



The Visual Object Tracking Challenge Results

VOT2018

Matej Kristan, Aleš Leonardis, Jiri Matas, Michael Felsberg, Roman Pflugfelder, Luka Čehovin,
Gustavo Fernandez, Alan Lukežič, Tomaš Vojir, Goutam Bhat, Abdelrahman Eldesokey, et al.



University of Ljubljana
Faculty of Computer and
Information Science

UNIVERSITY OF
BIRMINGHAM



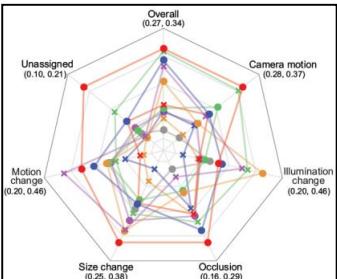
LIU LINKÖPING
UNIVERSITY

AIT
AUSTRIAN INSTITUTE
OF TECHNOLOGY

The emergence of VOT initiative

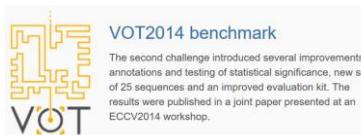
„Although tracking itself is by and large a solved problem...”
-- Jianbo Shi & Carlo Tomasi CVPR1994 --

- The **VOT initiative** (February 2013)
- Goal: Establish evaluation standards -> development of trackers
- Four pillars of VOT:
 - Evaluation system
 - Datasets
 - Evaluation methodology
 - Community building (VOT challenges)



VOT2013 benchmark

The first challenge introduced a new evaluation kit plus 16 well-known short videos, 27 single-target trackers submitted by 51 participants participated at the challenge. The results were published in a joint paper presented at an ICCV2013 workshop which was attended by over 70 researchers.



VOT2014 benchmark

The second challenge introduced several improvements in annotations and testing of statistical significance, new set of 25 sequences and an improved evaluation kit. The results were published in a joint paper presented at an ECCV2014 workshop.



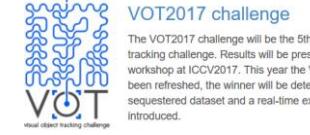
VOT2015 benchmark

The third challenge introduced a dataset of 60 challenging sequences, a formalized sequence selection methodology and improvements to evaluation methodology. The results were published in a joint paper presented at an ICCV2015 workshop.



VOT2016 benchmark

The fourth challenge updated the dataset of 60 sequences with new annotations. The results were published in a joint paper presented at a workshop at ECCV2016.



VOT2017 challenge

The VOT2017 challenge will be the 5th visual object tracking challenge. Results will be presented at VOT workshop at ICCV2017. This year the VOT dataset has been refreshed, the winner will be determined on sequestered dataset and a real-time experiment has been introduced.

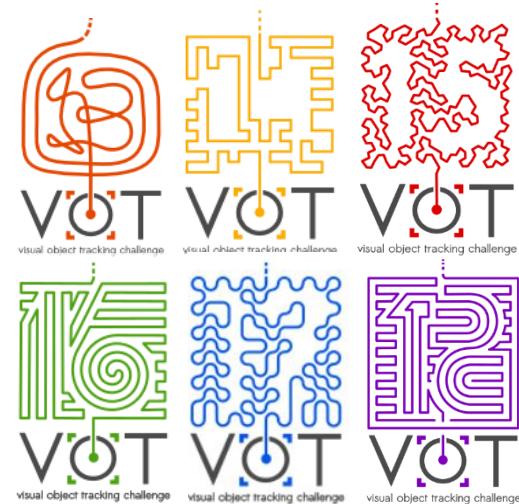


VOT2018 challenge

The VOT2018 challenge will be the 6th visual Object Tracking challenge. Results will be presented at VOT workshop at ECCV2018. This challenge introduces a long-term subchallenge VOT-LT2018.

The VOT challenge evolution

Perf. Measures		Dataset size	Target box	
VOT2013	ranks, A, R	16, manual select.	<input type="checkbox"/> manual	VOT-ST
VOT2014	ranks, A, R, EFO	25, manual select.	<input type="checkbox"/> manual	VOT-ST
VOT2015	EAO, A, R, EFO	60, fully auto	<input type="checkbox"/> manual	VOT-ST, VOT-TIR
VOT2016	EAO, A, R, EFO	60, fully auto	<input checked="" type="checkbox"/> auto	VOT-ST, VOT-TIR,
VOT2017	EAO, A, R, EAO _{realtime}	60x2, fully auto	<input checked="" type="checkbox"/> auto	VOT-ST, VOT-RT, VOT-TIR



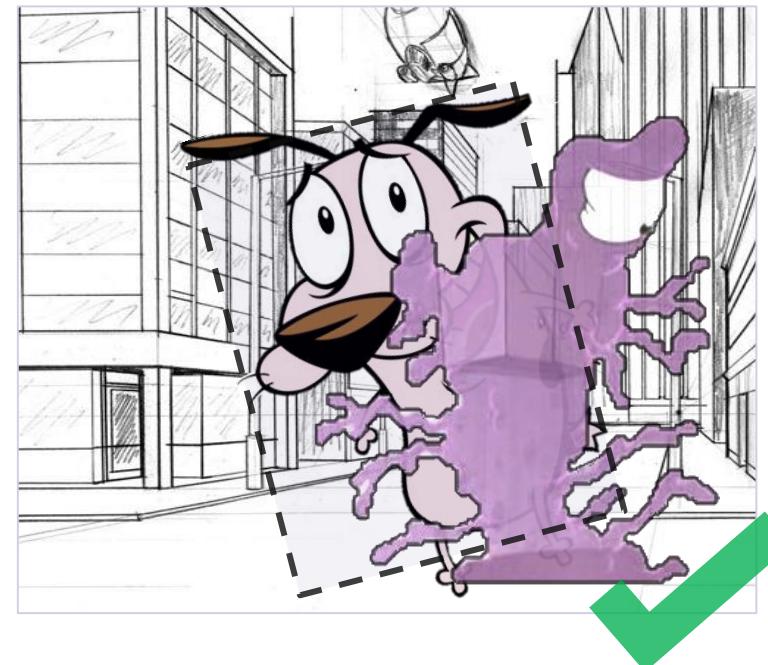
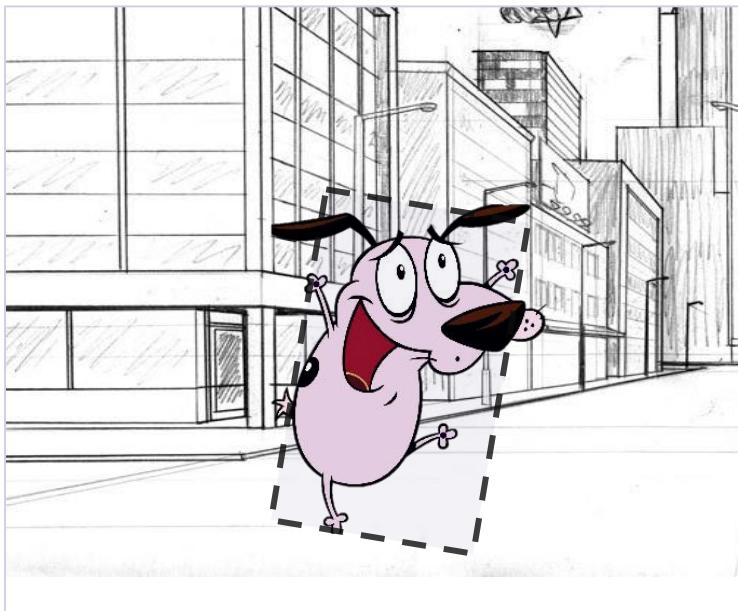
- Carefully developed datasets, annotation, measures, toolkits, subchallenges
- VOT2018:
 - Short-term tracking challenge
 - Short-term tracking real-time challenge
 - Long-term tracking challenge

Outline

1. Scope of the VOT2018 (sub) challenges
2. VOT2018 results overview
3. Winner announcement

VOT2018 short-term (ST) challenge

- Short-term, single-target, causal trackers
- Tracker reports the target state as a rotated bounding box



- No redetection: drift is considered a failure and **tracker is reset**

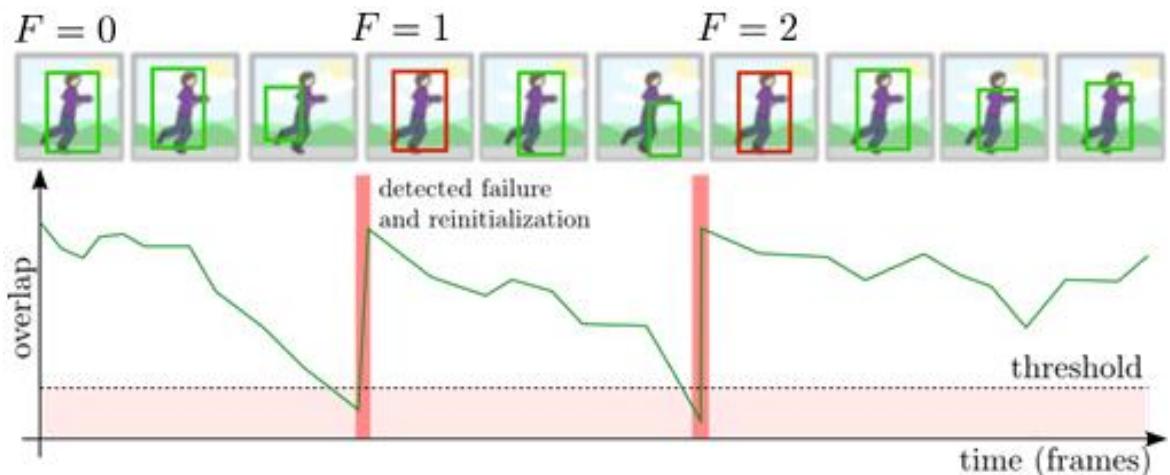
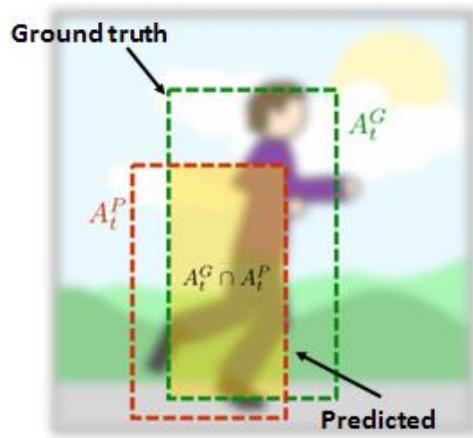
The VOT2018 ST dataset

- VOT2017 dataset did not saturate → same dataset used in VOT2018
- Public dataset (60 sequences) + Sequestered dataset (60 sequences)
- Each image annotated by 6 attributes:
Occlusion, Illumination change , Object motion, Object size change, Camera motion, Unassigned
- Rotated bounding box automatically computed from pre-segmented image

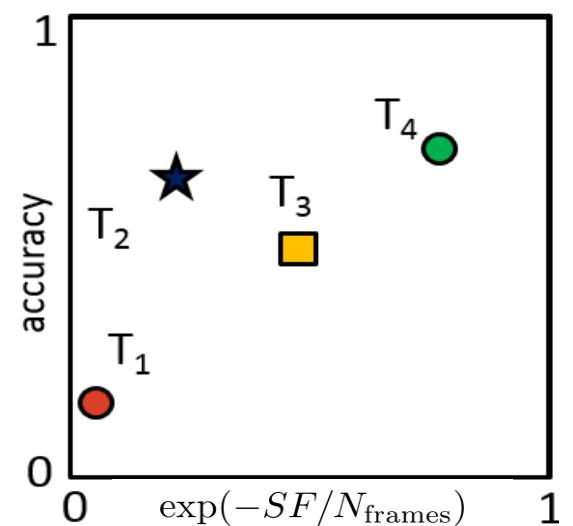
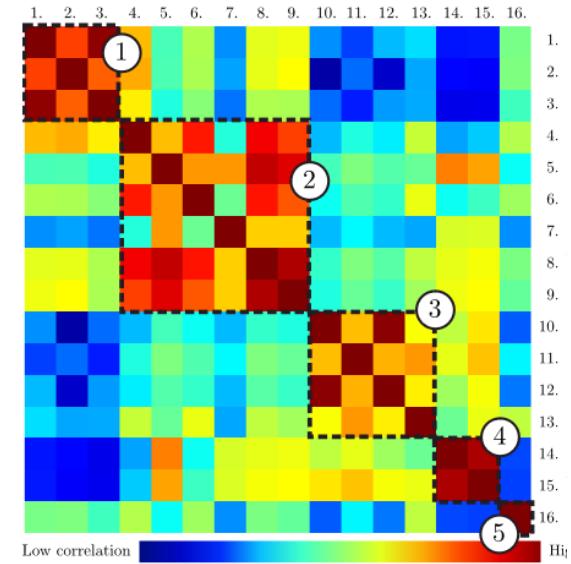


