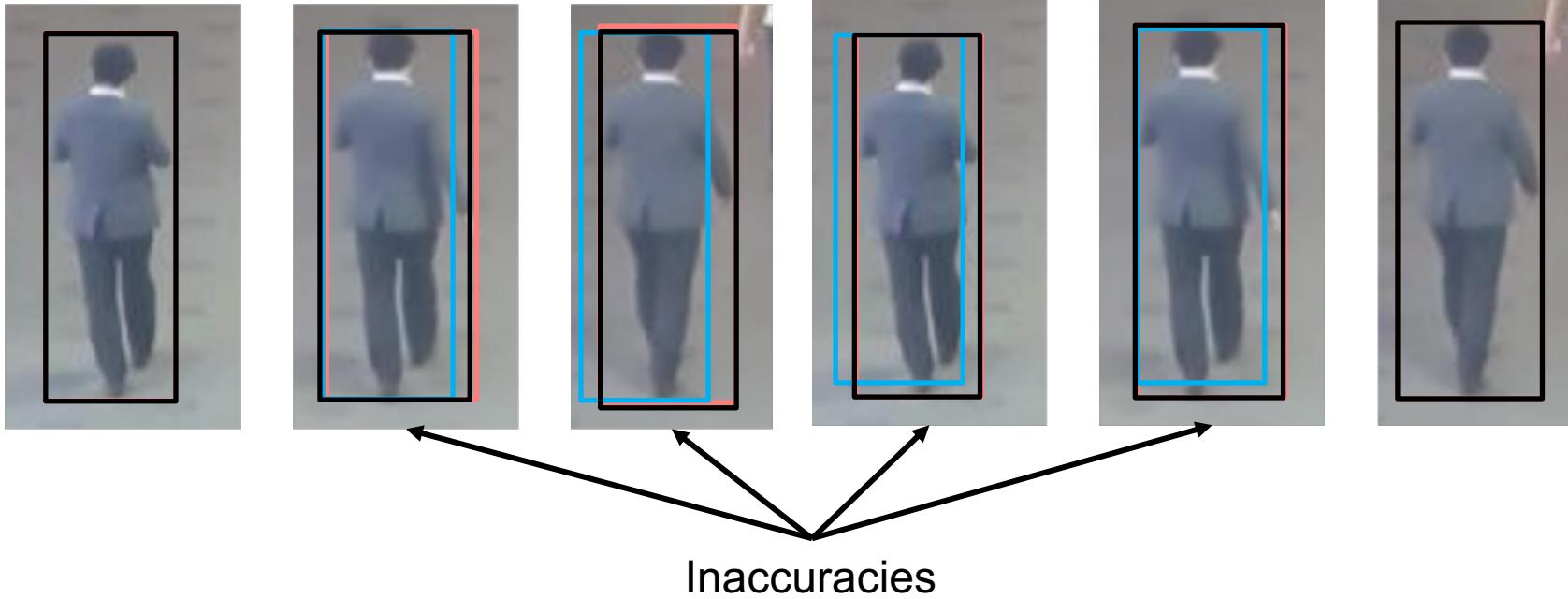
DukeMTMCT

Tracker	↑IDF1	IDP	IDR	MOTA	MOTP	FAF	MT	ML	FP	FN
MTMC_RelID	89.8	92.0	87.7	88.2	79.0	0.05	1,123	17	37,911	86,958
1.										Z. Zhang, J. Wu, X. Zhang, C. Zhang. Multi-Target, Multi-Camera Tracking by Hierarchical Clustering: Recent Progress on
DeepCC	89.2	91.7	86.7	87.5	77.1	0.05	1,103	29	37,280	94,399
2.										E. Ristani, C. Tomasi. Features for Multi-Target Multi-Camera Tracking and Re-
TAREIDMTMC	83.8	87.6	80.4	83.3	75.5	0.06	1,051	17	44,691	131,220
3. ⚡										N. Jiang, S. Bai, Y. Xu, C. Xing, Z. Zhou, W. Wu. Online Inter-Camera Trajectory Association Exploiting Person Re-Identification and Co
MYTRACKER	80.3	87.3	74.4	78.3	78.4	0.05	914	72	35,580	193,253
4. ⚡ ✓										K. Yoon, Y. Song, M. Jeon. Multiple hypothesis tracking algorithm for multi-target multi-camera tracking with disjoint views. In
MTMC_RelDp	79.2	89.9	70.7	68.8	77.9	0.07	726	143	52,408	277,762
5. ✓										Z. Zhang, J. Wu, X. Zhang, C. Zhang. Multi-Target, Multi-Camera Tracking by Hierarchical Clustering: Recent Progress on

