MCG-ICT-CAS: Multimedia Computing Group

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2nd ImageNet and COCO Visual Recognition Challenges Joint Workshop

MCG-ICT-CAS Object Detection at ILSVRC 2016

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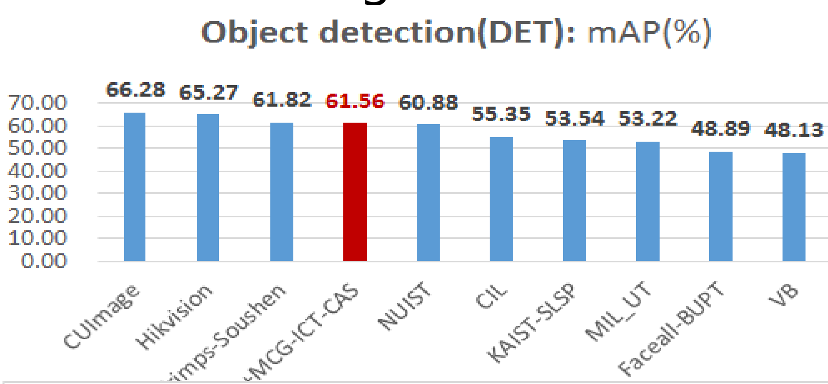
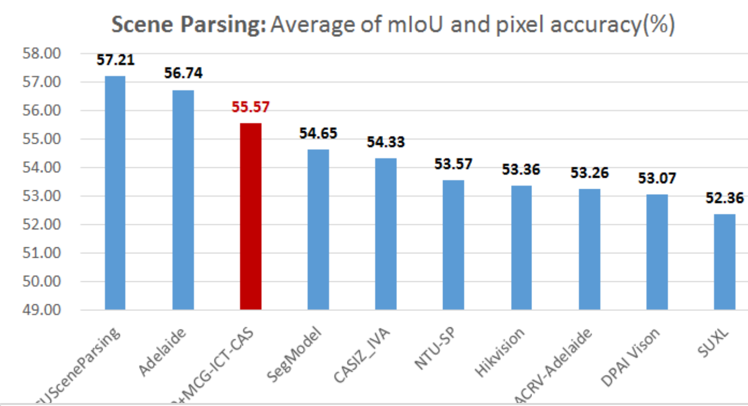
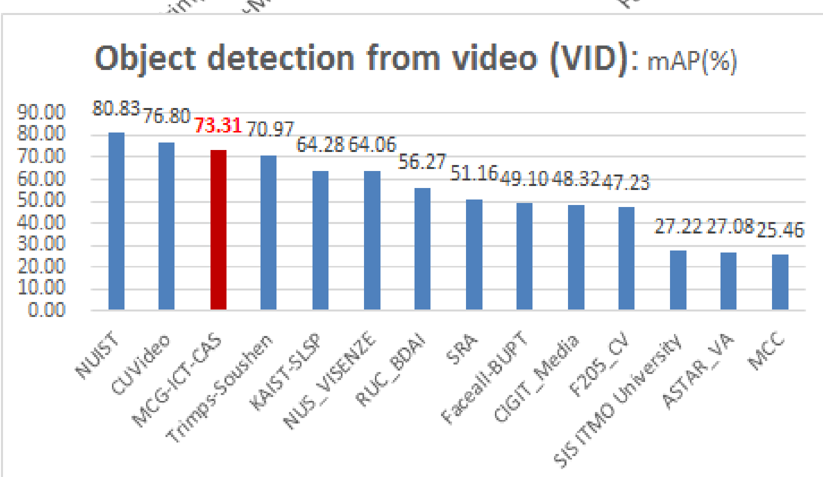
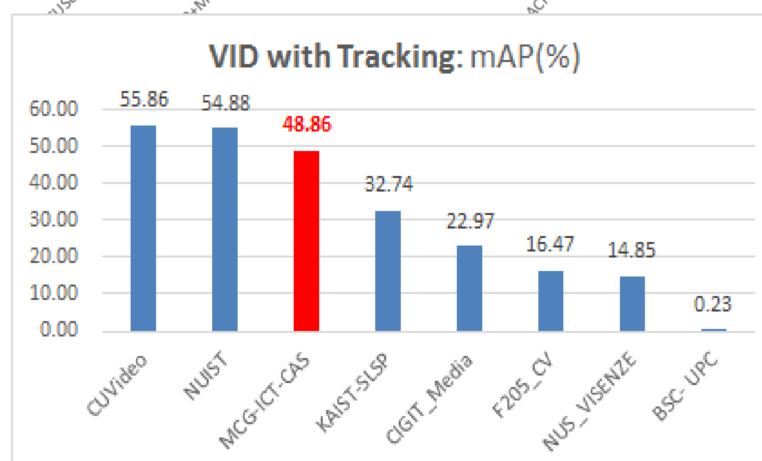
Results of our 3 tasks

- Three tasks with provided data:
  - Object detection (DET): 4th
  - Object detection from video (VID):3rd
  - Scene Parsing: 3rd









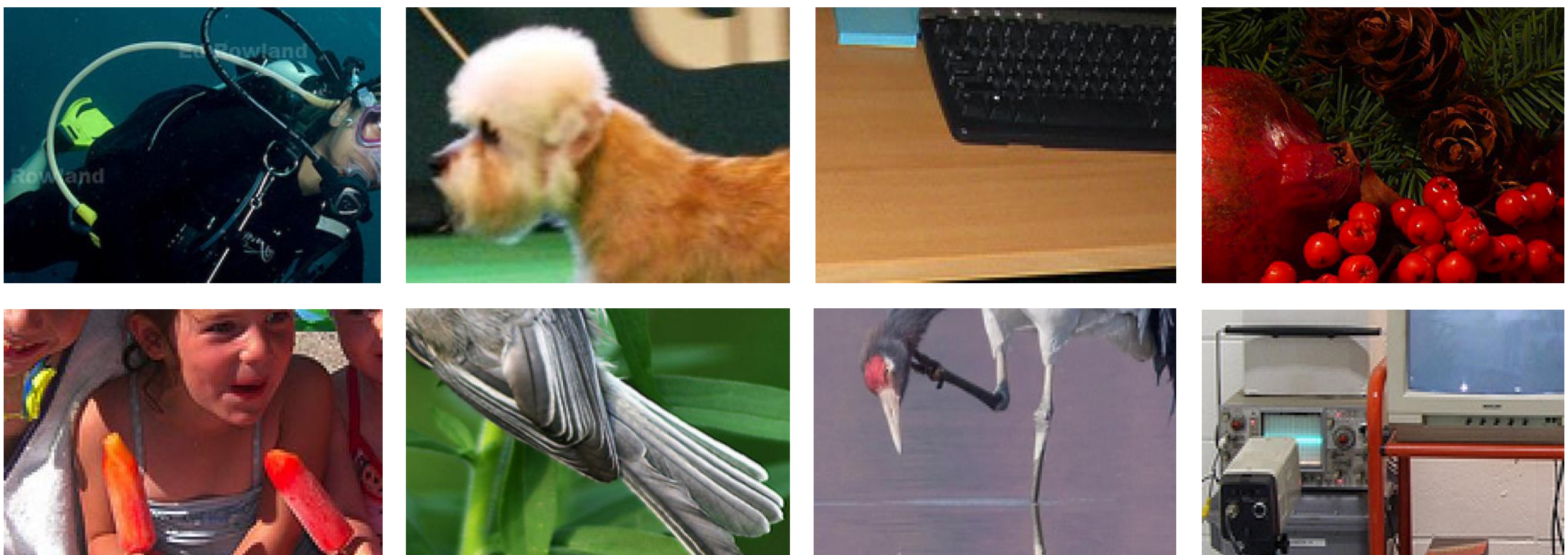
Object Detection (DET)

DET: Overview

- **Improvements of loss function**
  - Implicit sub-categories of background class
  - Sink class when necessary
- Other training and testing tricks
  - Segmentation feature
  - Dilation as context
  - Multi-scale testing
  - Box refinement && box voting

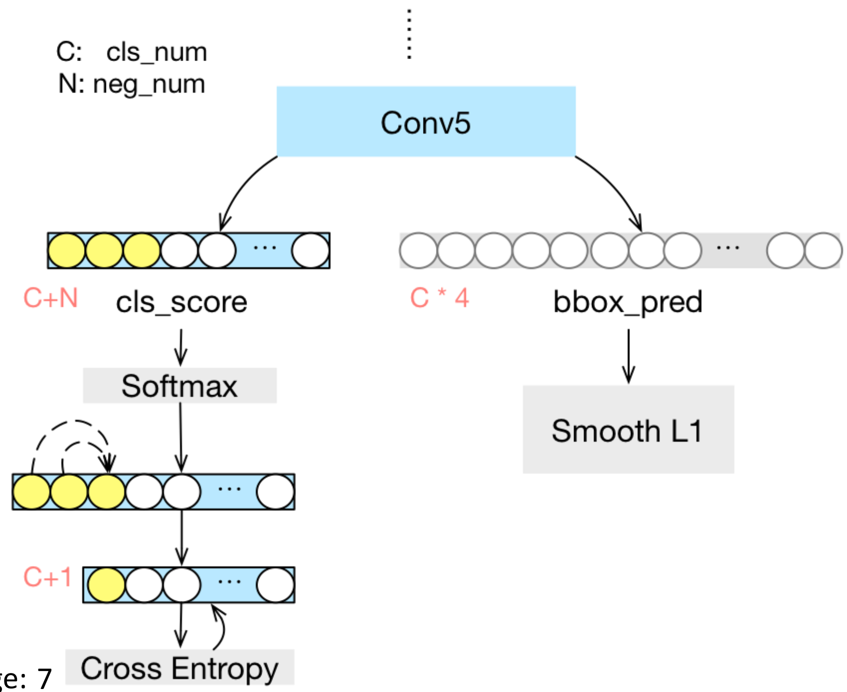
Implicit subcategories of BG

- Background(BG): **Indiscrimination**
  – As ONE class equally as other object classes
  – But: varies greatly
  – Unreasonable to describe as one pattern