The VOT2018 ST evaluation methodology

- Two weakly correlated measures² chosen according to¹:
 - Robustness (number of times a is reinitialized)
 - Accuracy (average overlap while tracking)
 - + Combination of basic measures (EAO)



Performance measure correlation analysis¹

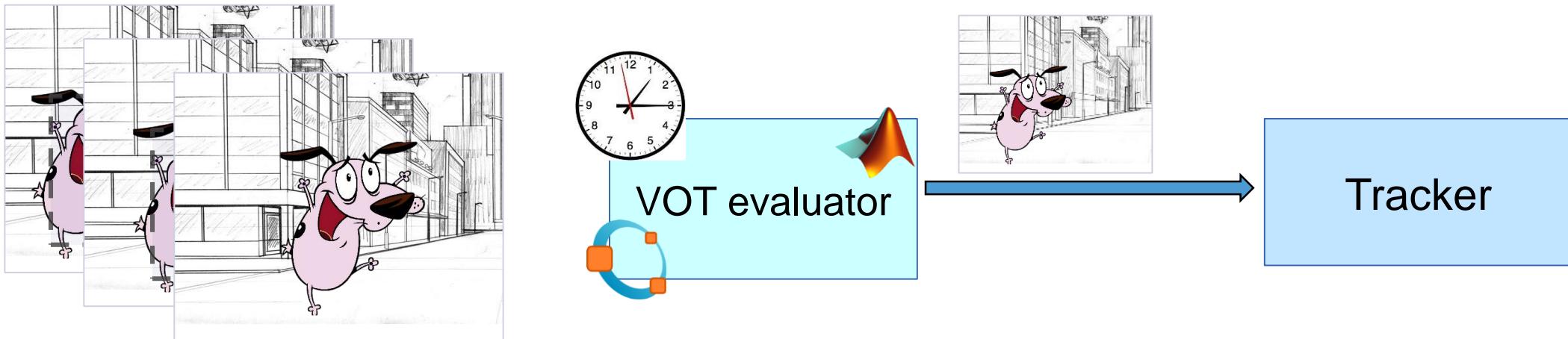


¹Čehovin, Leonardis, Kristan. *Visual object tracking performance measures revisited*, IEEETIP 2016

²Kristan et al., A Novel Performance Evaluation Methodology for Single-Target Trackers, IEEETPAMI 2016

The VOT2018 ST real-time challenge

- Required to process sequences at ~ 20 fps



- The VOT2018 ST public dataset used for this
- Same performance evaluation protocol and measures as VOT2018 ST

The VOT 2018 workshop

VOT2018 LONG-TERM TRACKING CHALLENGE

Long-term tracking (LTT)



- Required long-term tracker properties:
 - Determine when the target has been lost (or disappeared)
 - Re-detect the target after losing the target

Short-term vs long-term spectrum¹

ST/LT levels	Position reported	Determines target lost?	Target re-detection			
ST ₀ : Basic ST		each frame		no		no
ST ₁ : Basic ST with conservative updating		each frame		not explicitly, selective update of visual model		no
LT ₀ : Pseudo LT		only when visible		yes		no
LT ₁ : Re-detecting LT		only when visible		yes		yes

- ST₀ (e.g., KCF², MS³)
- ST₁ (e.g., MDNet⁴, ECO⁵) -> easily converted to LT₀
- LT₁ (e.g., TLD⁵)

¹Lukežić, Čehovin, Vojir, Matas, Kristan, *Now you see me: evaluating performance in long-term visual tracking*, arXiv2018

²Enriques et al. PAMI 2015 ; ³Comaniciu et al. PAMI 2002; ³Nam et al. CVPR2016;

⁴Danelljan et al. CVPR2017; ⁵Kalal et al. PAMI 2011

VOT2018 LT tracking dataset

- VOT approach: Keep it **sufficiently small**, well **annotated** and **diverse**
- Most challenging element: lots of target disappearances
- The dataset that meets these requirements: LTB35¹

LTB35 =

20 (from UAV20L² – small objects & many disappearances)

+3 (from³ – challenging long sequences)

+6 (new from Youtube – many disappearances)

+6 (new generated from⁴)

¹Lukežić, et al., Now you see me: evaluating performance in long-term visual tracking, Arxiv2018

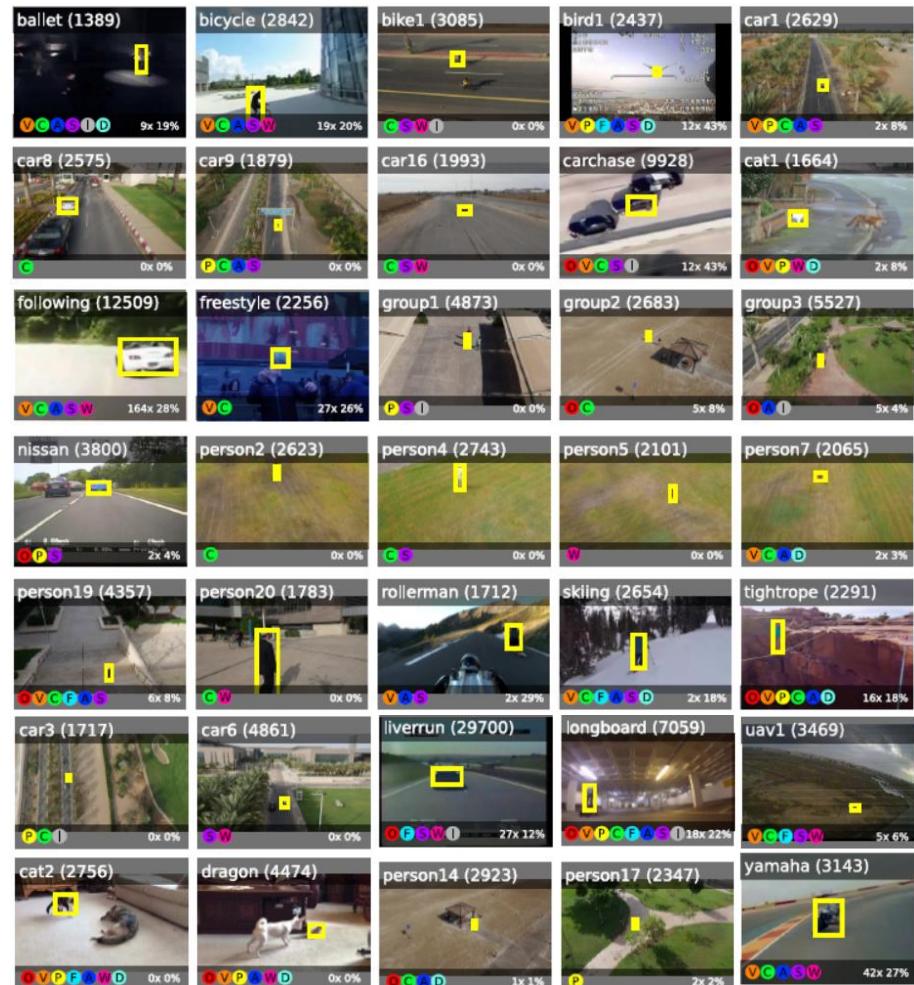
²Mueller et al., A benchmark and simulator for uav tracking, ECCV2016

³Kalal et al., Tracking-Learning-Detection, TPAMI2010

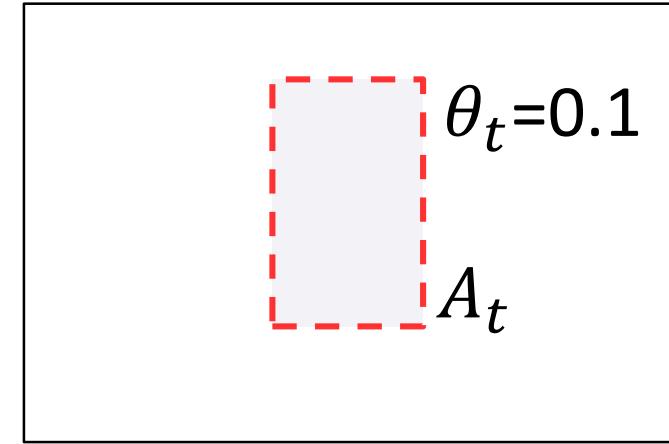
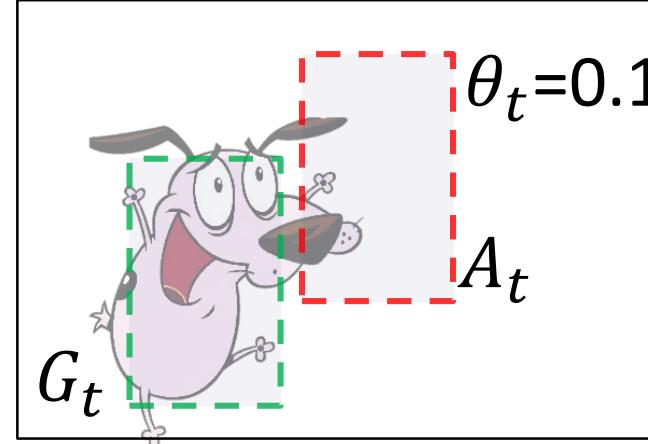
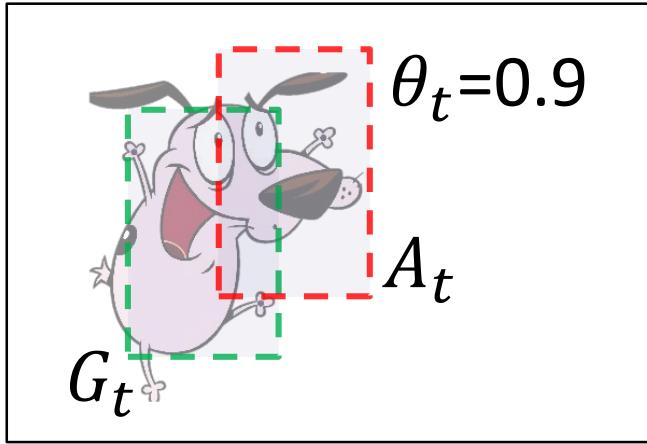
⁴Čehovin et al., Beyond Standard Benchmarks: Parameterizing Performance Evaluation in Visual Object Tracking, ICCV2017

VOT2018 LT tracking dataset

- 35 sequences (146,847 frames)
- Axis aligned bounding box annotations
(persons, car, motorcycle, bicycle, boat, animals, etc.)
- Resolution: 290x217 - 1280x720
- Average per sequence disappearance: 12
- Average target absence period: 40 frames
- Nine per-sequence attributes:
(1) full occlusion, (2) out-of-view motion, (3) partial occlusion, (4) camera motion, (5) fast motion, (6) scale change, (7) aspect ratio change, (8) viewpoint change, (9) similar objects