Ranking via direct score comparison in MOTB16 [1]



Annotation procedures



- Annotations
- Manual annotation
- Linearly interpolated annotation

Annotations in tracking datasets

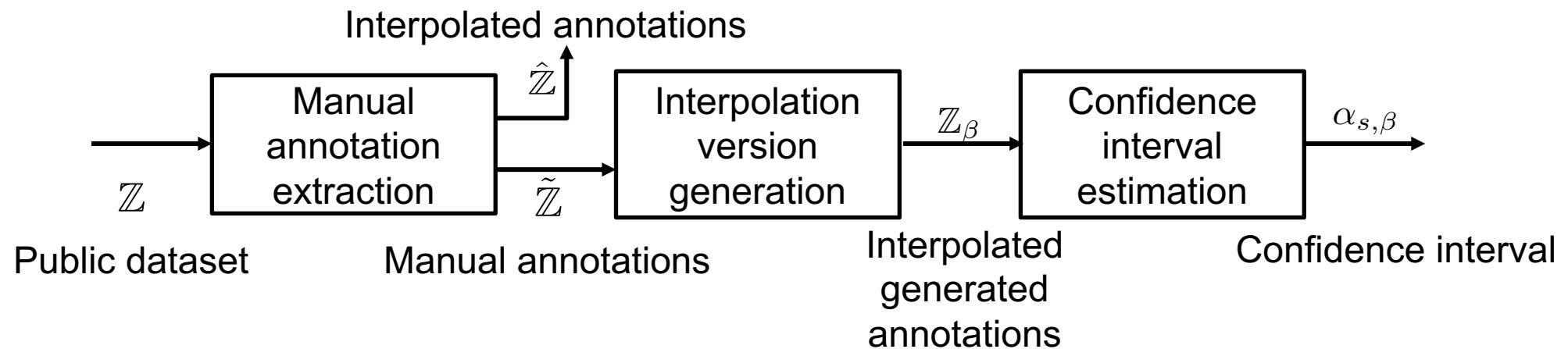
Dataset	Linear Interpolation
CAVIAR	✗
TUD	✓
ETH	✓
PETS09	✓
KITTI	Not available
i-LIDS	✓
MOTB15	✓
MOTB16	✓
MOTB17	✓

Annotations in tracking

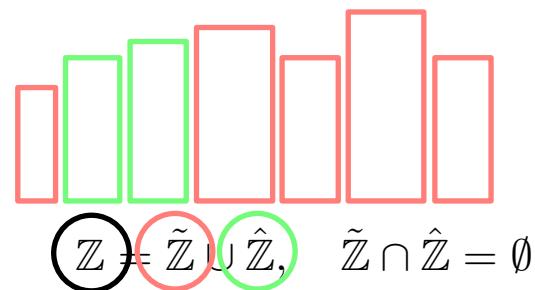
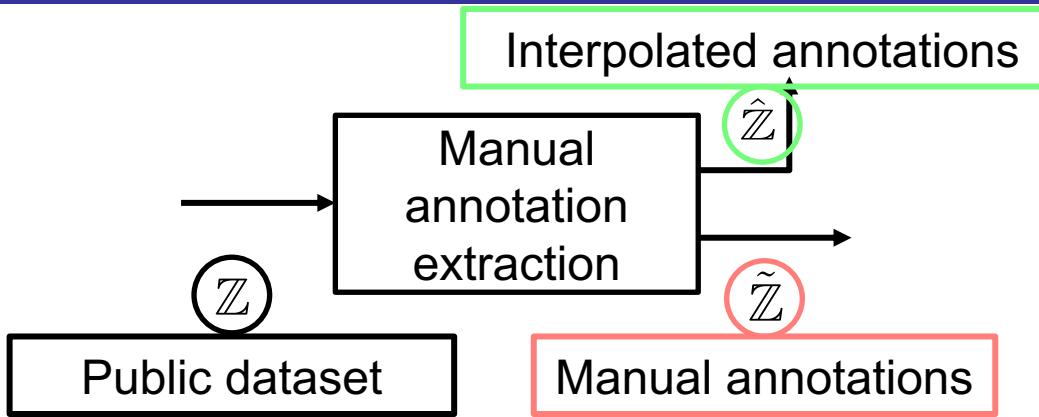
- Performance evaluation uses manual annotations
- Manual annotation process [2]
 - Tedious
 - Expensive
 - (Potentially) unfeasible
- Semi-automatic annotation process
 - Less tedious and less expensive
 - (Potentially) Inaccurate → inaccurate evaluations
- This work: accounts for inaccuracies due to linear interpolation

How to account for annotation inaccuracies?