Implicit subcategories of BG

- Add N output nodes in last FC layer
  - Represent N subcategories of BG, Cross entropy loss
  - Allocate more parameters to many BG class by adding latent BG subclasses. Improve identification capability.
  - Voc 2007 with Resnet50: ↑ **1%**

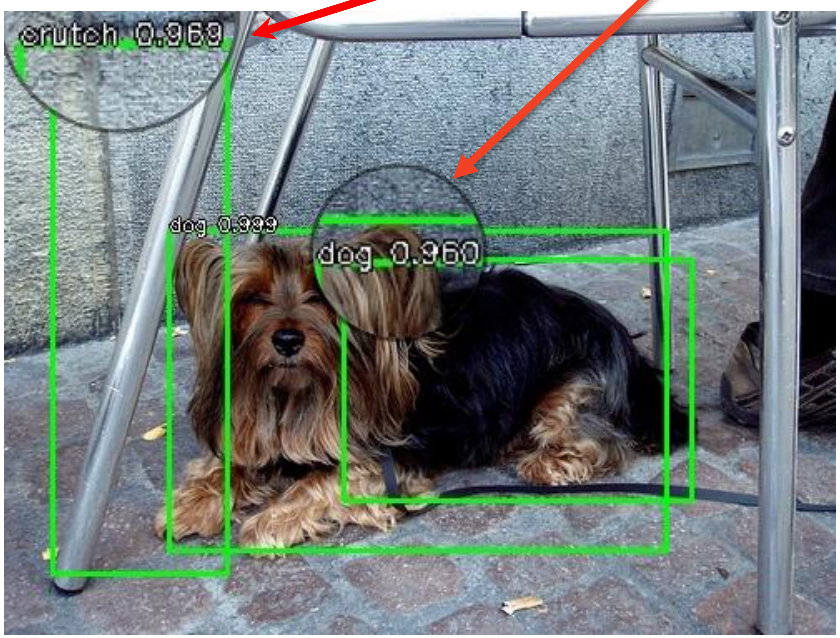


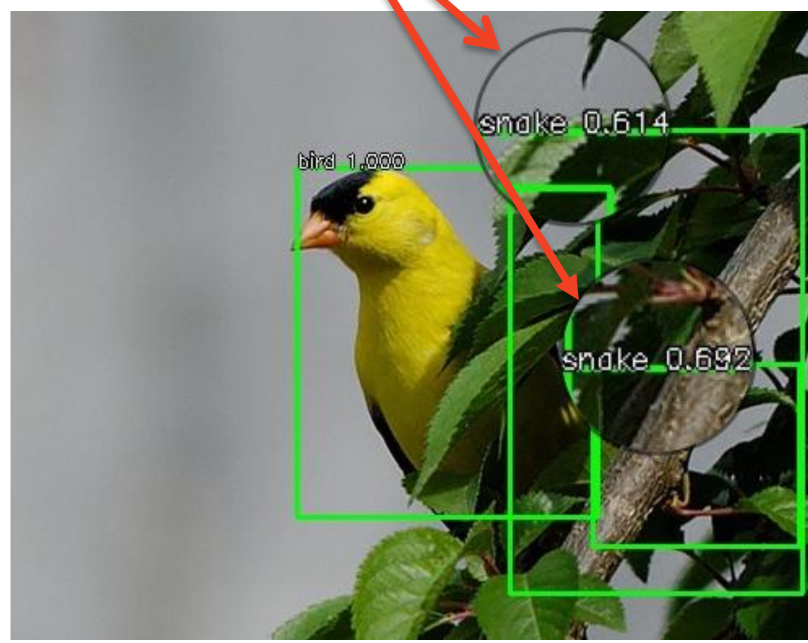
Model	mAP on VOC07
Res50 baseline	77.5%
Res50+Implicit Sub categories-5 nodes	78.5% ↑**1%**

Sink class when necessary

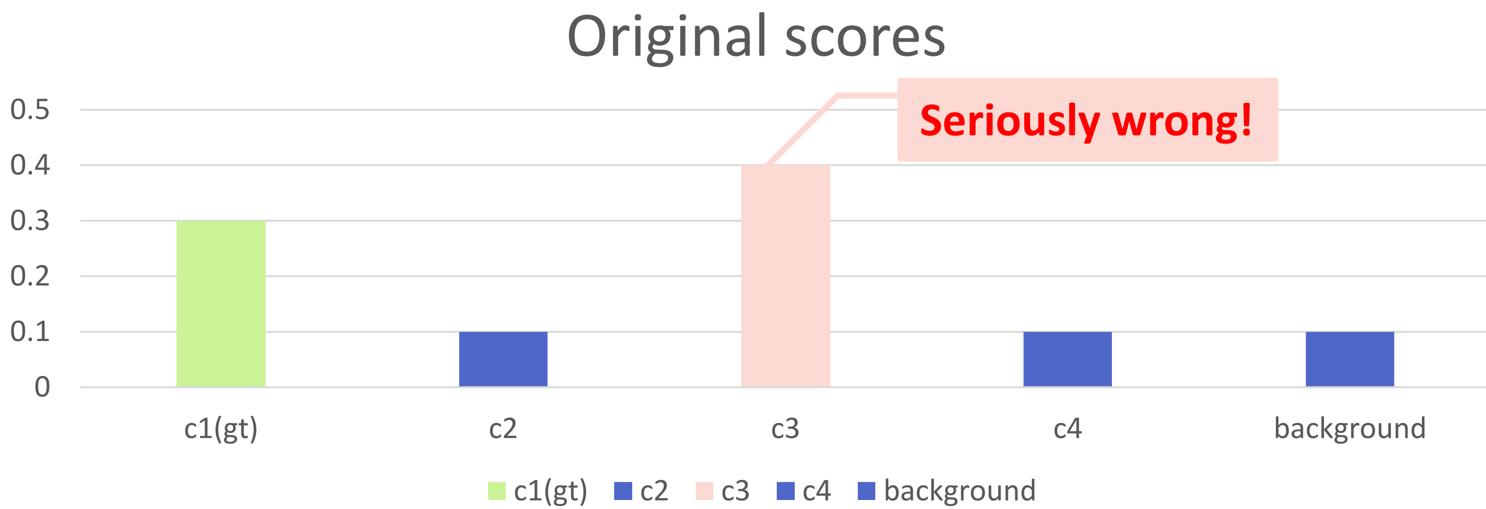
- **Flow diversion** of score to wrong classes
  - Scores of true classes become relatively low

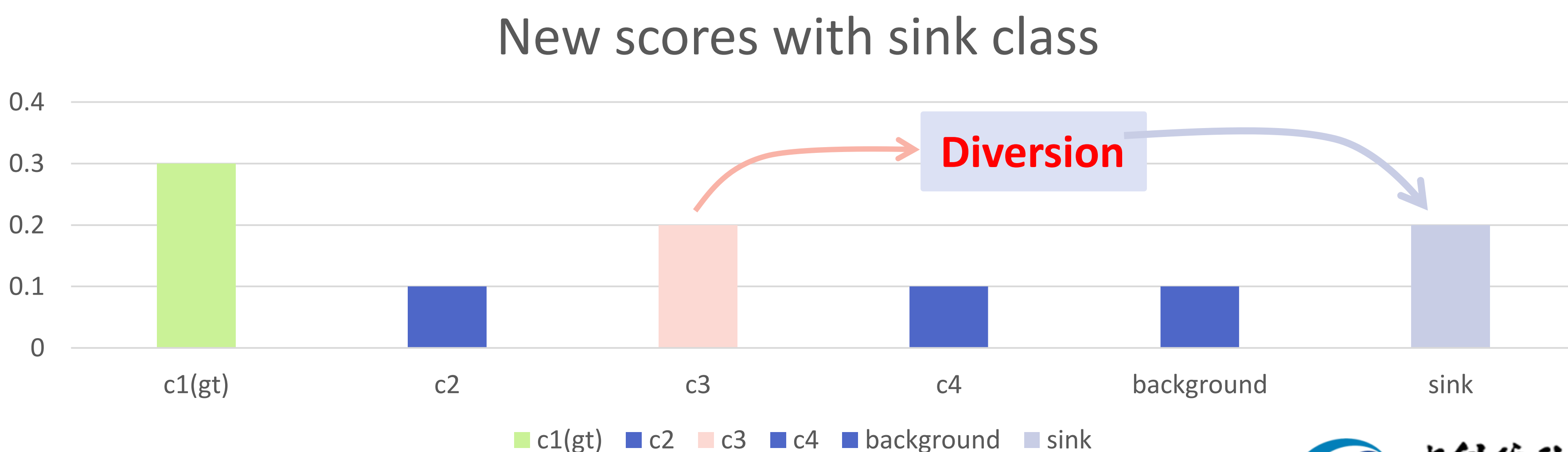
Score: High, wrong!