LT performance measure design¹

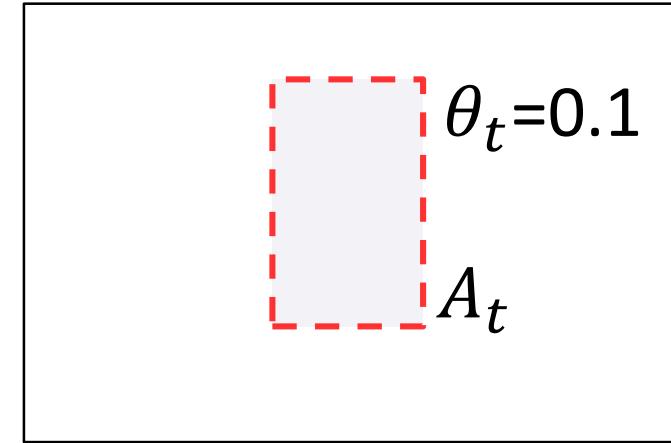
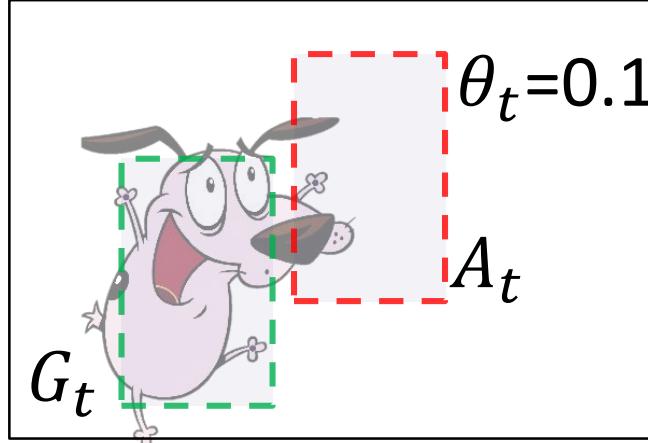
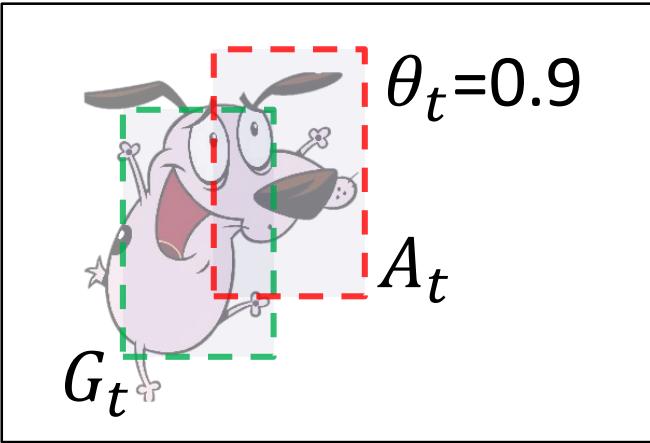


- Requirements: (i) **localization** accuracy, (ii) **target absence** prediction accuracy, (iii) **re-detection** accuracy
- Precision (Pr) ... % of all predictions A_t that agree with GT G_t
- Recall (Re) ... % of all GT boxes that agree with predictions A_t
- F-measure ... a standard Pr/Re tradeoff

$$F = 2PrRe/(Pr + Re)$$

¹Lukežić, et al., Now you see me: evaluating performance in long-term visual tracking, Arxiv 2018

LT performance measure design



- Agreement = sufficient overlap:

$$\Omega(A_t, G_t) \geq \tau_\Omega \longrightarrow \Omega(A_t(\tau_\theta), G_t) \geq \tau_\Omega$$

Detection “certainty” threshold

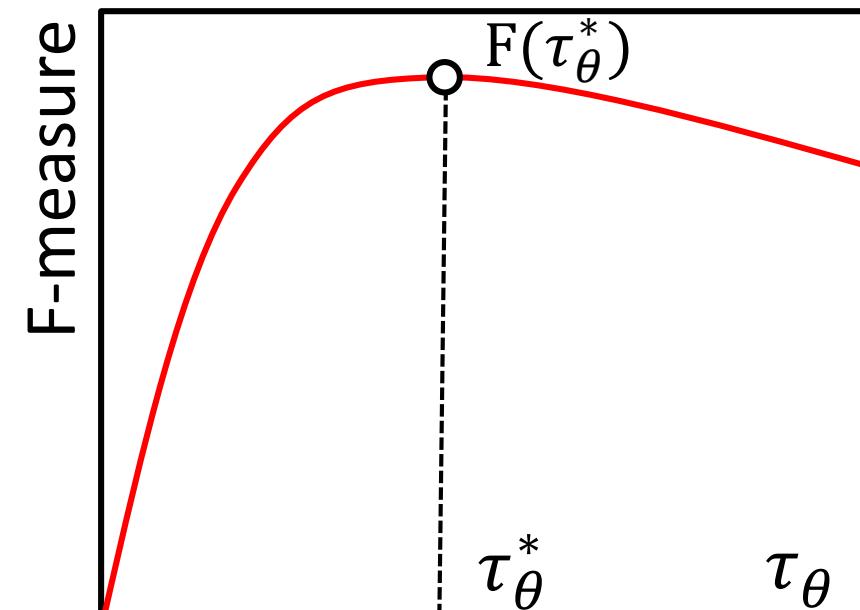
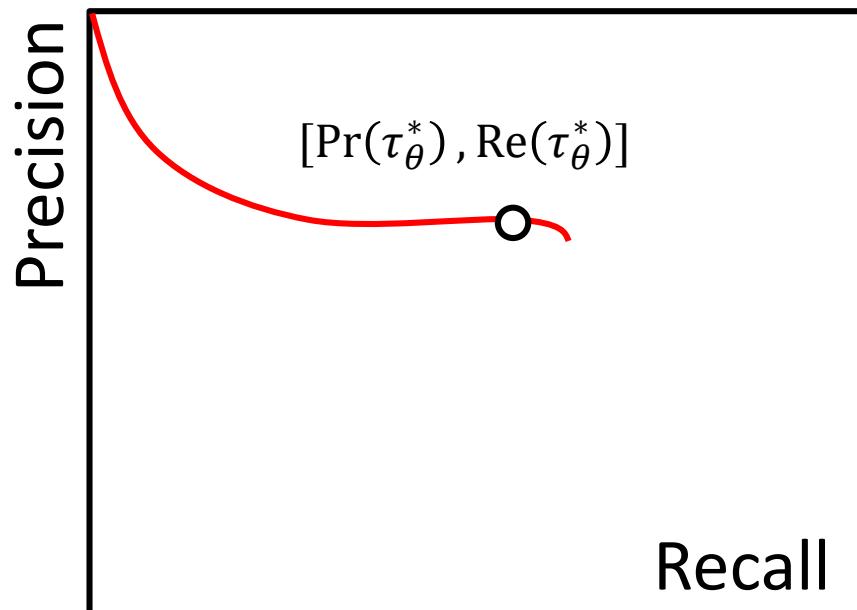
- Precision and Recall depend on two thresholds: $\text{Pr}(\tau_\theta, \tau_\Omega)$, $\text{Re}(\tau_\theta, \tau_\Omega)$
- The overlap threshold is avoided by integrating it out

$$\text{Pr}(\tau_\theta) = \int_0^1 \text{Pr}(\tau_\theta, \tau_\Omega) d\tau_\Omega = \frac{1}{N_p} \sum_{t \in \{t : A_t(\tau_\theta) \neq \emptyset\}} \Omega(A_t(\tau_\theta), G_t),$$

$$\text{Re}(\tau_\theta) = \int_0^1 \text{Re}(\tau_\theta, \tau_\Omega) d\tau_\Omega = \frac{1}{N_g} \sum_{t \in \{t : G_t \neq \emptyset\}} \Omega(A_t(\tau_\theta), G_t)$$

Primary LT performance measures

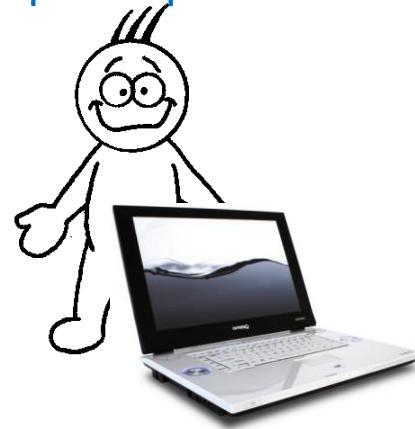
- Primary measures are $\text{Pr}(\tau_\theta^*)$, $\text{Re}(\tau_\theta^*)$ and $F(\tau_\theta^*)$ evaluated at detection certainty threshold that maximizes the tracker F-measure



- Primary scores thus fully avoid manually setting the thresholds
- In short-term setup, $F(\tau_\theta^*)$ reduces to a standard ST measure!

VOT2018 participation

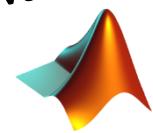
The VOT challenge
participant



Raw results, tracker
description, source code



VOT Page



Evaluation system + Dataset

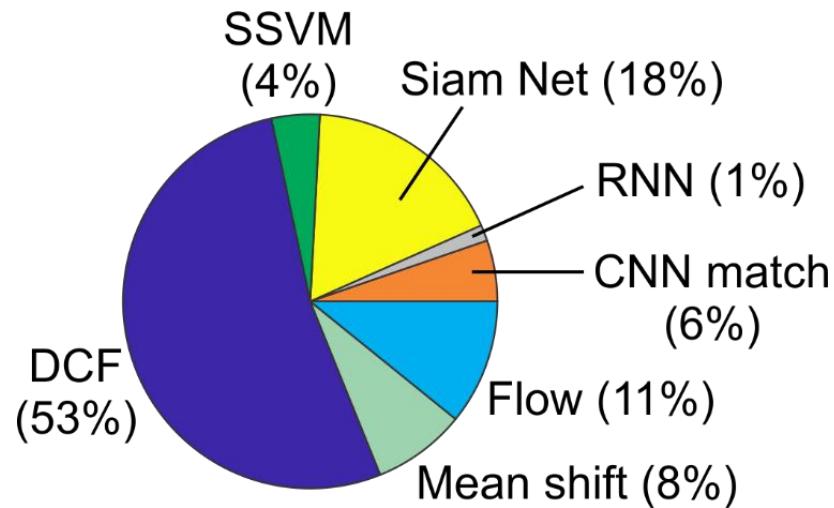
- Participants **download** the toolkit and the VOT2018 datasets
- Toolkit automatically performs all experiments
- Submission of raw results + tracker code required
- **Top ten trackers** re-run by VOT committee on the sequestered dataset

The VOT 2018 workshop

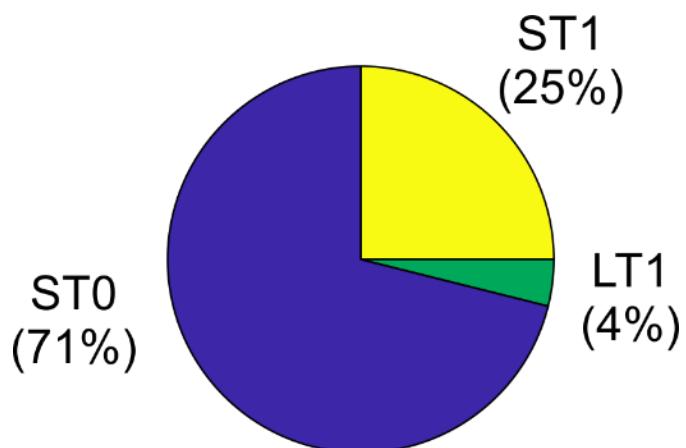
VOT2018 ST CHALLENGE RESULTS

VOT2018: 72 trackers tested

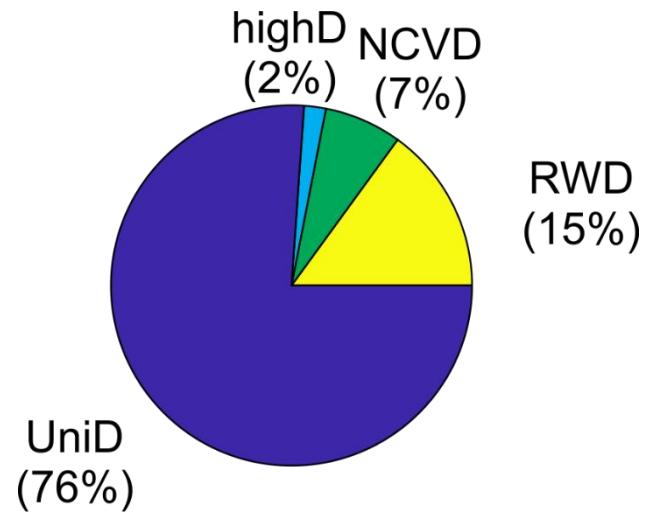
Tracking approach:



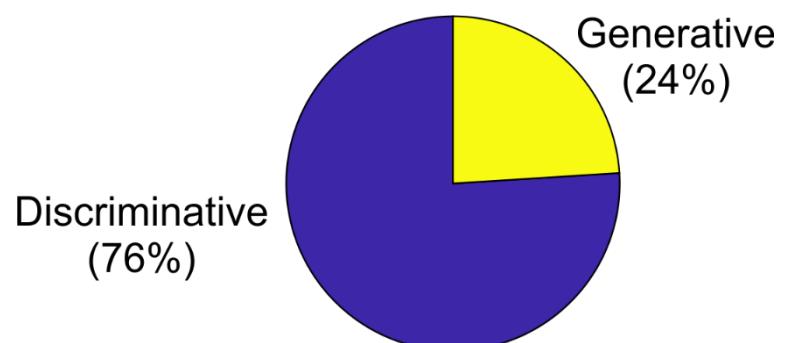
ST/LT category:



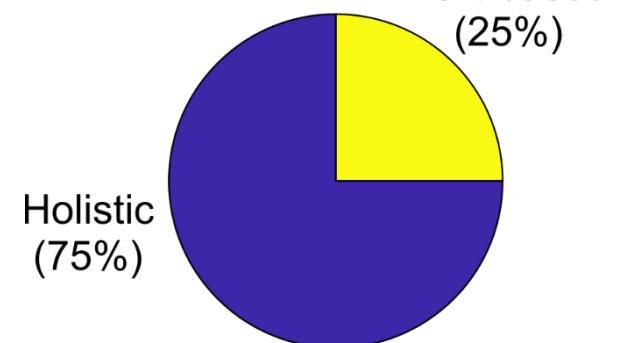
Motion model:



Generative/discriminative:

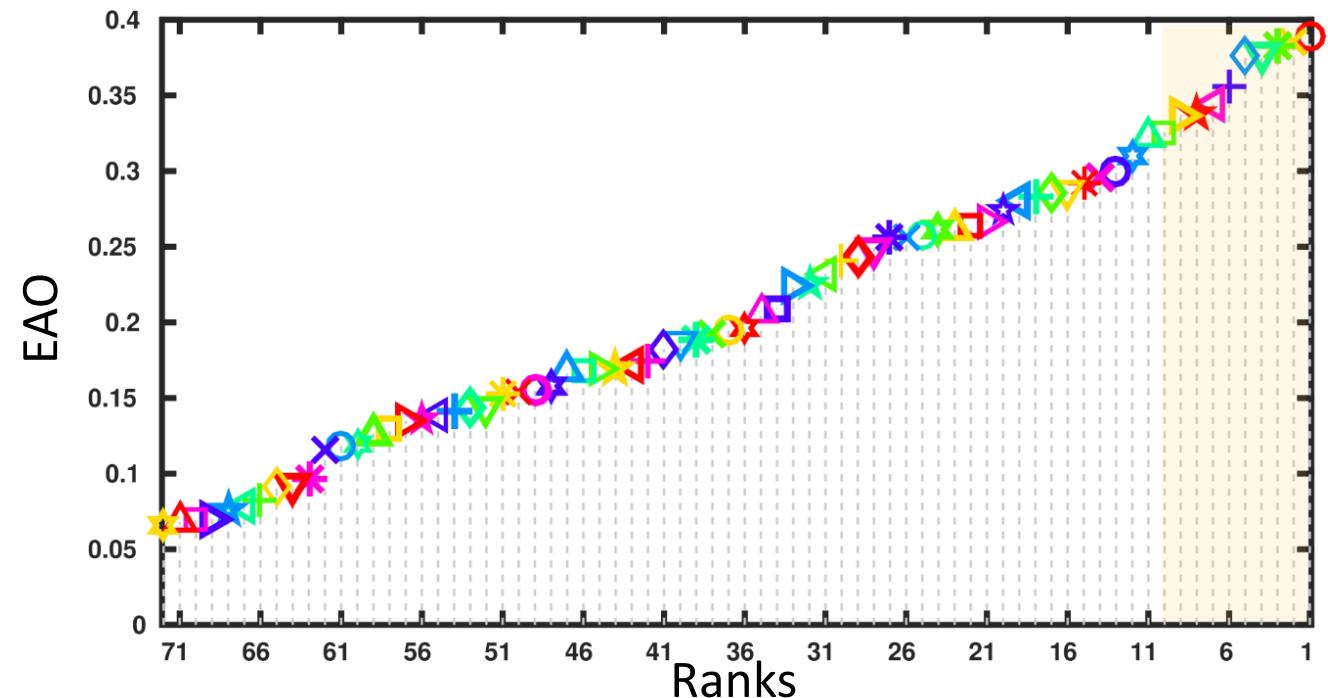


Holistic/parts:



VOT2018 ST results on public dataset

- **Top trackers:** (1) LADCF, (2) MFT, (3) SiamRPN, (4) UPDT, (5) RCO, (6) DRT, (7) DeepSTRCF1, (8) SA_Siam_R, (9) CPT , (10) DLSTpp
- **Tracking approach in top 10:**
8 DCF, except SiamPRN and SA_Siam_R (based on Siamese nets)
- **Features:**
 - All CNN (+handcrafted)
 - Top two apply Resnet50
 - Most CNN trained for detection
 - Some trained for localization,
(e.g. MFT)

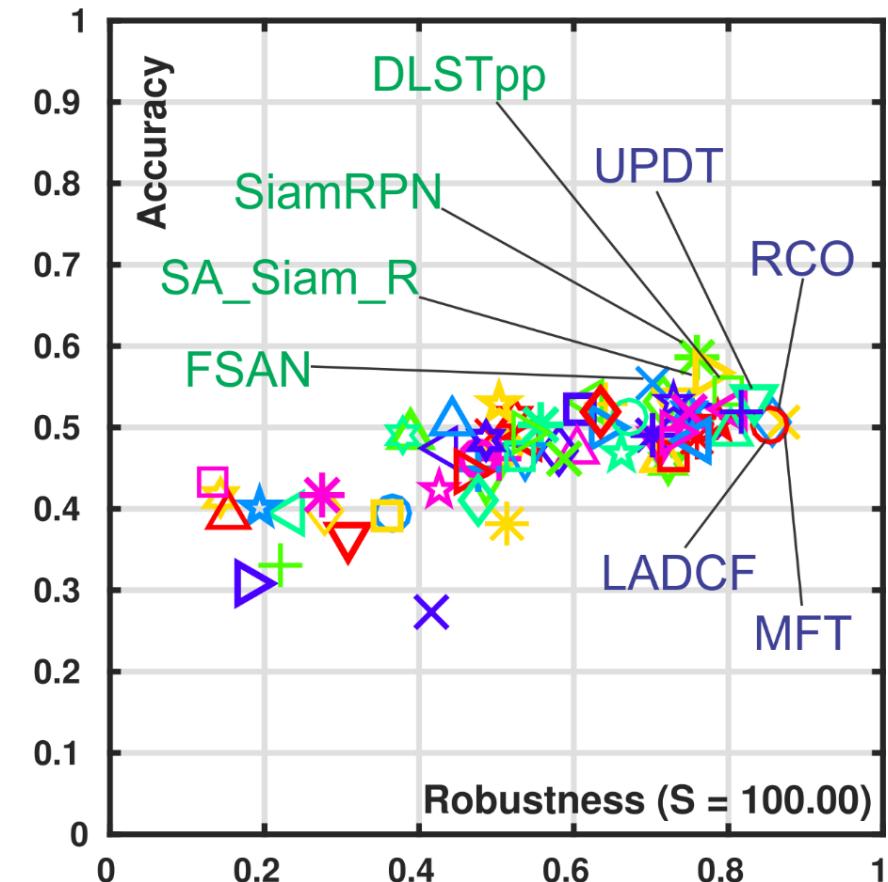


VOT2018 results on public dataset

- Top trackers are among the most robust trackers
(1) MFT, (2) LADCF, (3) RCO, (4) UPDT
- Top in accuracy:
(1) SiamRPN, (2) SA_Siam_R, (3) FSAN, (4) DLSTpp
- Per-attribute analysis:

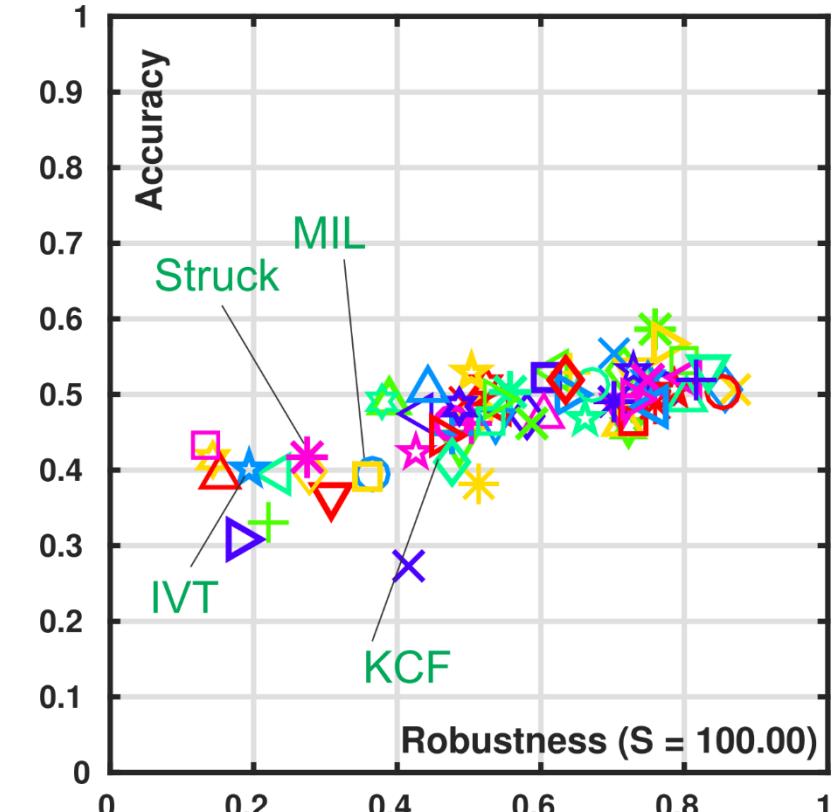
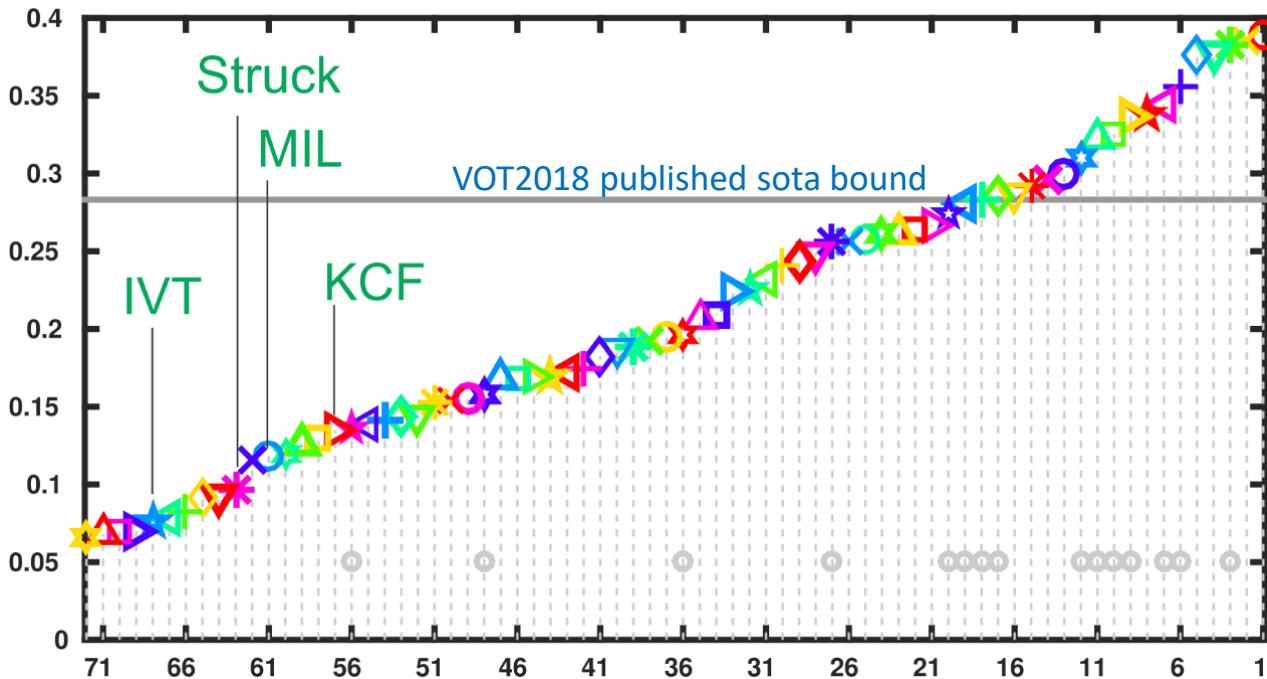
	CM	IC	MC	OC	SC
Accuracy	0.49	0.47	0.47	③ 0.40	① 0.43 ②
Robustness	0.74	1.05 ②	0.87 ③	1.19 ①	0.61