- We propose to estimate confidence intervals for a given dataset:
 - With **unknown** annotation procedure
 - **Without** further annotations



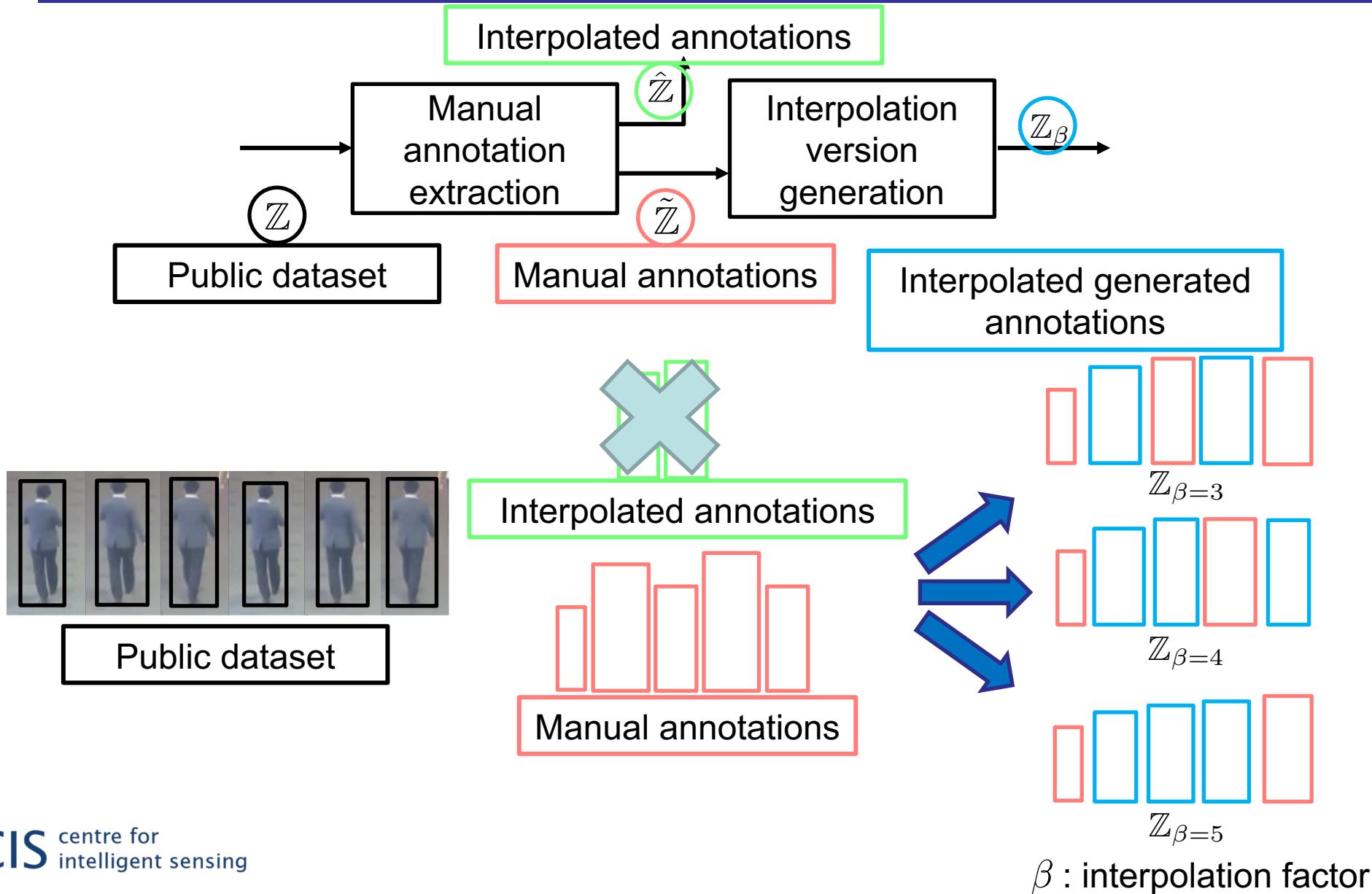
Manual annotation extraction