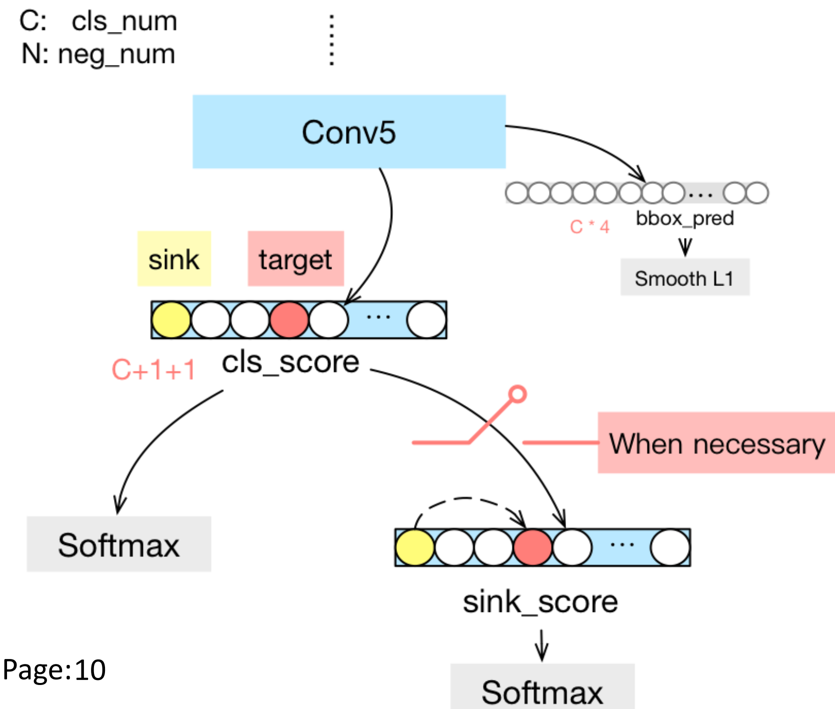
Sink class when necessary





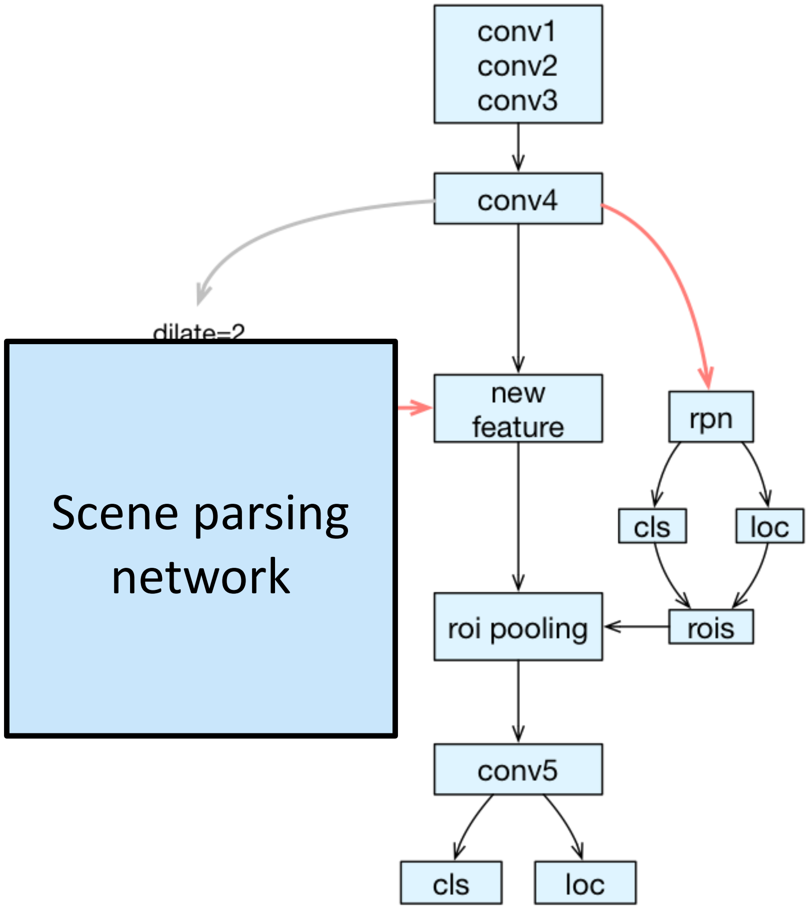
Sink class when necessary

- Add a Sink class
  - Optimize: Minimize((loss (target) && loss (target+sink)), only if all the Top-*K* results are wrong during training
  - Flow diversion of high wrong scores during testing
  - Give true class with low scores more chances to win
  - Voc 2007 with Resnet50: ↑ **0.7%**

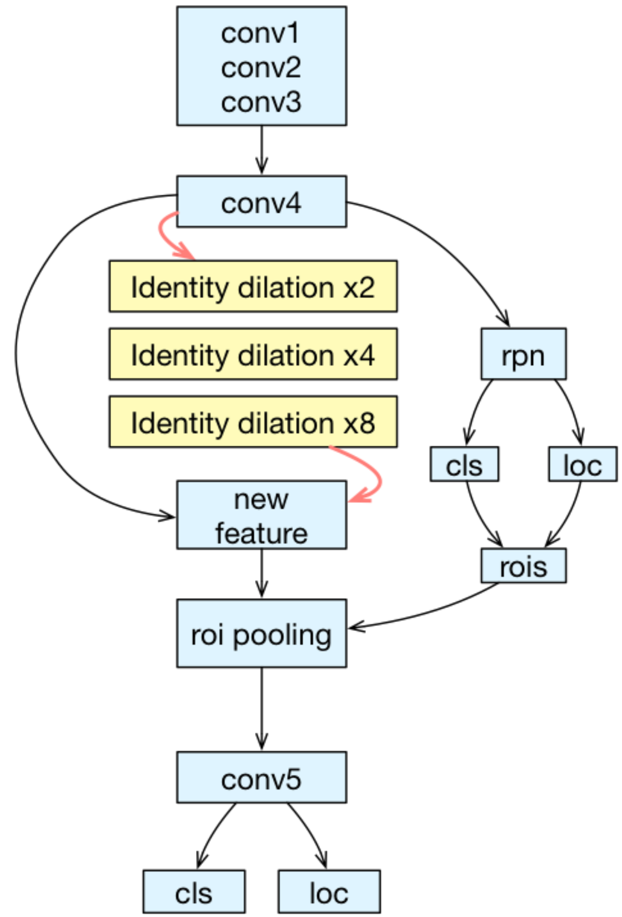


Model	mAP on VOC07
Res50 baseline	77.5%
Res50+Sink-top5	78.2% ↑**0.7%**

Tricks: Segmentation+Dilation



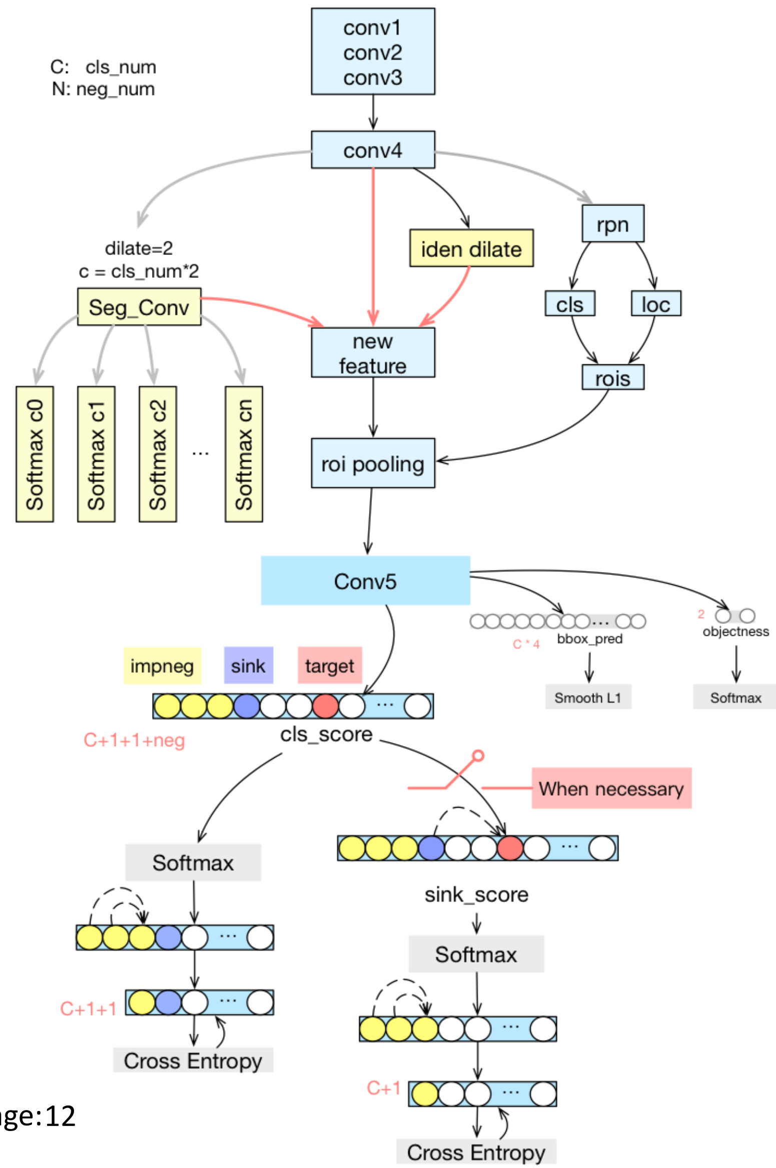
Segmentation feature[2]



Dilation as context[3]

VOC 2007: Segmentation ↑ 0.8%, Dilation ↑ 0.8%

All together



Model	mAP on VOC07
Res50 baseline	77.5%
+dilation as context +sink class when necessary +implicit sub-categoris +segmentation feature +testing tricks	80.62% +3.1%

Results on ILSVRC 2016 DET

Model	mAP on val	mAP on test
Res200 baseline+tt(testing tricks)	62.9	59.1
Res200+all+tt	62.3	57.7 T_T
Res101	58.0	
Res152	57.8	
Res200	60.5	
Res101+all	57.8	
Res152+all	58.0	61.6(with tt)
Res200+all	60.3	
Res152+scene parsing feature	55.6	
Res200+all in half	60.2	
Res200+logistic	57.9	