- Most failures due to: **Occlusion**
- Mostly affects accuracy: **Occlusion + Scale change**



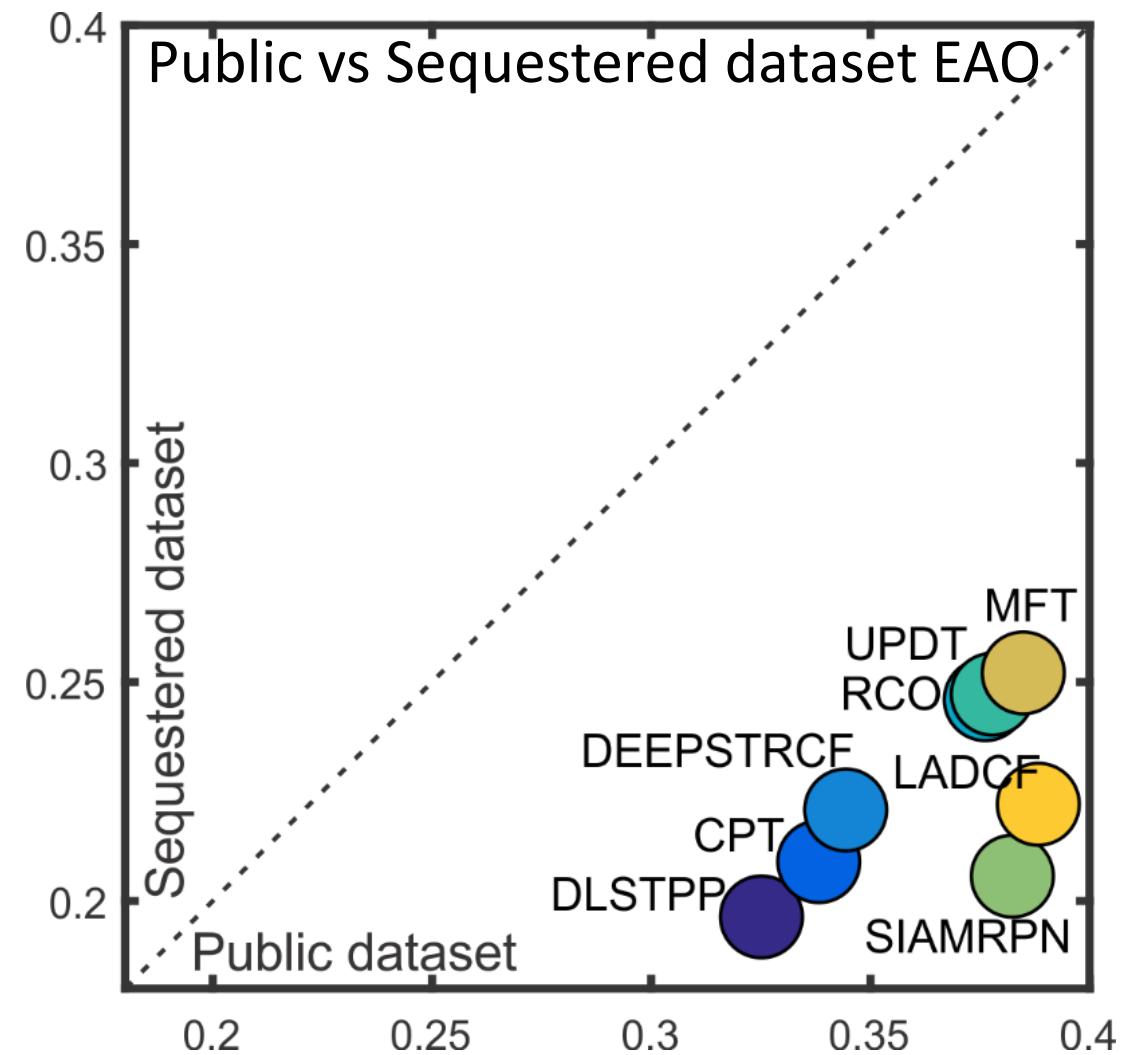
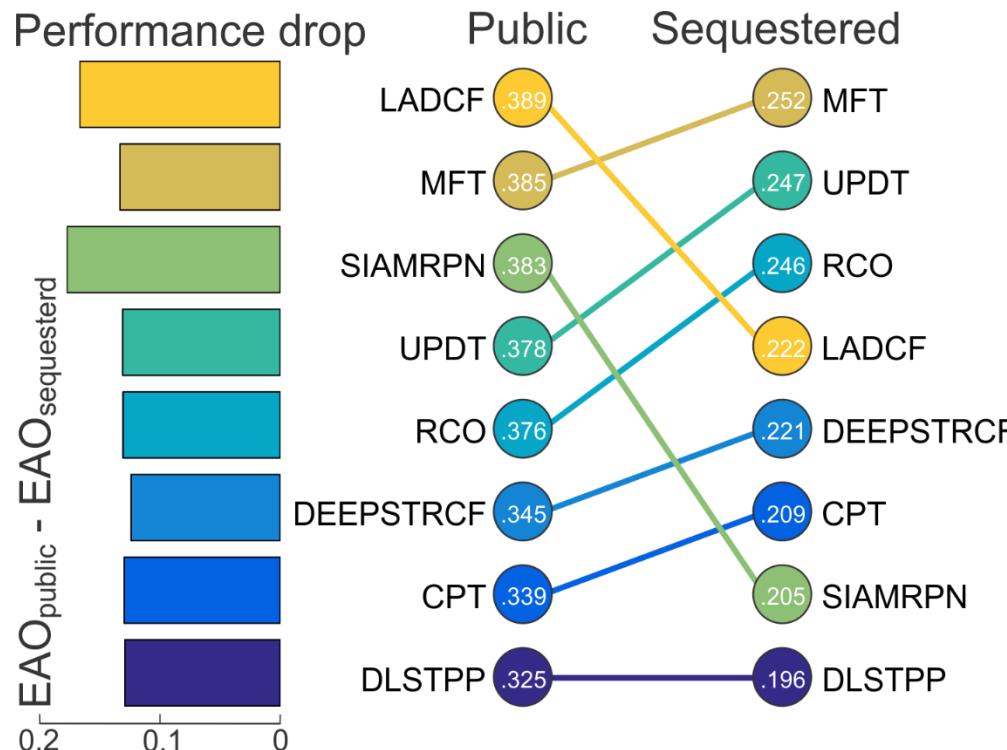
VOT2018 results on public dataset

- Baselines ranked at the very tail of the benchmark
- 19 trackers published at major CV venues ($2017 \leq$)
 - Their average performance: VOT2018 sota bound
 - Over 26% submissions exceed this bound



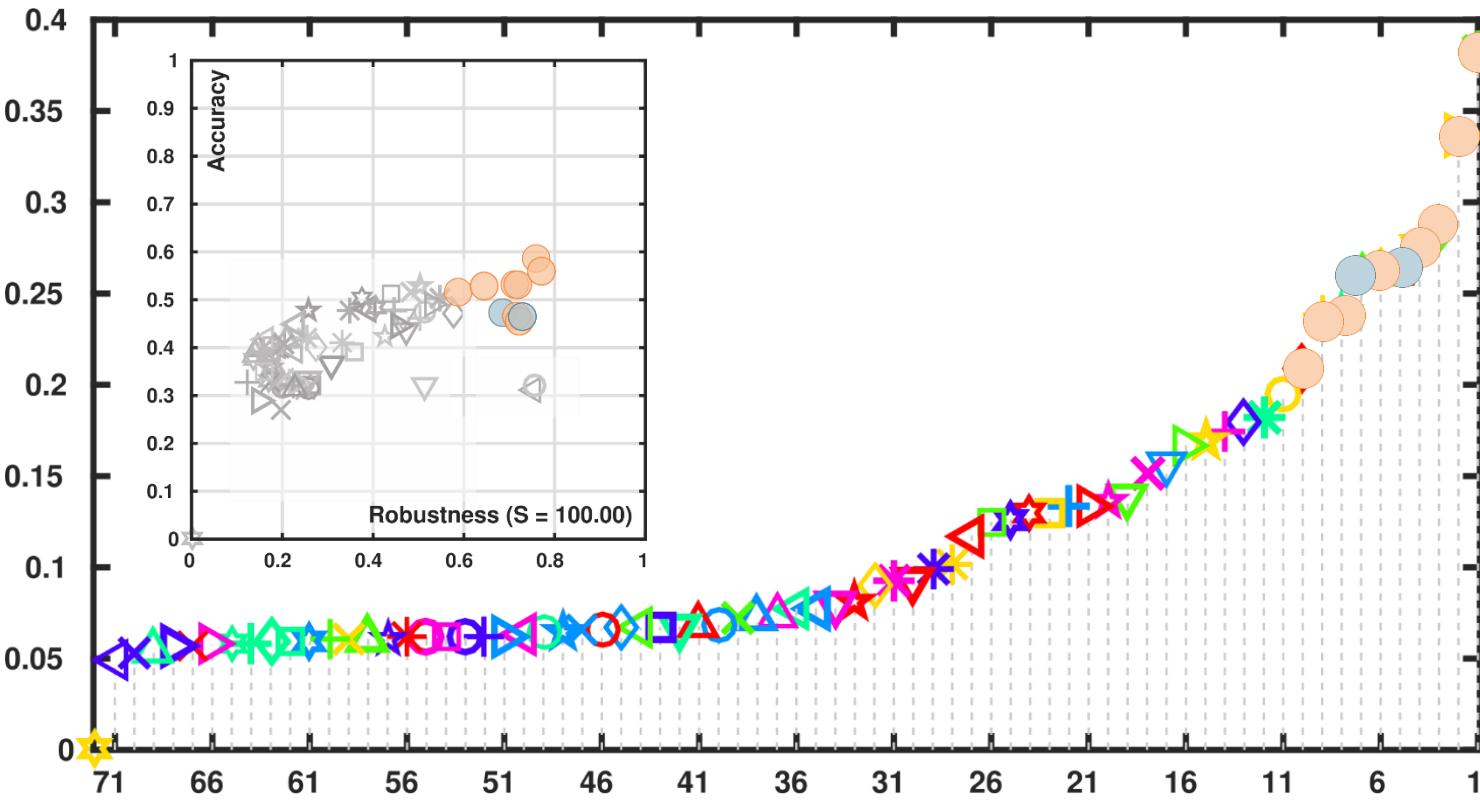
VOT2018 results on sequestered dataset

- Fairly stable ranks
- Greatest change: SiamRPN
- Smallest rank change: MFT



VOT2018 ST realtime results

- Top 10: (1) SiamRPN, (2) SA_Siam_R, (3) SA_Siam_P, (4) SiamVGG, (5) CSRTPP, (6) LWDNTm, (7) LWDNTthi, (8) CSTEM, (9) MBSiam, (10) UpdateNet