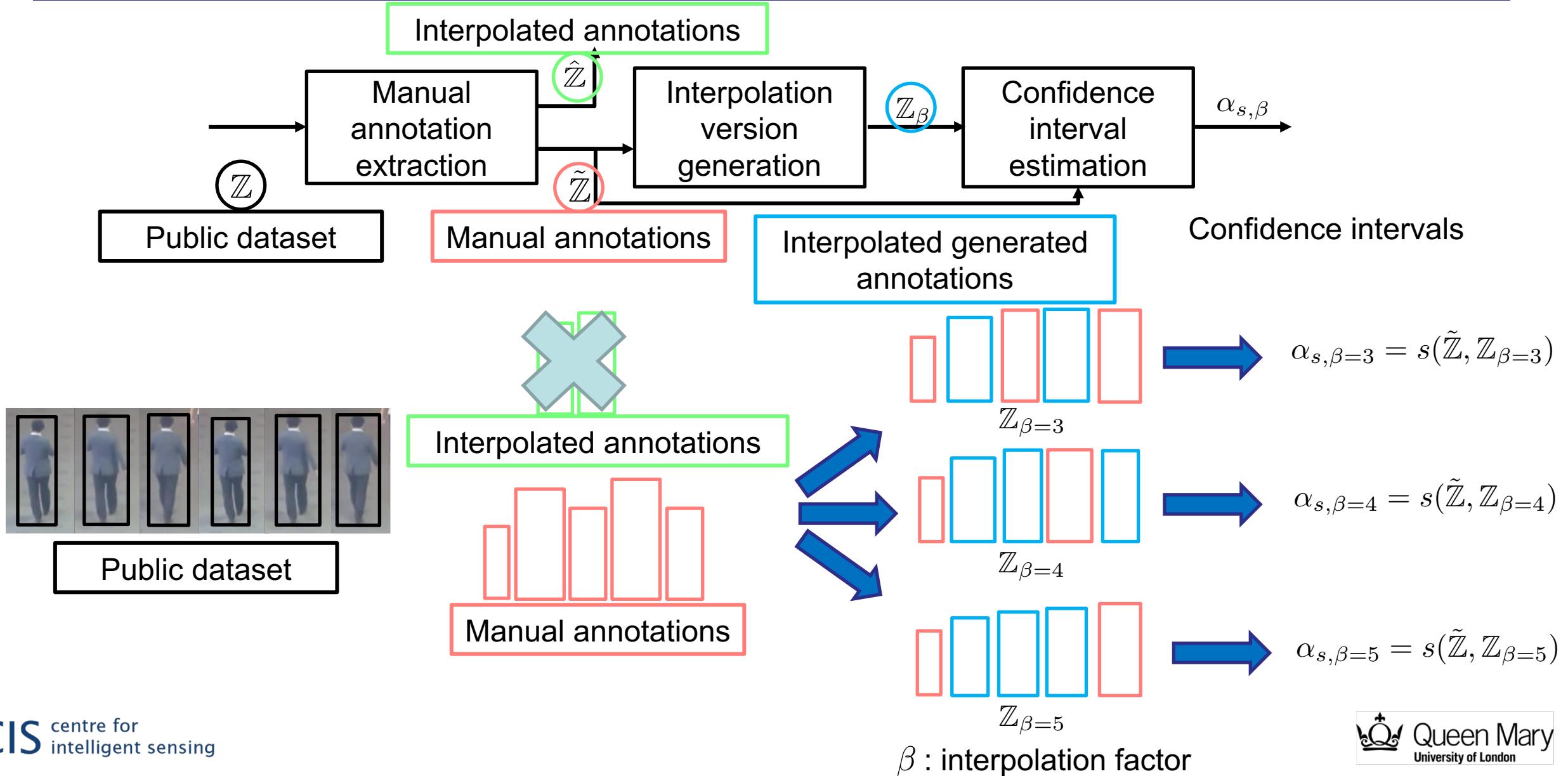
- Linear interpolation detection:
$$\tilde{Z}^\lambda = \{\mathbf{z}_k^\lambda : \mathbf{z}_{uu}^\lambda, \mathbf{z}_{vv}^\lambda, \mathbf{z}_{ww}^\lambda, \mathbf{z}_{hh}^\lambda \neq 0\}$$