Results on ILSVRC 2016 DET

Model	mAP on val2	mAP on test
Res200 baseline+tt(testing tricks)	62.9 ↑ 2.4%	59.1 ↑ 0.3%
Res200+all+tt	62.3	57.7
Res101+Res152+Res200	64.0 ↑ 0.4%	60.6 ↓1.5%
Res101	58.0	
Res101+all	57.8	
Res152	57.8	
Res152+all	58.0	
Res200	60.5	61.6(with tt)
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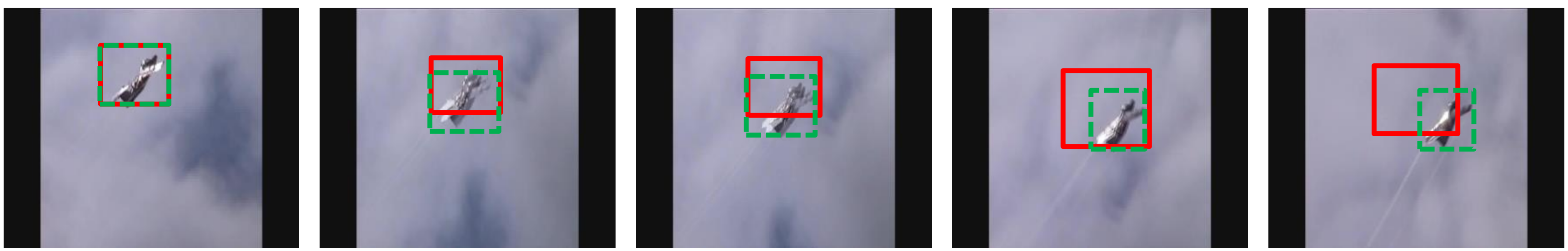
Object Detection from Video (VID)

Motivation: Tracking-based

- VID: Challenging task
  - Frame detection performance & adjacent motion information
  - Tracking-based tubelet generation is an effective solution



Ground Truth

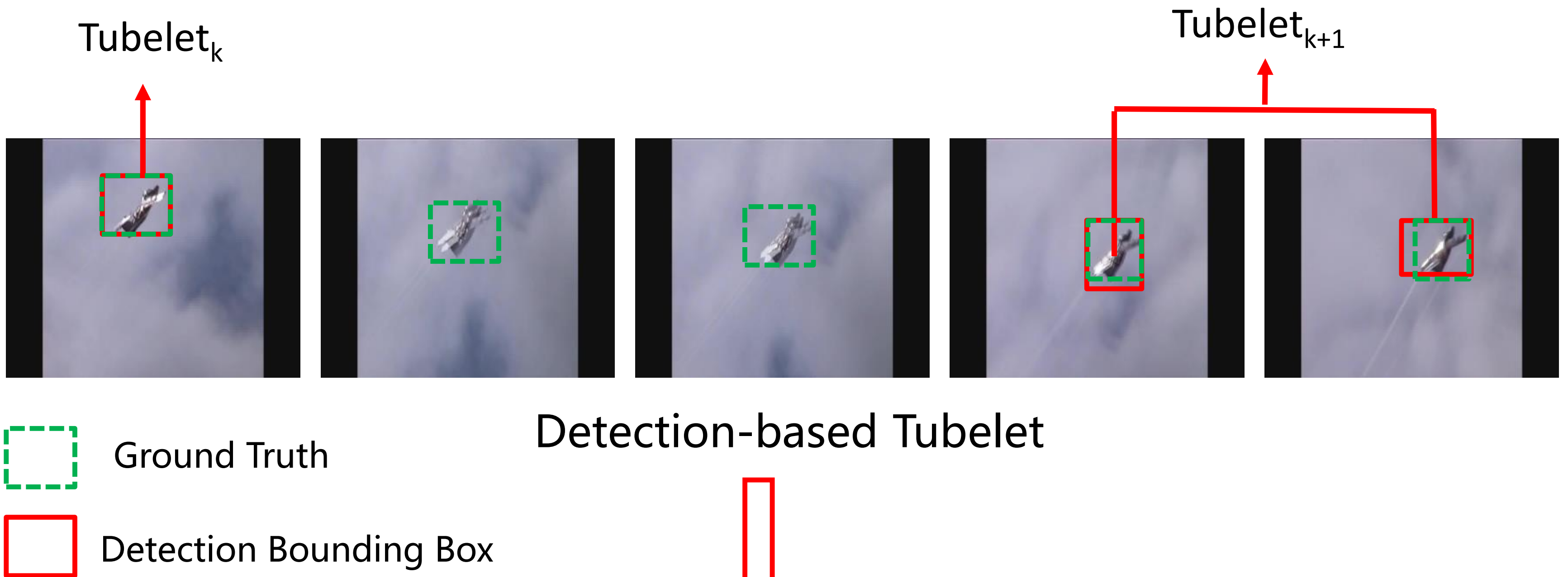
Tracking Bounding Box

Tracking-based Tubelet

Drifting location!

Our Detection-based

- Detection Box Sequentialization
- Adjacent Checking with optical-flow

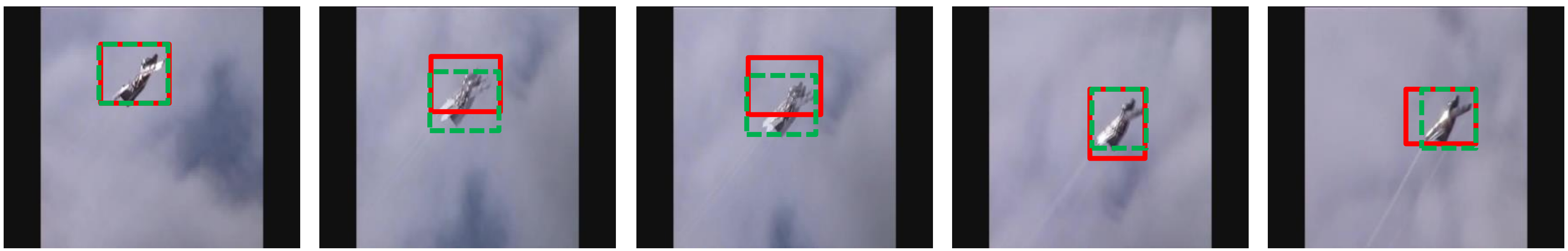


Detection-based Tubelet

Target missing & discrete trajectory!

Our DAT Framework

- **DAT** tubelet generation & fusion framework
  - Tubelet generation: complementary Detection And Tracking (DAT)
  - Focused on precision & recall respectively
  - Followed by a novel tubelet merging method



Ground Truth

Detection Bounding Box

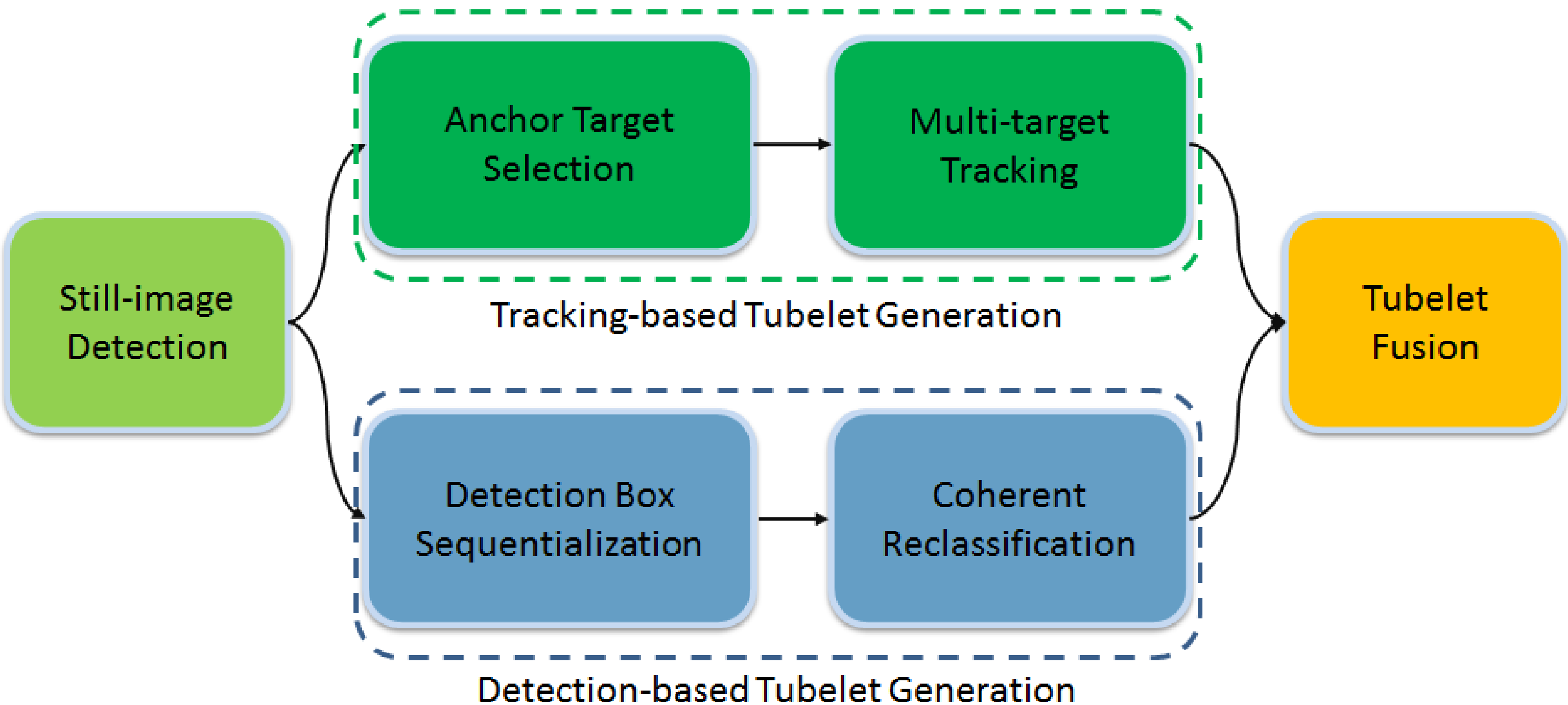
Fusion Tubelet

Improve location quality &

Recall missing objects

VID: Overview

- Two main contributions:
  - Tubelet generation: sequentialize detection box with optical-flow
  - Overlapping and successive tubelet fusion