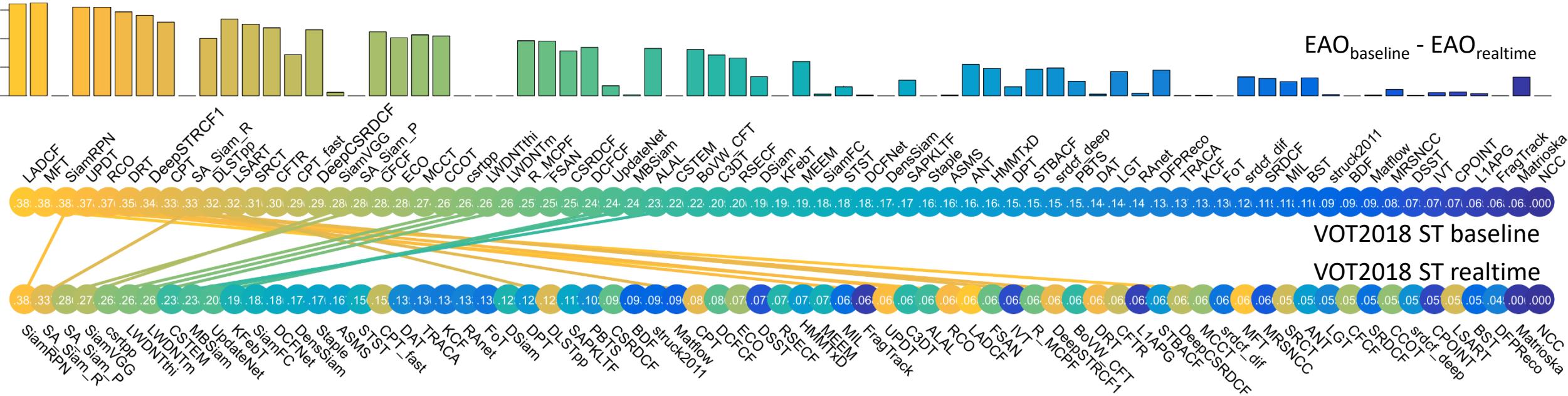


Two classes:

- Approach: **Siamese**
(e.g., SiamFc¹)
- Features: CNN
- Hardware: GPU
- Approach: **CSRDCF**²
- Features: HOG+CN
- Hardware: CPU

¹Bertinetto, et al., VOT2016, ²Lukežić, et. al., CVPR2017

VOT2018 ST Realtime vs Baseline results



- Most of the **top baseline performers** drop with real-time constraint
- The **drop is smaller for real-time trackers** on baseline challenge
- Some **achieve top real-time performance AND perform well on the baseline**

The VOT 2018 workshop

VOT LONG-TERM CHALLENGE RESULTS

VOT2018 long-term challenge: trackers tested

- 15 trackers tested
- 5 trackers from ST_0 class (elevated to LT0)
- 10 trackers from LT_1 class
- LT trackers composed of: a short-term component and a detector

Image-wide re-detection test

- Designed to test a crucial ingredient: *Image-wide re-detection*
- Created artificial sequences: *Only target position changes*

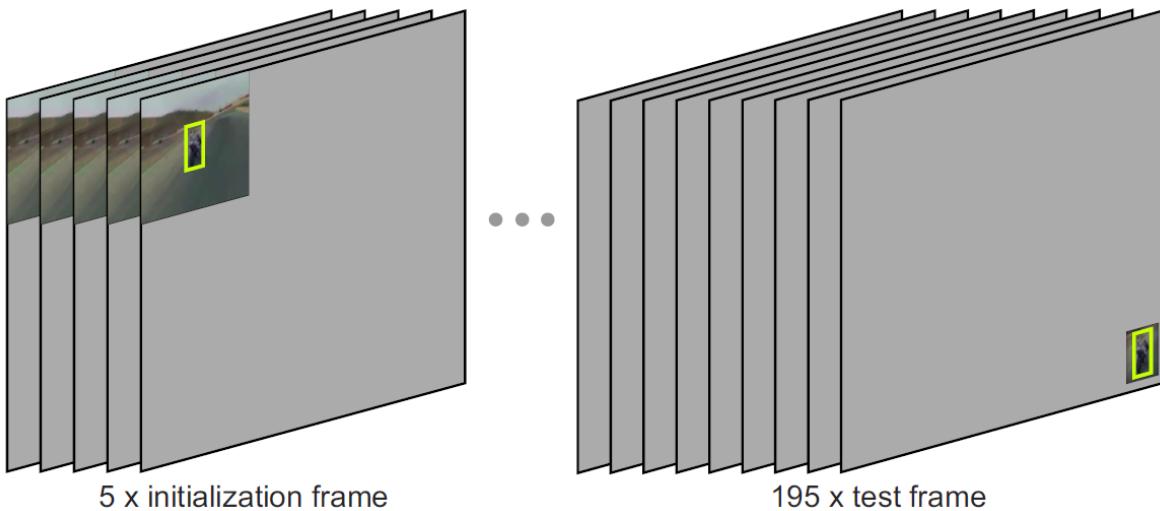
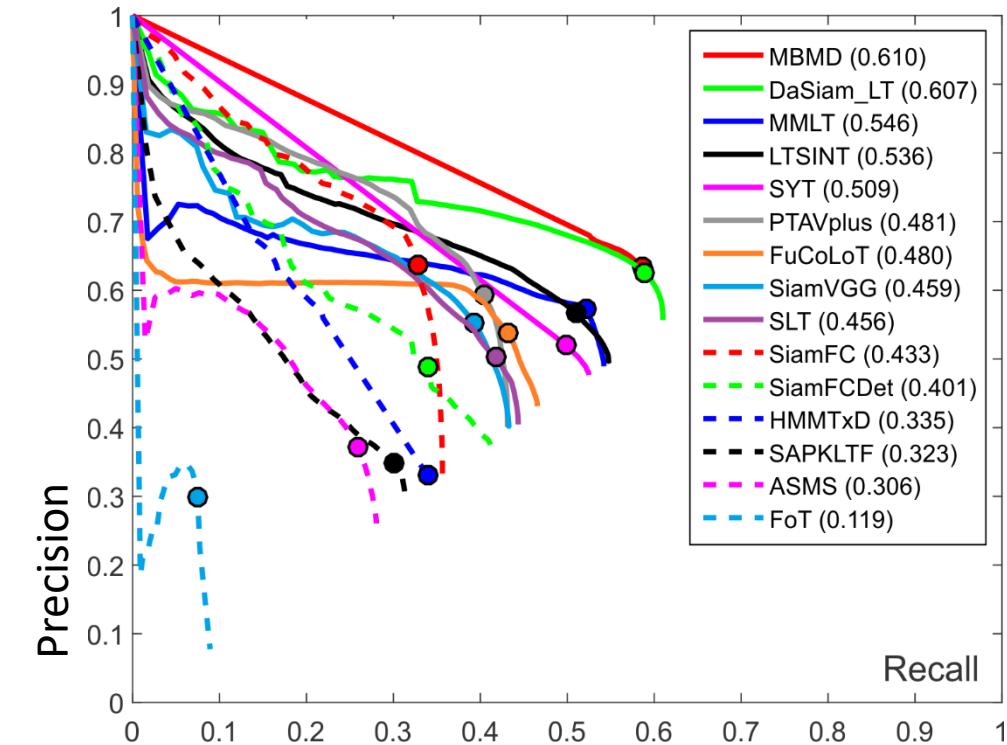
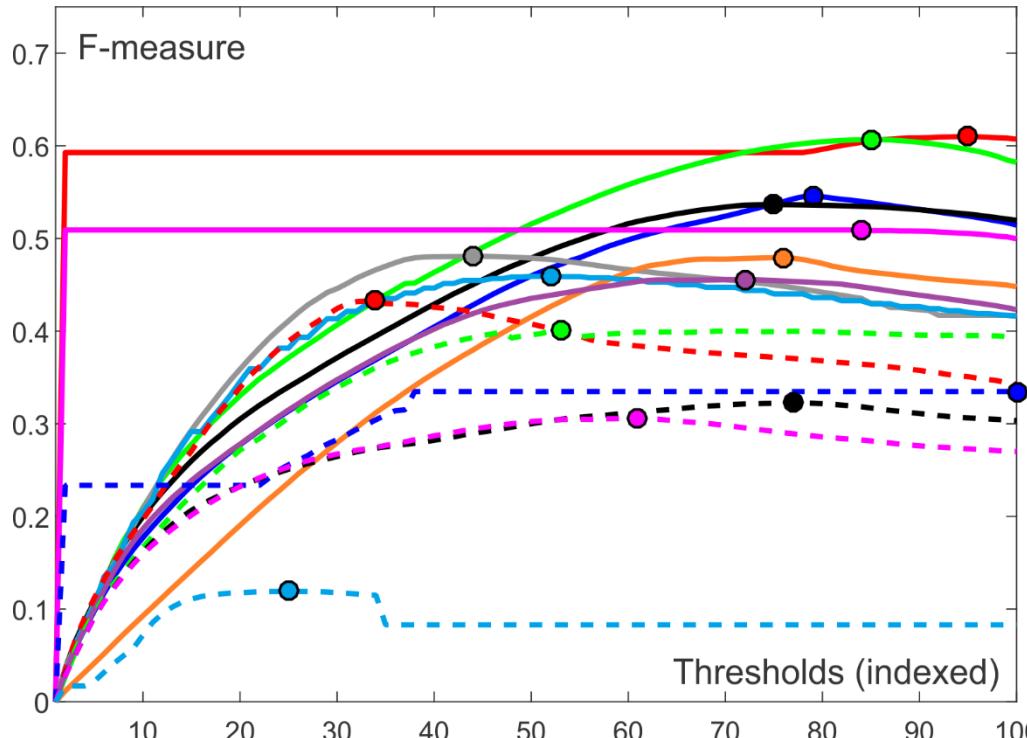


Image-wide detection: 8 trackers
(nearly instant detection, with exceptions)

7 trackers did not pass the LT1 test: Local detection at most

Tracker	Frames (Success)
1. MBMD	1 (100%)
2. DaSiam_LT	- (0%)
3. MMLT	0 (100%)
4. LTSINT	2 (100%)
5. SYT	0 (43%)
6. PTAVplus	0 (11%)
7. FuCoLoT	78 (97%)
8. SiamVGG	- (0%)
9. SLT	0 (100%)
10. SiamFC	- (0%)
11. SiamFCDet	0 (83%)
12. HMMTxD	3 (91%)
13. SAPKLT	- (0%)
14. ASMS	- (0%)
15. FoT	0 (6%)