 λ : target identity
 $\mathbf{z}_{..}^\lambda$: second derivative on .. component

Interpolation version generation



Confidence interval estimation



Experiment setup

- Benchmark dataset: MOTB16 [2]
- Interpolation factor: $\beta \in \{3, 6, 9, 12\}$
- Detected percentage of annotations with linear interpolation: $39.7\% \approx \beta = 3$

Confidence interval

$$\alpha_{s,\beta} = s(\tilde{\mathbb{Z}}, \mathbb{Z}_\beta)$$

$$s(\cdot, \cdot) = 100 - MOTA$$

$\tilde{\mathbb{Z}}$: manually annotated subset

\mathbb{Z}_β : linearly interpolated

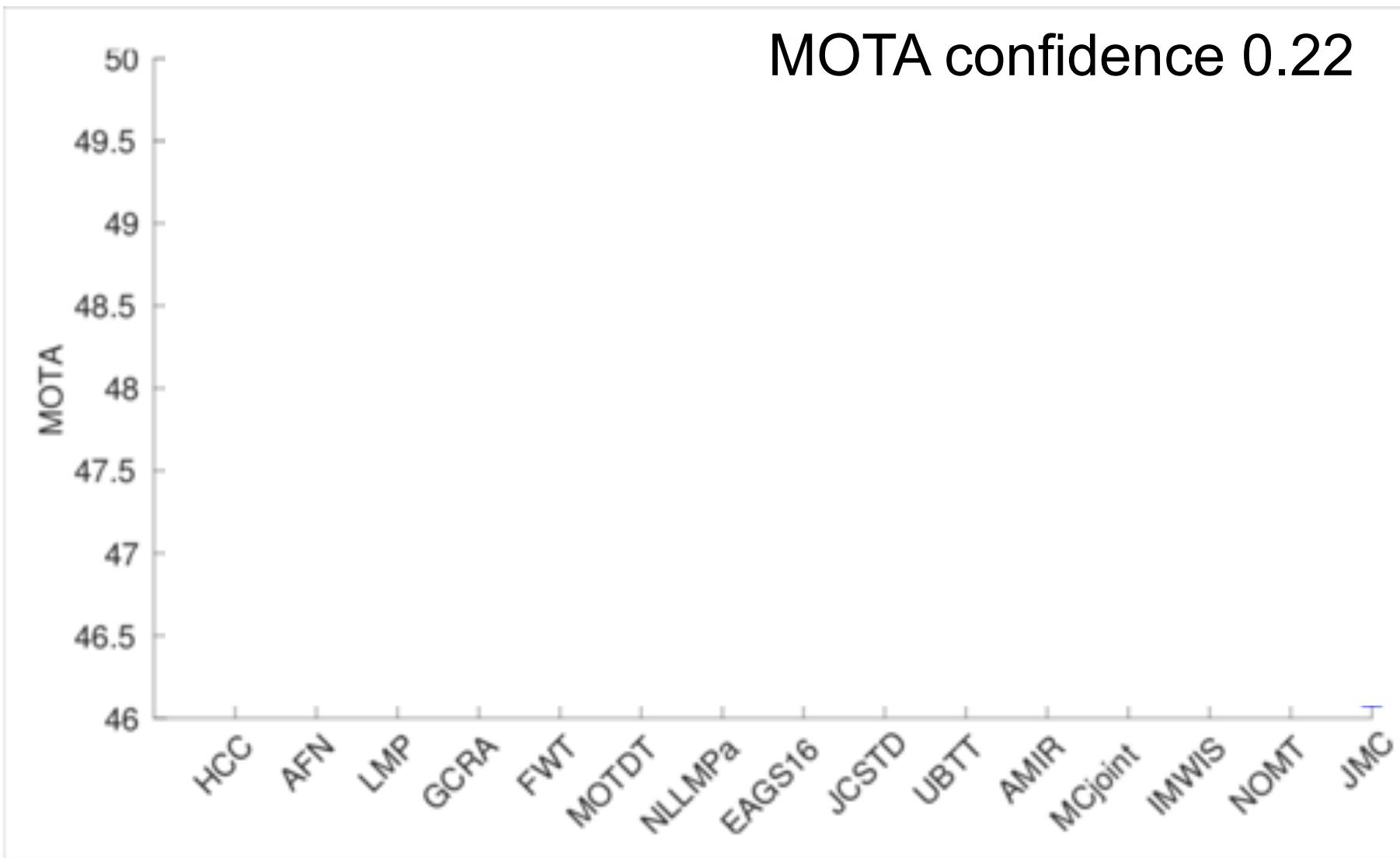
$$s(\cdot, \cdot) = 100 - MOTP$$

$$MOTA = 1 - \frac{1}{N} \sum_{\lambda=0}^{\Lambda} \sum_{k=0}^{\tilde{K}_\lambda-1} (FN_k^\lambda + FP_k^\lambda + IDSW_k^\lambda)$$