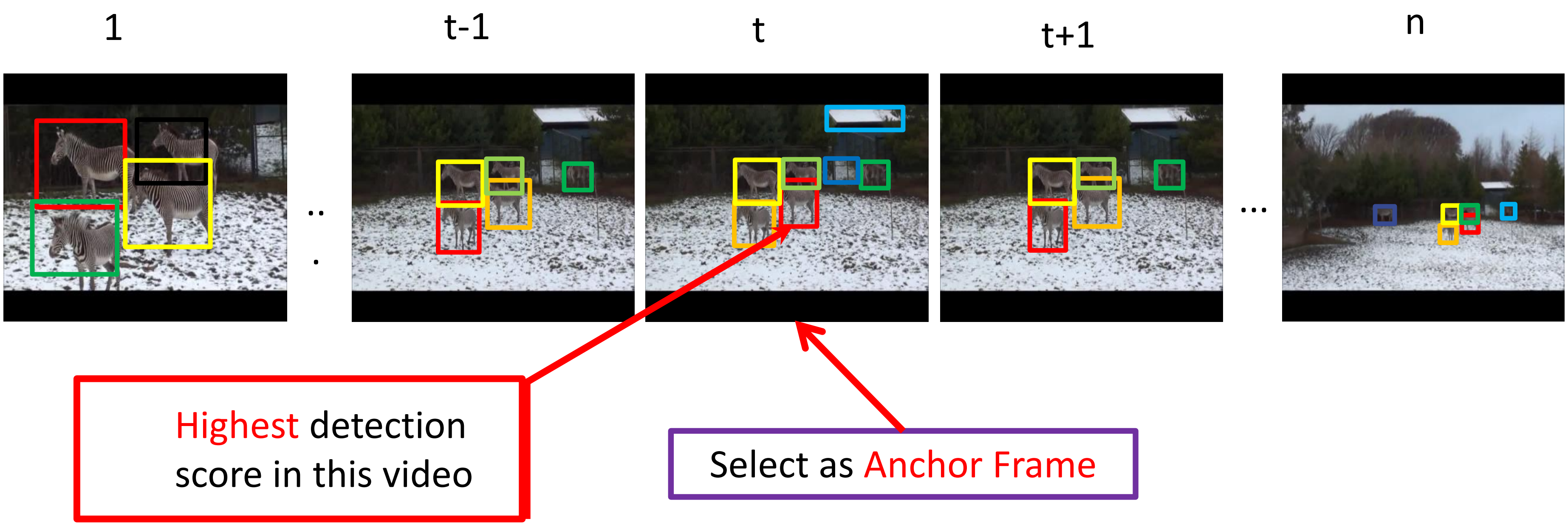


Still-image Detection

- Training Data
  - DET train&val + VID train (1/6)
- Architecture
  - Faster R-CNN [1] + ResNet [4]
  - Add RPN anchor with size = 64
- Model Ensemble
  - ResNet101, ResNet200
  - Weighting average for coordinate position and category score.

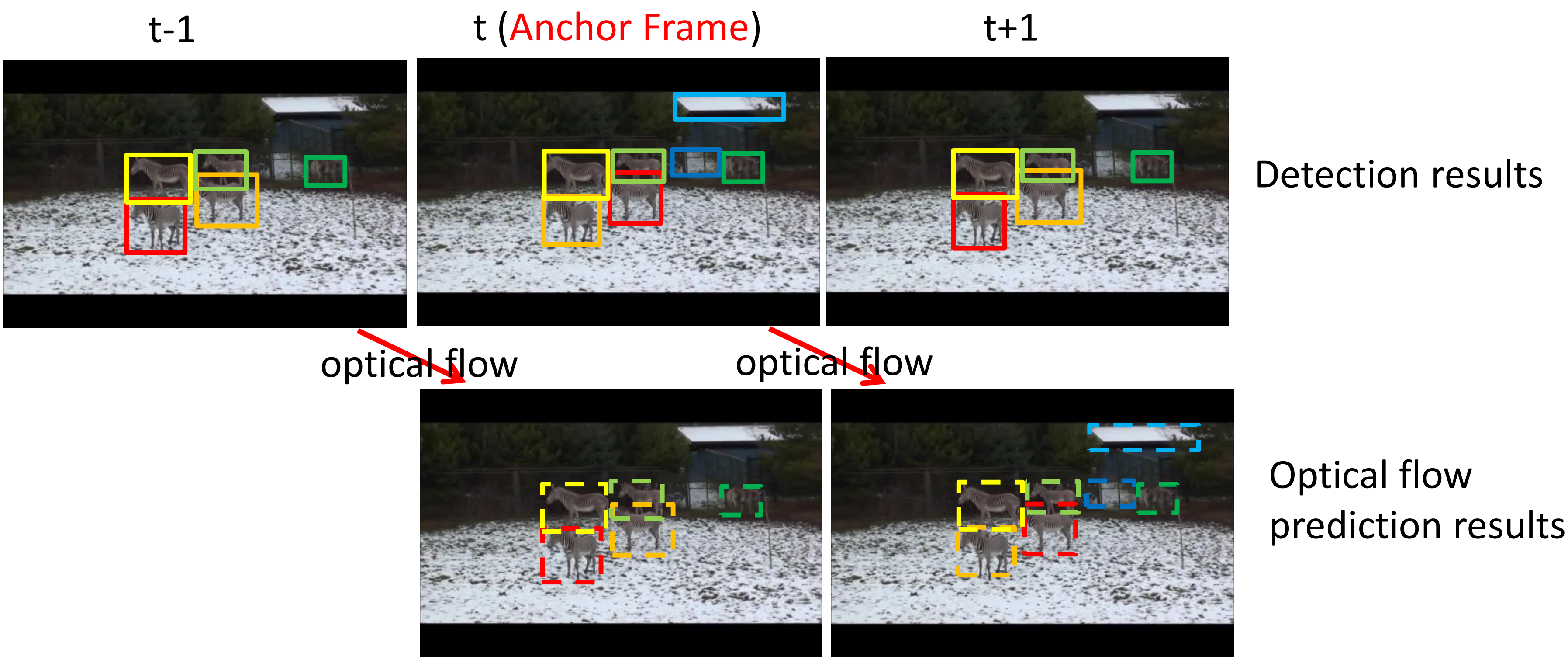
Tracking-based Tubelet Generation

- Anchor Frame Selection
  - Select the frame with highest detection score object



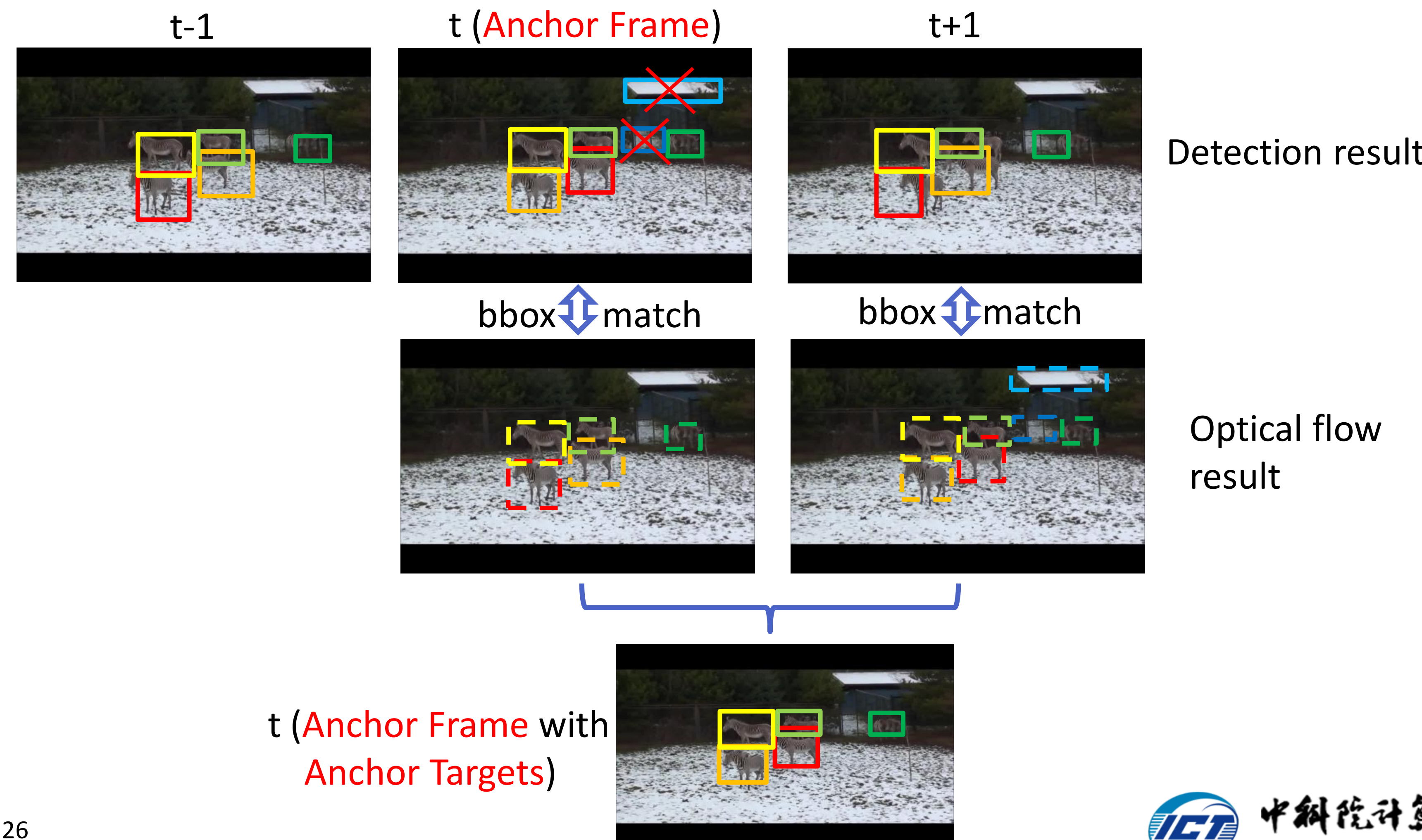
Tracking-based Tubelet Generation

- Anchor Target Selection
  - Exploit the adjacent information with optical flow [5] to determine the reliable anchor targets