Overall results – the benchmark

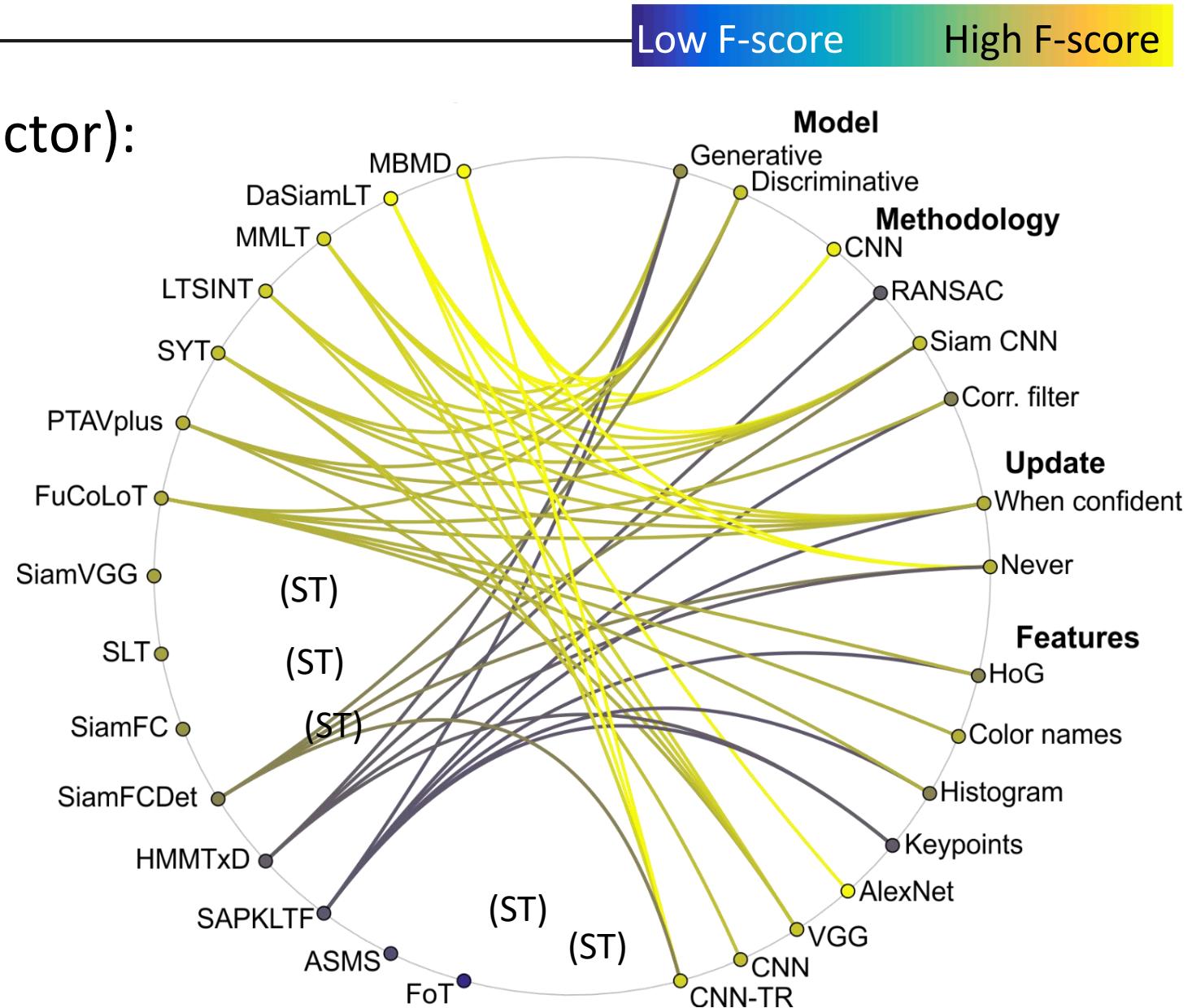


- Top 10: 9 **CNN-based** (mostly Siamese architectures), 2 apply **DCF**
- Best: MBMD (Based on MDNet¹) – bounding box regression + classification
- All top trackers are LT₁ with **image-wide detection** except DaSiam_LT

¹Nam, Han, Learning Multi-Domain Convolutional Neural Networks for Visual Tracking, CVPR2016

Architecture analysis:

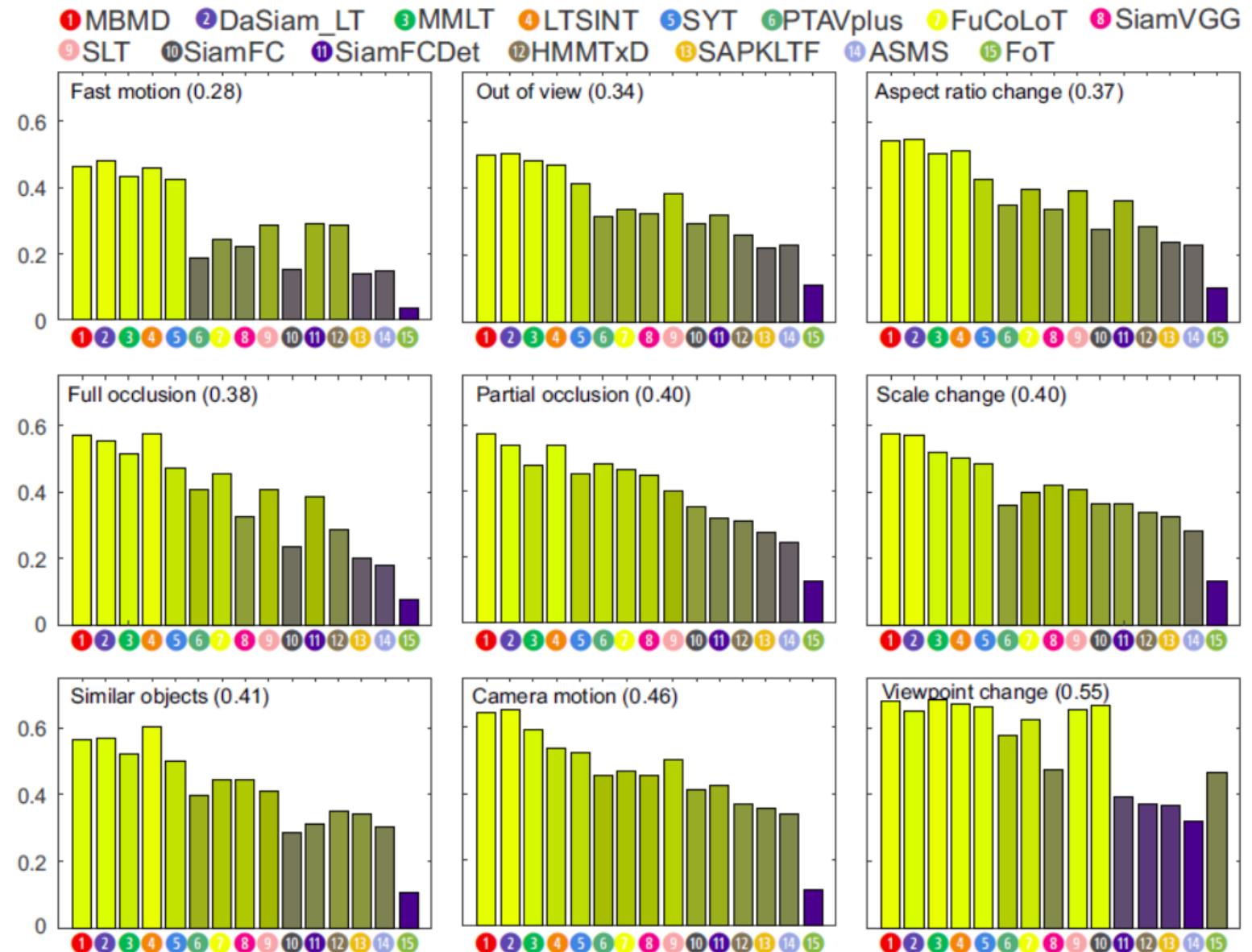
- Long-term component (Detector):
 - CNNs consistently deliver top performance
 - DCFs show great promise (when properly learned)
 - Deep features dominate
- Short-term component:
 - Follow trend observed in ST tracking benchmarks



Attribute analysis

Most challenging:

- Fast motion
- Out of view
- Aspect ratio change

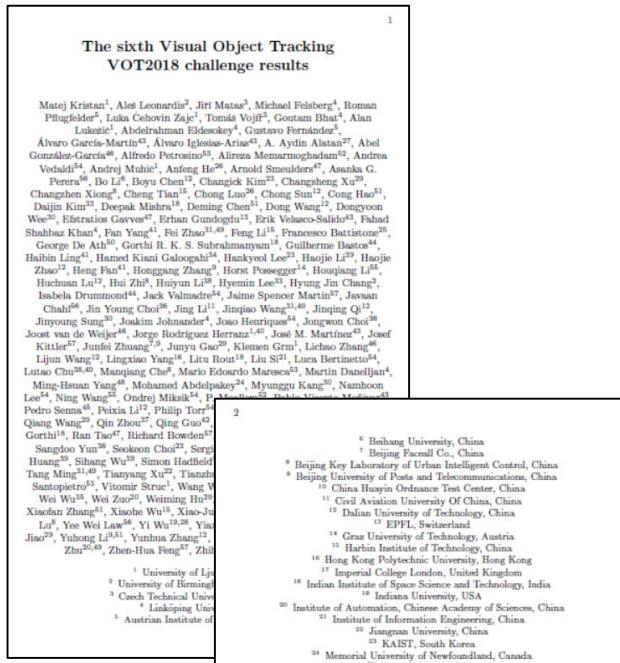


VOT2018 challenges Summary

- VOT2018 ST baseline:
 - DCF the dominant methodology, Deep features the dominant features
 - Wider use of deep features trained for localization
- VOT2018 ST realtime:
 - Best performance: fully convolutional deep approaches and DCFs
 - Some of the fastest trackers also rank among best on baseline
- VOT2018 LT:
 - Explicit object detection integrated
 - Nearly all top-performers CNN-based, only one purely DCF
 - Top two performers do not update the detector

VOT2018 online resources

- Results in 155 coauthor paper (58 institutions)
- Available at <http://www.votchallenge.net/vot2018>
 - Presentations + papers + Dataset + Evaluation kit
 - Guidelines on how to evaluate your trackers on VOT2018 and produce graphs for your papers (directly comparable to 72 ST and ~10 LT trackers!)
- VOT is open source:
 - All toolkits and protocols on Github
 - Trackers code available:
VOT2018 (72 ST, 15 LT), VOT2017 (36), VOT2016 (39)



¹ Beijing University, China
² Beijing Fossel Co., China
³ Beijing Key Laboratory of Urban Intelligent Control, China
⁴ Beijing University of Posts and Telecommunications, China
⁵ China Huayu Ordnance Test Center, China
⁶ Civil Aviation University of China, China
⁷ Dalian University of Technology, China
⁸ EPFL, Switzerland
⁹ Graz University of Technology, Austria
¹⁰ Harbin Institute of Technology, China
¹¹ Hong Kong Polytechnic University, Hong Kong
¹² Imperial College London, United Kingdom
¹³ Indian Institute of Space Science and Technology, India
¹⁴ Institute of Automation, Chinese Academy of Sciences, China
¹⁵ Institute of Information Engineering, Slovakia
¹⁶ Jiangnan University, China
¹⁷ KAIST, South Korea
¹⁸ Memorial University of Newfoundland, Canada
¹⁹ Merit Research S.p.A., Italy
²⁰ Middle East Technical University, Turkey
²¹ Nanjing Audit University, China
²² National Laboratory of Pattern Recognition, China
²³ Naver Corporation, South Korea
²⁴ NLPR, Institute of Automation, Chinese Academy of Sciences, China
²⁵ North China University of Technology, China
²⁶ POSTECH, South Korea
²⁷ Robotics Institute, Carnegie Mellon University, USA
²⁸ Senescope, China
²⁹ Seoul National University, South Korea
³⁰ Shanghai Jiaotong University, China
³¹ Shenzhen Institute of Microelectronics, Chinese Academy of Sciences, China
³² South China University of Technology, China
³³ Technical University of Madrid, Spain
³⁴ Temple University, USA
³⁵ Tsinghua University
³⁶ Universidad Autónoma de Madrid, Spain
³⁷ Universitat Autònoma de Barcelona, Spain
³⁸ Universitat Autònoma de Barcelona, Spain
³⁹ Universitat Autònoma de Barcelona, Spain
⁴⁰ University of Alberta, Canada
⁴¹ University of Chinese Academy of Sciences, China
⁴² University of Illinois at Urbana-Champaign, USA
⁴³ University of North Carolina at Chapel Hill, USA
⁴⁴ University of North Carolina at Charlotte, USA
⁴⁵ University of North Carolina at Charlotte, USA
⁴⁶ University of North Carolina at Charlotte, USA
⁴⁷ University of North Carolina at Charlotte, USA
⁴⁸ University of North Carolina at Charlotte, USA
⁴⁹ University of North Carolina at Charlotte, USA
⁵⁰ University of North Carolina at Charlotte, USA