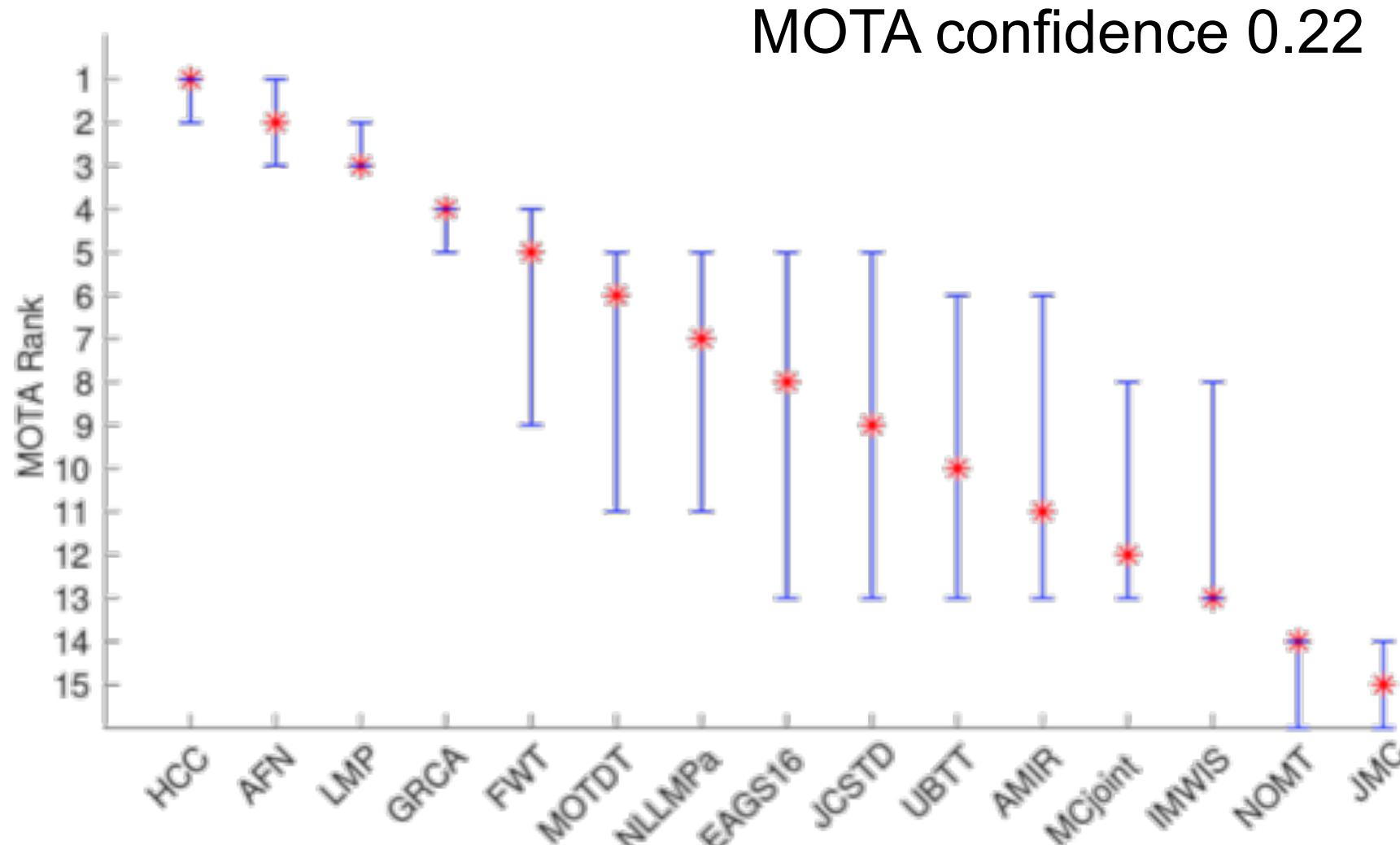
$$MOTP = \frac{1}{N} \sum_{\lambda=0}^{\Lambda} \sum_{k=0}^{\tilde{K}'_\lambda-1} \frac{\tilde{\mathbf{z}}_k^\lambda \cap \mathbf{z}_{k,\beta}^\lambda}{\tilde{\mathbf{z}}_k^\lambda \cup \mathbf{z}_{k,\beta}^\lambda}$$