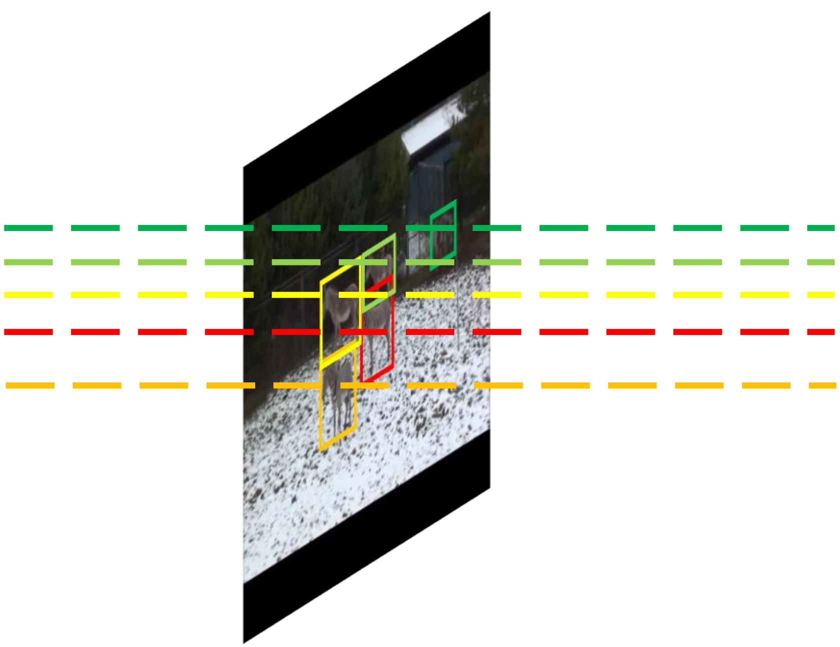
Tracking-based Tubelet Generation

- Anchor Target Selection: remove the unreliable

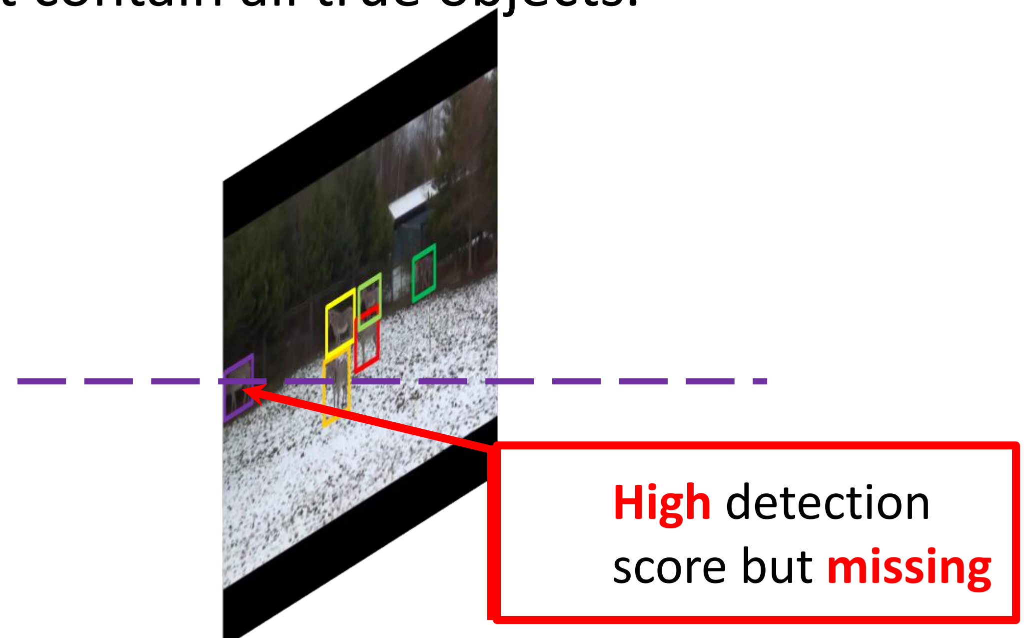


Tracking-based Tubelet Generation

- Multi-target tracking with **detection recall**
  - Allocate each anchor target with a MDNet tracker [6]
  - Track them in parallel
  - Then use detection results to recall missing tubelets since the anchor frame may not contain all true objects.



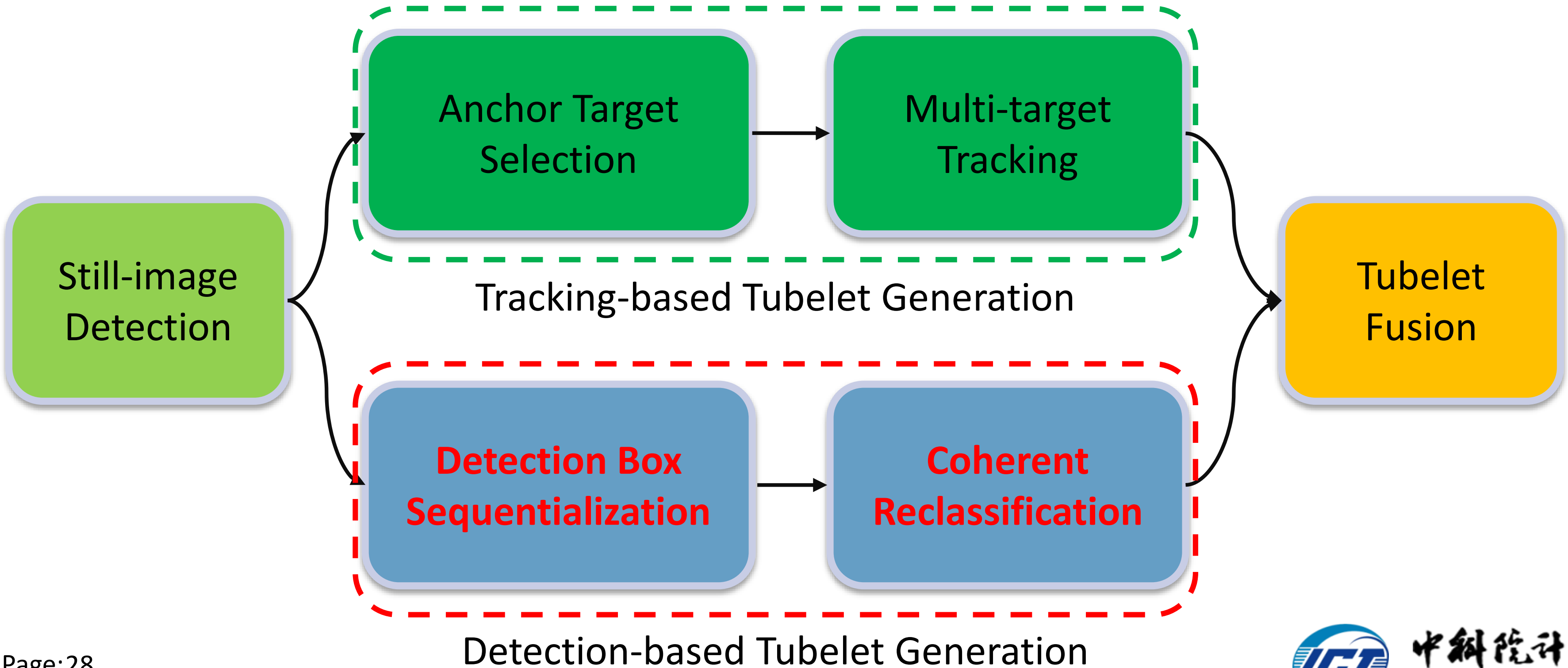
(a) existed tubelets



(b)Recall missing tubelets

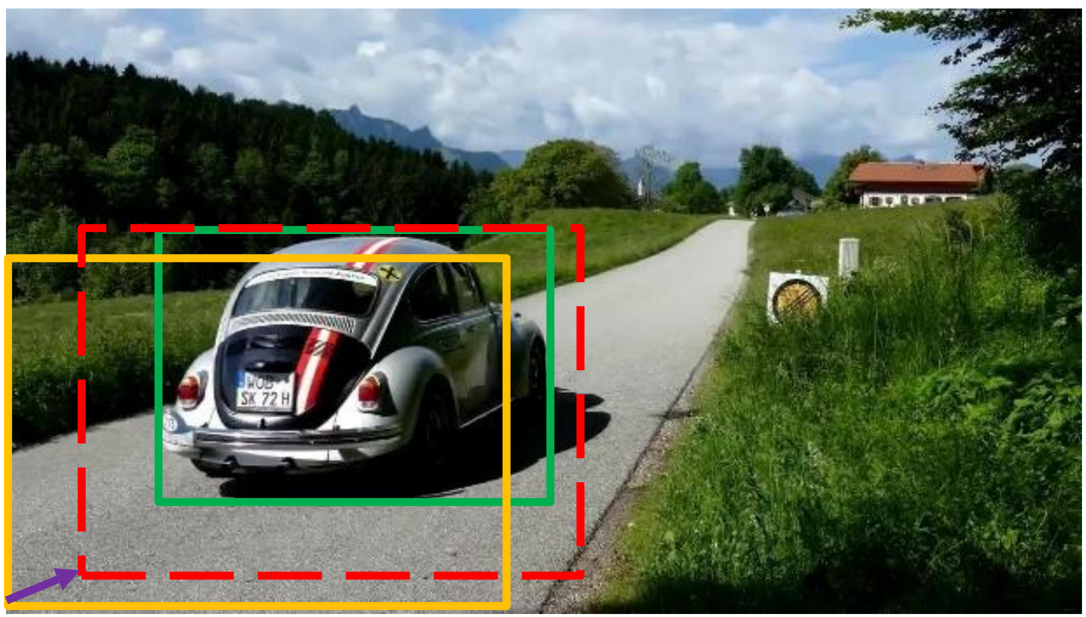
Detection-based Tubelet Generation

- Motivation
  - Overcome **drifting location** problem
  - Excellent object detectors (Faster R-CNN) can generate precise bounding box of high location quality