Abstract. The Visual Object Tracking challenge VOT2018 is the sixth annual tracker benchmarking activity organized by the VOT initiative and the tracker community. Results of eight tracking proposals, namely state-of-the-art trackers published in the field of computer vision, are presented in this paper. The recent years have seen a significant increase in the number of tracked objects and the complexity of the tracking scenarios. The evaluation included the standard VOT and other popular methodologies for short-term tracking analysis and a “real-time” experiment simulating a situation where a tracker processes images as if provided by a continuously running sensor. A long-term tracking sub-challenge was introduced to the set of standard VOT tasks. The new challenge is the new sub-challenge focused on tracking multiple objects coping with target disappearance and re-appearance. A new dataset has been compiled and a performance evaluation methodology that focuses on long-term tracking capabilities has been adopted. The VOT toolkit has been updated to support both standard short-term and the new long-term tracking sub-challenges. Performance of the tested trackers typically by far exceeds the baseline trackers. The toolkit, the dataset, the evaluation kit and the results are publicly available from the VOT page. The dataset, the evaluation kit and the results are publicly available at the challenge website.¹

VOT2018 awards:

Winners of the VOT2018 short-term challenge:

MFT by: S. Bai, Z. He, J. Zhuang

“Multi-solution Fusion for Visual Tracking”



University of Ljubljana
Faculty of Computer and
Information Science

SICK
Sensor Intelligence.

VOT2018 awards:

Winners of the VOT2018 ST realtime challenge:

SiamRPN by: Q. Wang, Z. Zhu, B. Li, W. Wu, W. Hu, W. Zou

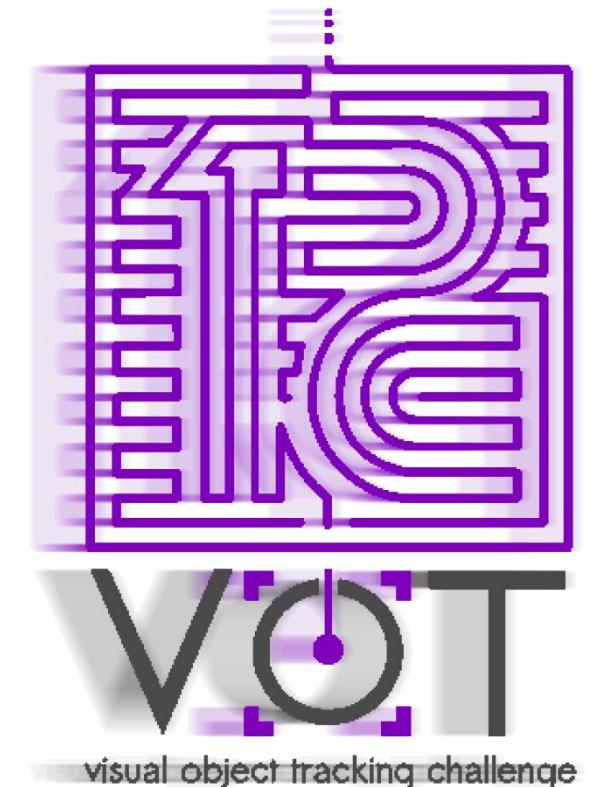
“High Performance Visual Tracking with Siamese Region Proposal Network”

(talk after the Poster session!)



University of Ljubljana
Faculty of Computer and
Information Science

SICK
Sensor Intelligence.



VOT2018 awards:

Winners of the VOT2018 long-term challenge:

MBMD by: Y. Zhang, L. Wang, D. Wang, J. Qi,
H. Lu

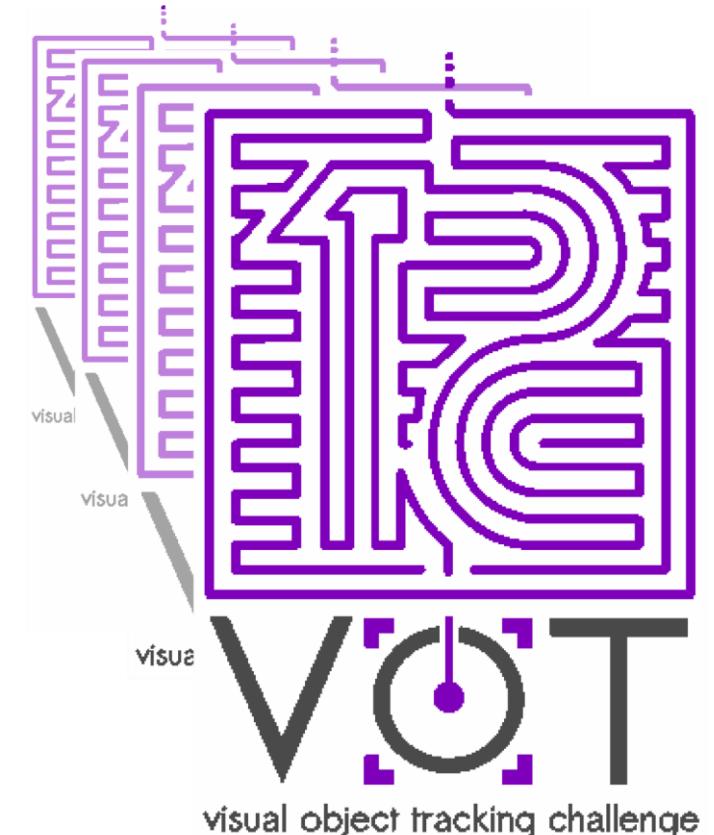
“MobileNet based tracking by detection
algorithm”

(talk after the Poster session!)



University of Ljubljana
Faculty of Computer and
Information Science

SICK
Sensor Intelligence.



Thanks

- The VOT2018 committee



M. Kristan



J. Matas



A. Leonardis



M. Felsberg



R. Pflugfelder



G. Fernandez



L. Čehovin



T. Vojir



A. Lukežič



G. Bhat



A. Eldesokey

- Everyone who participated or contributed

Matej Kristan¹, Ales Leonardis², Jir Matas³, Michael Felsberg⁴, Roman Pfugfelder⁵, Luka Cehovin Zajc¹, Tomas Voj~r³, Goutam Bhat⁴, Alan Lukezic¹, Abdelrahman Eldesokey⁴, Gustavo Fernandez⁵, Alvaro Garca-Martn⁴³, Alvaro Iglesias-Arias⁴³, A. Aydin Alatan²⁷, Abel Gonzalez-Garcia⁴⁶, Alfredo Petrosino⁵³, Alireza Memarmoghadam⁵², Andrea Vedaldi⁵⁴, Andrej Muhic¹, Anfeng He²⁶, Arnold Smeulders⁴⁷, Asanka G. Perera⁵⁶, Bo Li⁶, Boyu Chen¹², Changick Kim²³, Changsheng Xu²⁹, Changzhen Xiong⁸, Cheng Tian¹⁵, Chong Luo²⁶, Chong Sun¹², Cong Hao⁵¹, Daijin Kim³³, Deepak Mishra¹⁸, Deming Chen⁵¹, Dong Wang¹², Dongyoon Wee³⁰, Efstratios Gavves⁴⁷, Erhan Gundogdu¹³, Erik Velasco-Salido⁴³, Fahad Shahbaz Khan⁴, Fan Yang⁴¹, Fei Zhao^{31;49}, Feng Li¹⁵, Francesco Battistone²⁵, George De Ath⁵⁰, Gorthi R. K. S. Subrahmanyam¹⁸, Guilherme Bastos⁴⁴, Haibin Ling⁴¹, Hamed Kiani Galoogahi³⁴, Hankyeol Lee²³, Haojie Li³⁹, Haojie Zhao¹², Heng Fan⁴¹, Honggang Zhang⁹, Horst Possegger¹⁴, Houqiang Li⁵⁵, Huchuan Lu¹², Hui Zhi⁸, Huiyun Li³⁸, Hyemin Lee³³, Hyung Jin Chang², Isabela Drummond⁴⁴, Jack Valmadre⁵⁴, Jaime Spencer Martin⁵⁷, Javaan Chahl⁵⁶, Jin Young Choi³⁶, Jing Li¹¹, Jinqiao Wang^{31;49}, Jinqing Qi¹², Jinyoung Sung³⁰, Joakim Johnander⁴, Joao Henriques⁵⁴, Jongwon Choi³⁶, Joost van de Weijer⁴⁶, Jorge Rodriguez Herranz^{1;40}, Jose M. Martnez⁴³, Josef Kittler⁵⁷, Junfei Zhuang^{7;9}, Junyu Gao²⁹, Klemen Grm¹, Lichao Zhang⁴⁶, Lijun Wang¹², Lingxiao Yang¹⁶, Litu Rout¹⁸, Liu Si²¹, Luca Bertinetto⁵⁴, Lutao Chu^{38;49}, Manqiang Che⁸, Mario Edoardo Maresca⁵³, Martin Danelljan⁴, Ming-Hsuan Yang⁴⁸, Mohamed Abdelpakey²⁴, Myunggu Kang³⁰, Namhoon Lee⁵⁴, Ning Wang⁵⁵, Ondrej Miksik⁵⁴, P. Moallem⁵², Pablo Vicente-Morinvar⁴³, Pedro Senna⁴⁵, Peixia Li¹², Philip Torr⁵⁴, Priya Mariam Raju¹⁸, Qian Ruihe²¹, Qiang Wang²⁹, Qin Zhou³⁷, Qing Guo⁴², Rafael Martn-Nieto⁴³, Rama Krishna Gorthi¹⁸, Ran Tao⁴⁷, Richard Bowden⁵⁷, Richard Everson⁵⁰, Runling Wang³², Sangdoo Yun³⁶, Seokeon Choi²³, Sergio Vivas⁴³, Shuai Bai^{7;9}, Shuangping Huang³⁹, Sihang Wu³⁹, Simon Had eld⁵⁷, Siwen Wang¹², Stuart Golodetz⁵⁴, Tang Ming^{31;49}, Tianyang Xu²², Tianzhu Zhang²⁹, Tobias Fischer¹⁷, Vincenzo Santopietro⁵³, Vitomir Struc¹, Wang Wei¹⁰, Wangmeng Zuo¹⁵, Wei Feng⁴², Wei Wu³⁵, Wei Zuo²⁰, Weiming Hu²⁹, Wengang Zhou⁵⁵, Wenjun Zeng²⁶, Xiaofan Zhang⁵¹, Xiaohe Wu¹⁵, Xiao-Jun Wu²², Xinmei Tian⁵⁵, Yan Li⁸, Yan Lu⁸, Yee Wei Law⁵⁶, Yi Wu^{19;28}, Yiannis Demiris¹⁷, Yicai Yang³⁹, Yifan Jiao²⁹, Yuhong Li^{9;51}, Yunhua Zhang¹², Yuxuan Sun¹², Zheng Zhang⁵⁸, Zheng Zhu^{20;49}, Zhen-Hua Feng⁵⁷, Zhihui Wang¹², and Zhiqun He^{7;9}

- VOT2018 sponsors:



University of Ljubljana
Faculty of Computer and
Information Science

SICK
Sensor Intelligence.