N : # annotations
 β : interpolation factor

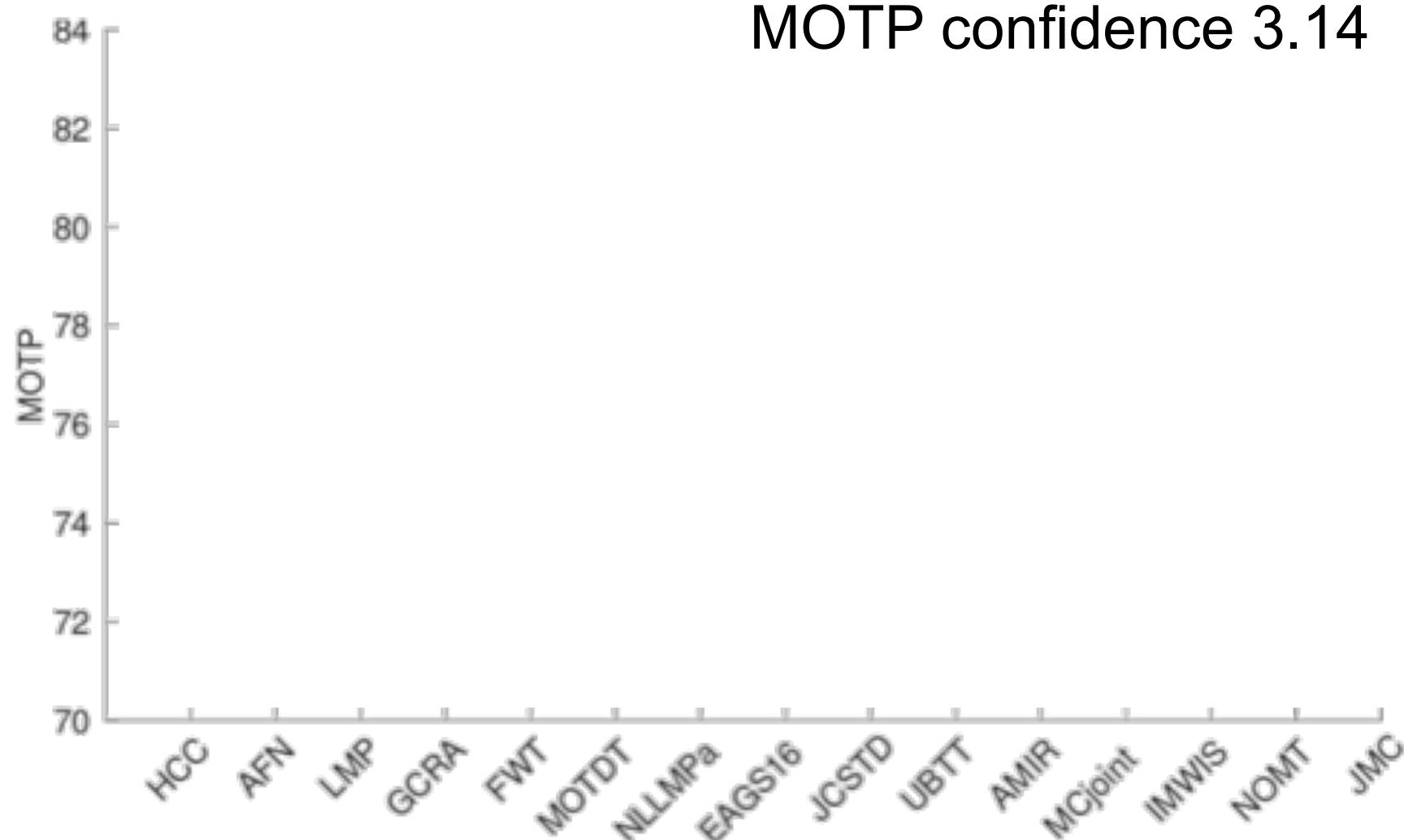
Impact on MOTB16 – MOTA



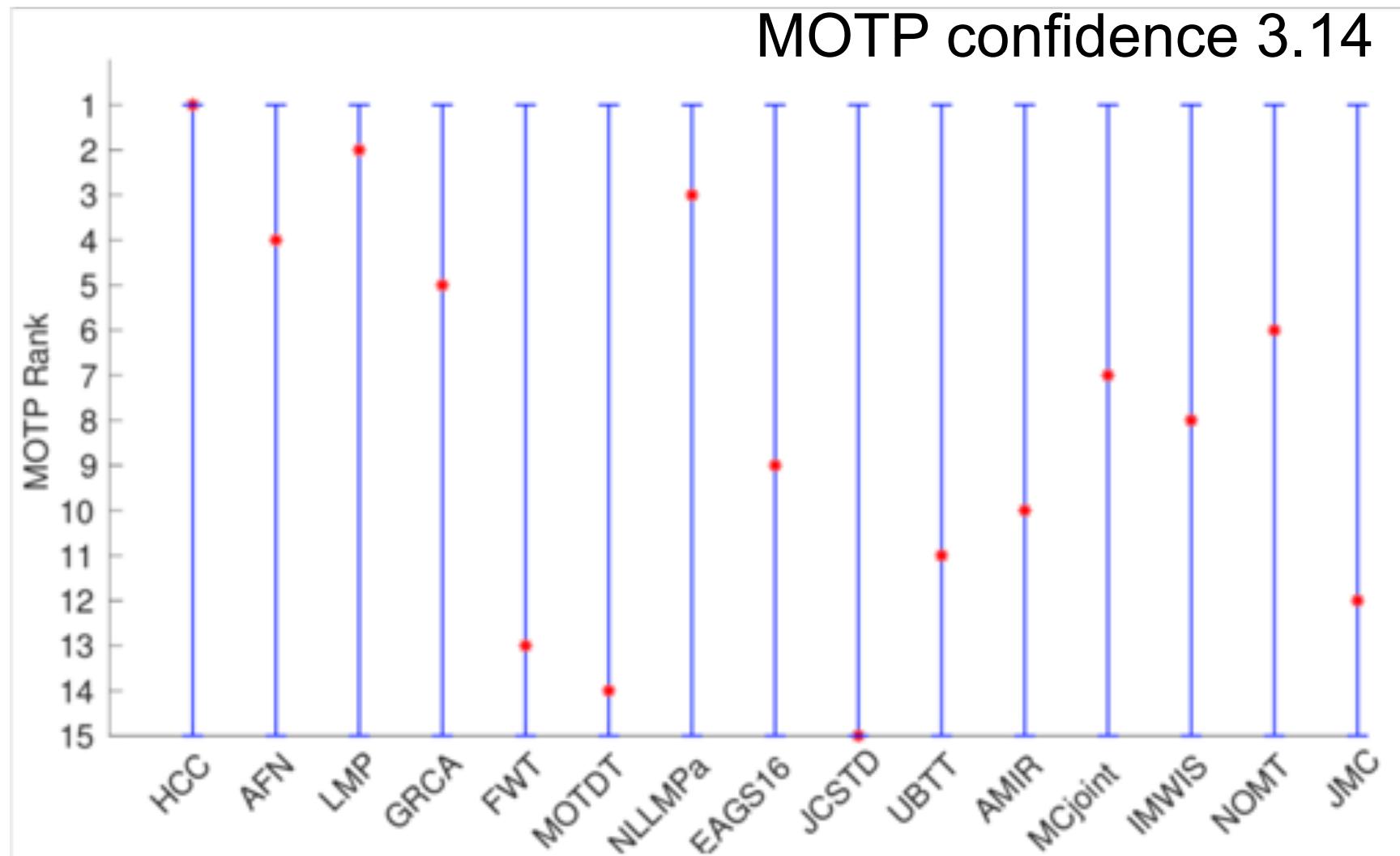
Impact on MOTB16 – MOTA ranking



Impact on MOTB16 – MOTP



Impact on MOTB16 – MOTP ranking



Conclusion

- Interpolation
 - large scale datasets 
 - inaccuracies 
- Confidence intervals
 - consider annotation inaccuracies from an already annotated dataset 
 - no need of further annotations 
- Future work
 - consider other type of semi-automatic annotation (e.g. tracking)
 - consider other applications (e.g. DNN tasks)



Paper