Detection-based Tubelet Generation

- Adjacent Checking:
  - By optical-flow for precise tubelet



Current Detection Box

Prev Detection Box

Prev Prediction Box

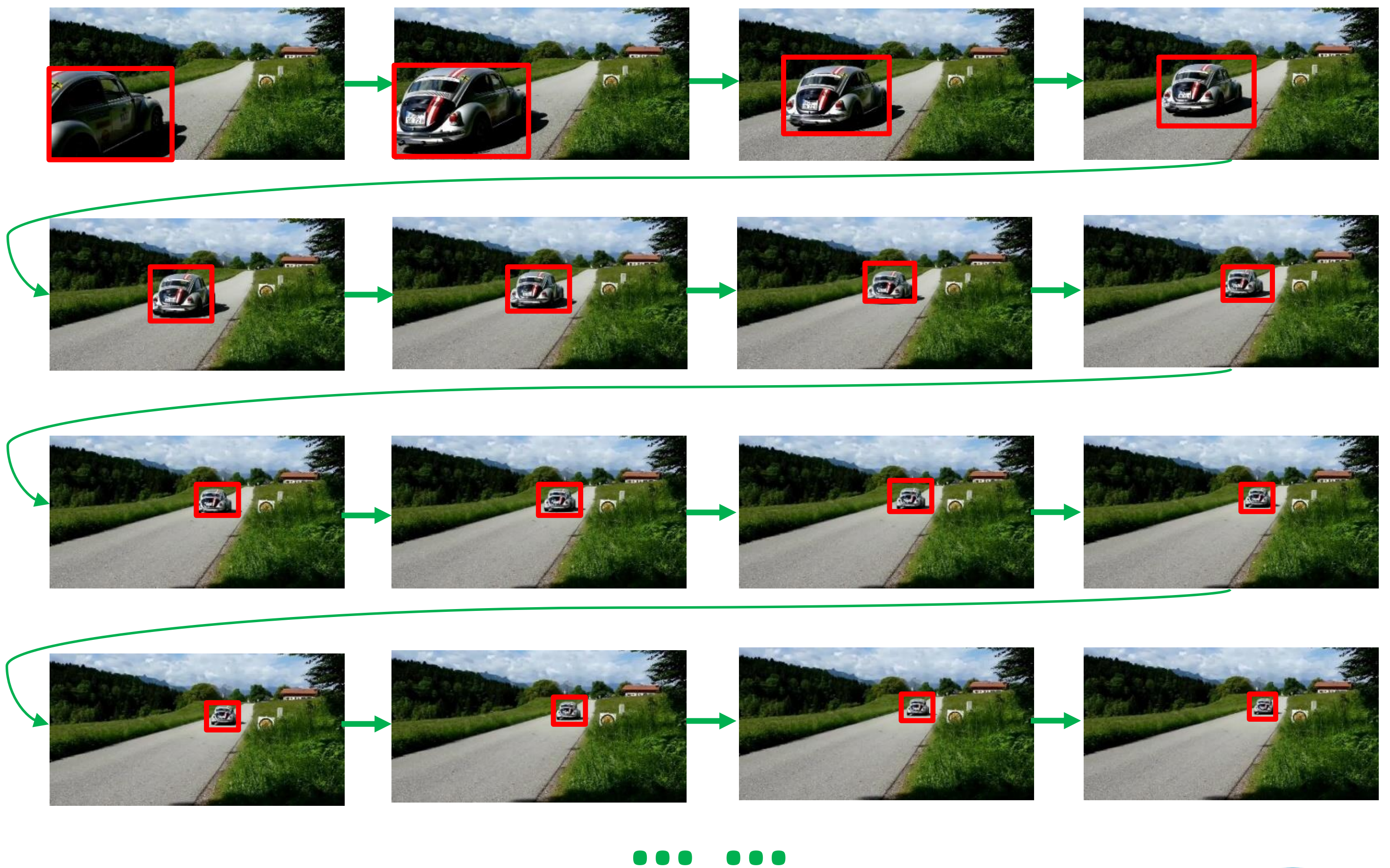
Optical Flow

Current Frame

If IoU (Red, Green) > a given threshold: same tubelet
else: a new tubelet

Detection-based Tubelet Generation

- Detection Box Sequentialization



Detection-based Tubelet Generation

- Coherent reclassification
  - Use majority voting to get coherent categories throughout a given tubelet

	Start Frame							End Frame
Tub	C_p:S_1	C_p:S_2	C_p:S_3	C_p:S_4	C_p:S_5	…	C_p:S_{N-1}	C_q:S_{N-1}	C_p:S_N

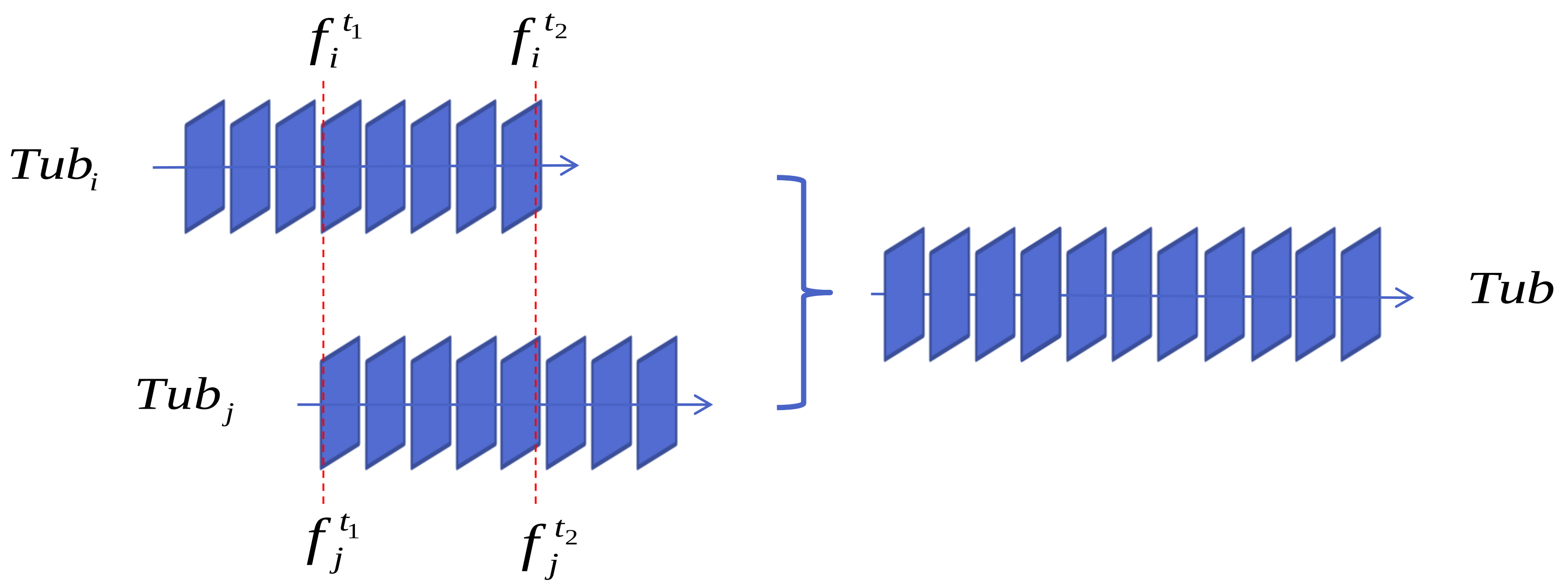
$$Tub_{cls} = \max_k \ \text{count}(C_k)\ (k \in [1,30]) \Longrightarrow$$ Tubelet Category: C_p

$$S_k = \frac{1}{N_k}\sum_{i=1}^{N_k} S_i \Longrightarrow$$ Tubelet Box Score: S

	Start Frame							End Frame
Tub	C_p:S	C_p:S	C_p:S	C_p:S	C_p:S	…	C_p:S	C_p:S	C_p:S

Tubelet Fusion

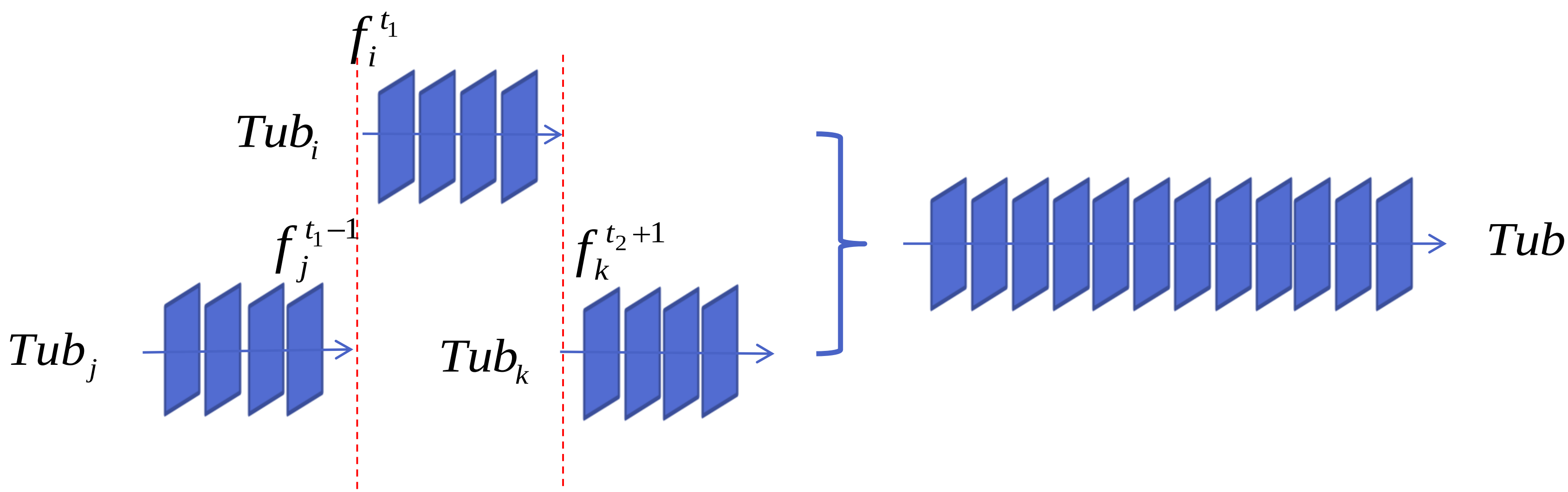
- Union Fusion
  - Merge overlapping tubelets



Union Fusion

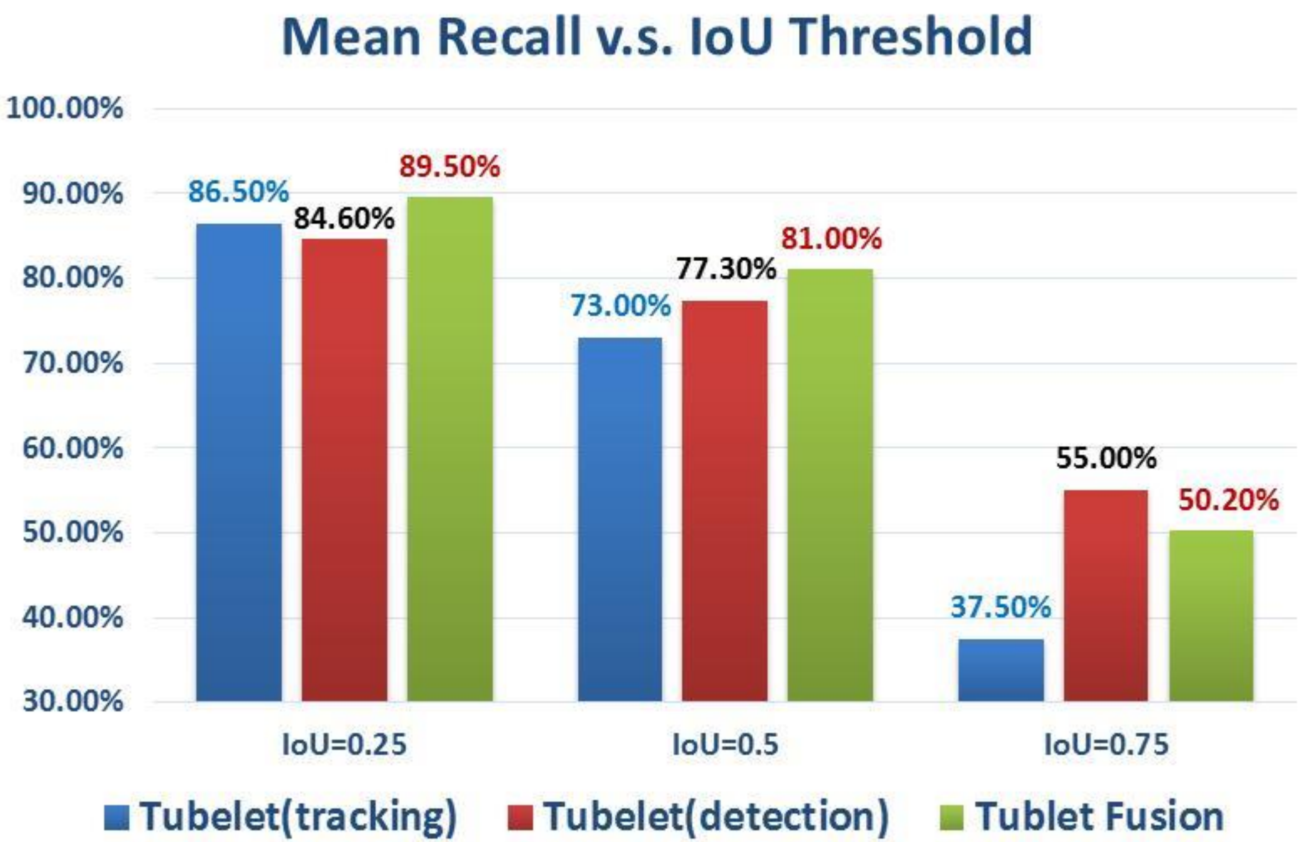
Tubelet Fusion

- Concatenation Fusion
  - Merge successive tubelets



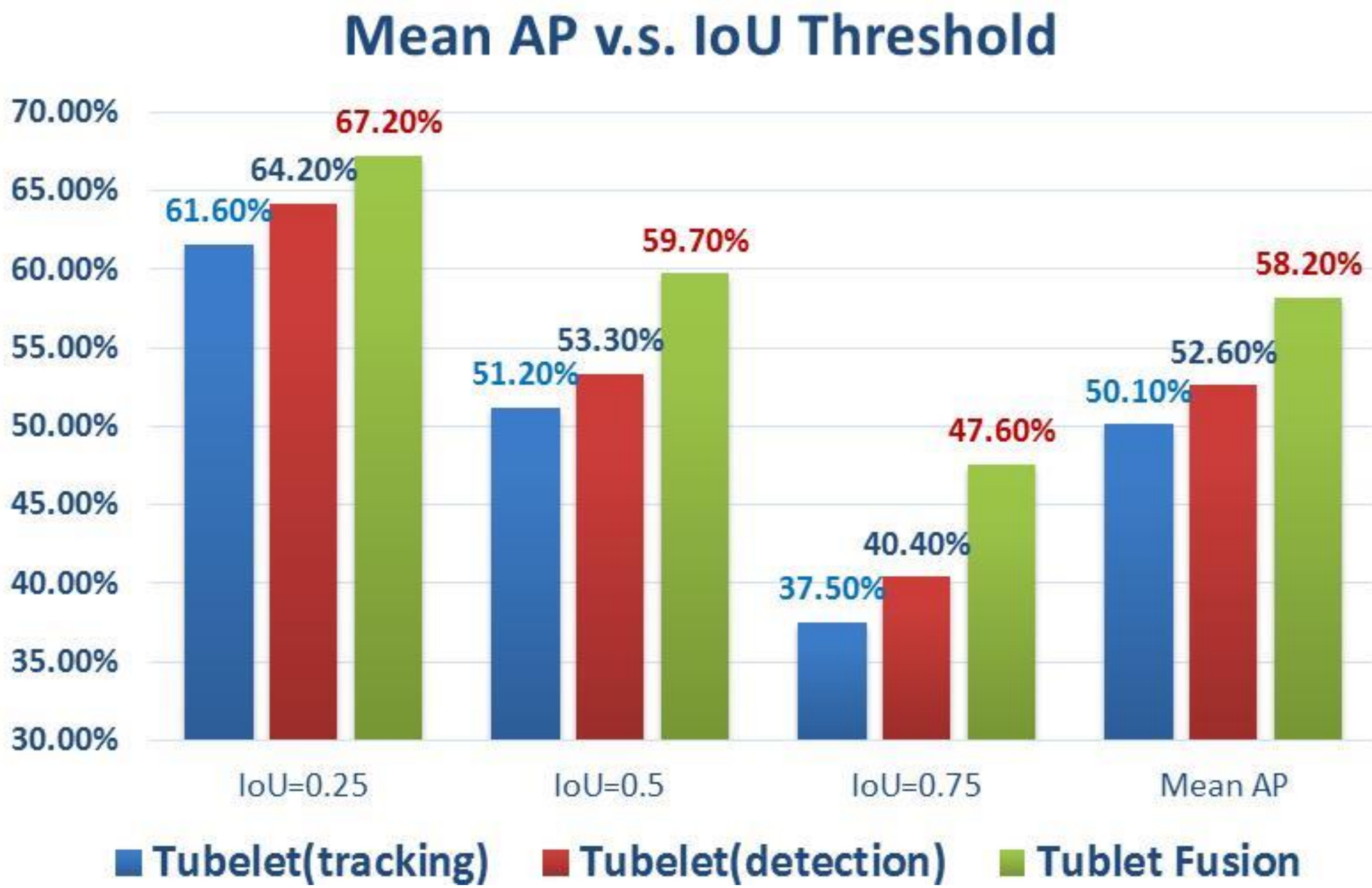
Concatenation Fusion

ILSVRC 2016 VID Val Results



Mean Recall:
Lower IoU: tracking-based is higher
Higher IoU: detection-based is higher

ILSVRC 2016 VID Val Results



Mean AP: Detection-based is higher than Tracking-based, Fusion is best!

References

- [1] Ren S, He K, Girshick R, Sun J. “Faster R-CNN: Towards real-time object detection with region proposal networks”, NIPS 2015: 91-99.
- [2] Gidaris, Spyros, and Nikos Komodakis. "Object detection via a multi-region and semantic segmentation-aware cnn model." ICCV 2015.
- [3] Yu, Fisher, and Vladlen Koltun. "Multi-scale context aggregation by dilated convolutions." ICLR 2016.
- [4] He K, Zhang X, Ren S, Sun J. “Deep residual learning for image recognition”, CVPR 2016.
- [5] Kang K, Ouyang W, Li H, Wang X. “Object Detection from Video Tubelets with Convolutional Neural Networks”, CVPR 2016.
- [6] Nam H, Han B. “Learning multi-domain convolutional neural networks for visual tracking”, CVPR 2016.

Welcome:

Questions and Comments

Thank You!