Multimedia Laboratory

SENSETIME
商湯集團

SenseTime Group

Object Detection in Videos with Tubelets and Multi-context Cues

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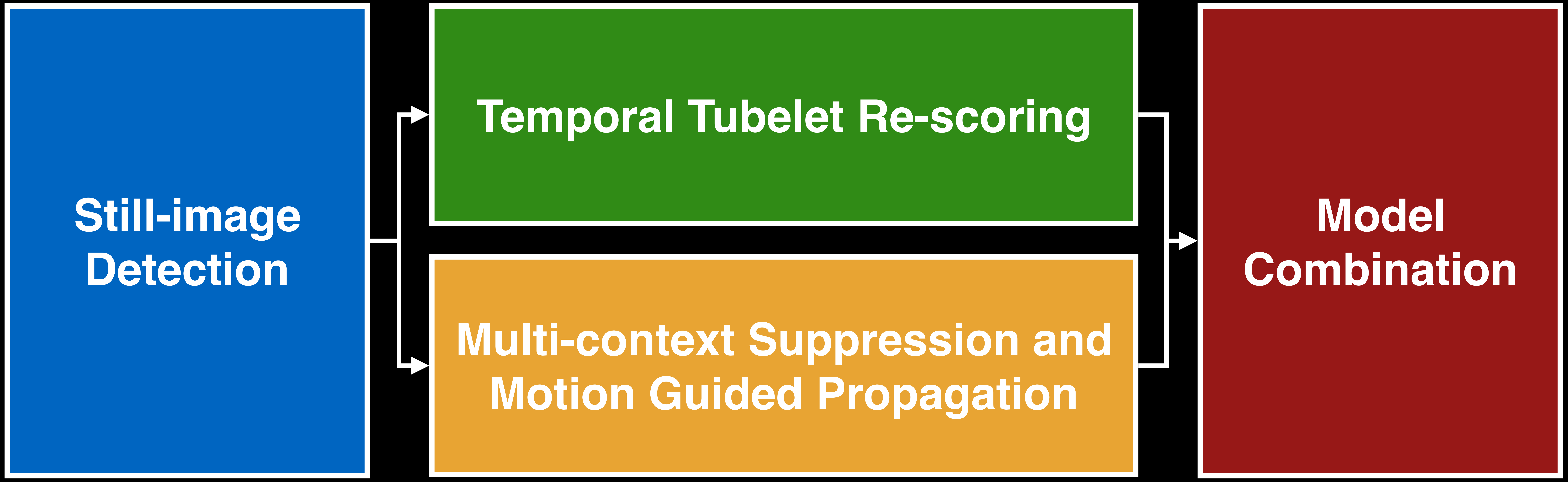
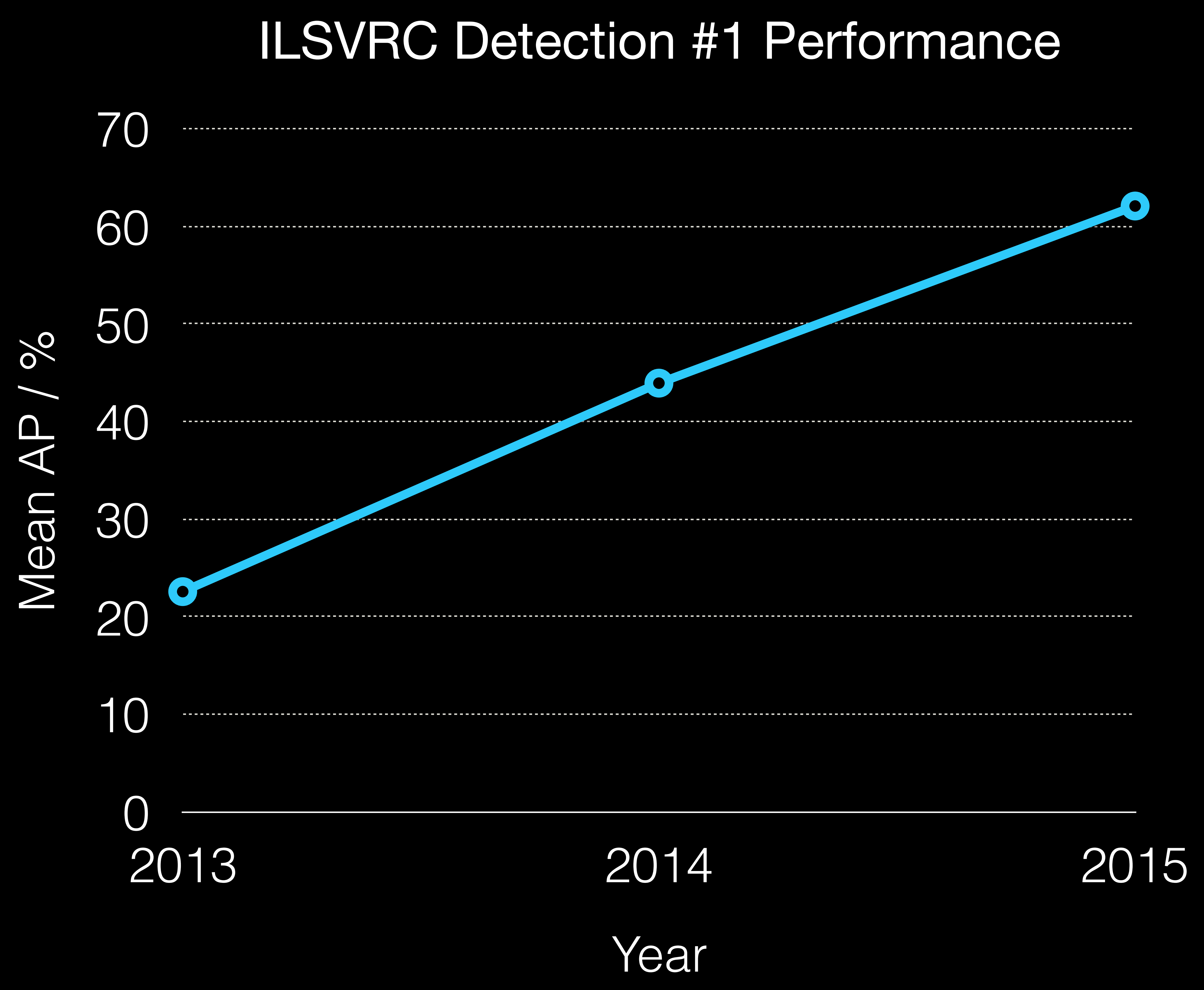
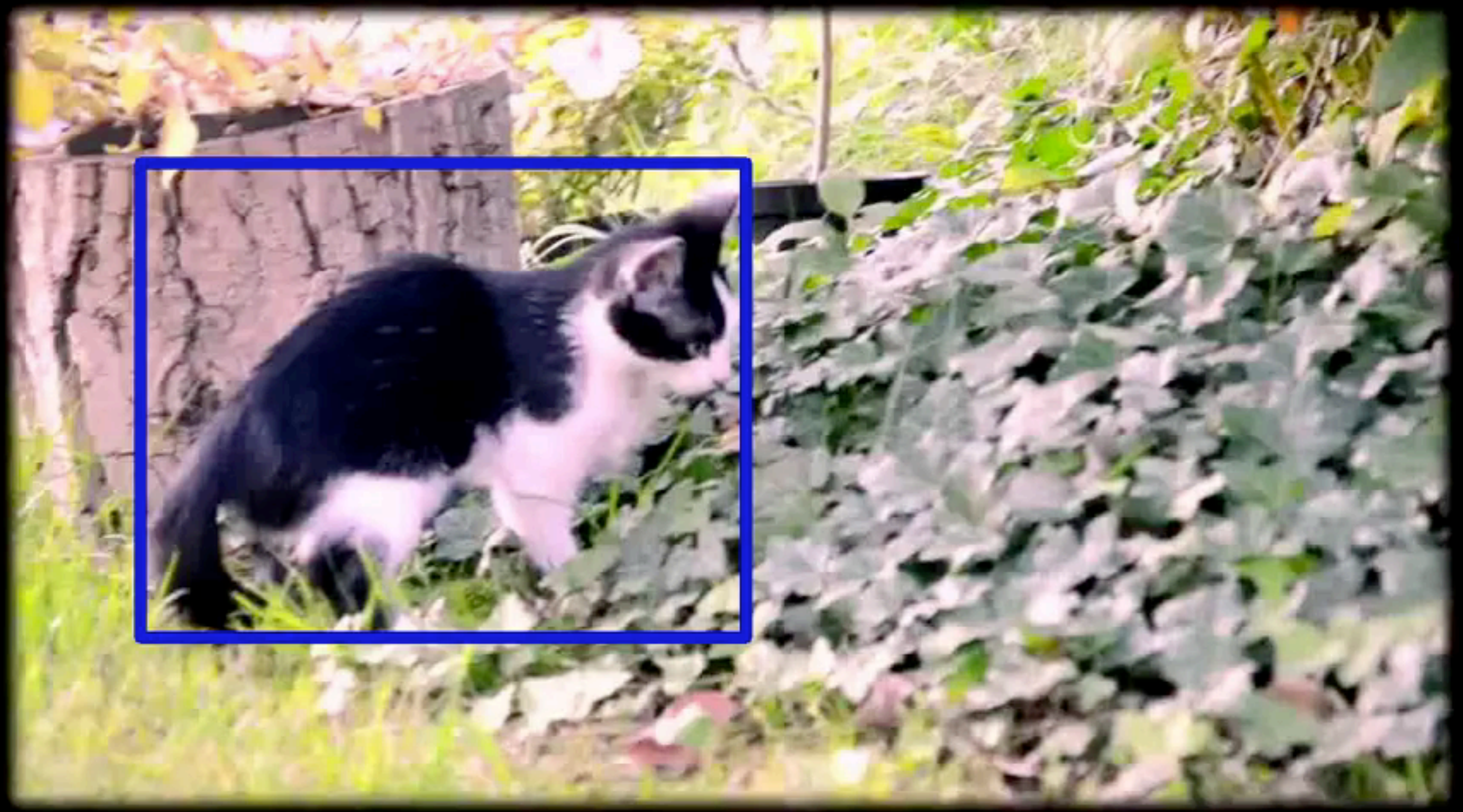
Proposed Framework



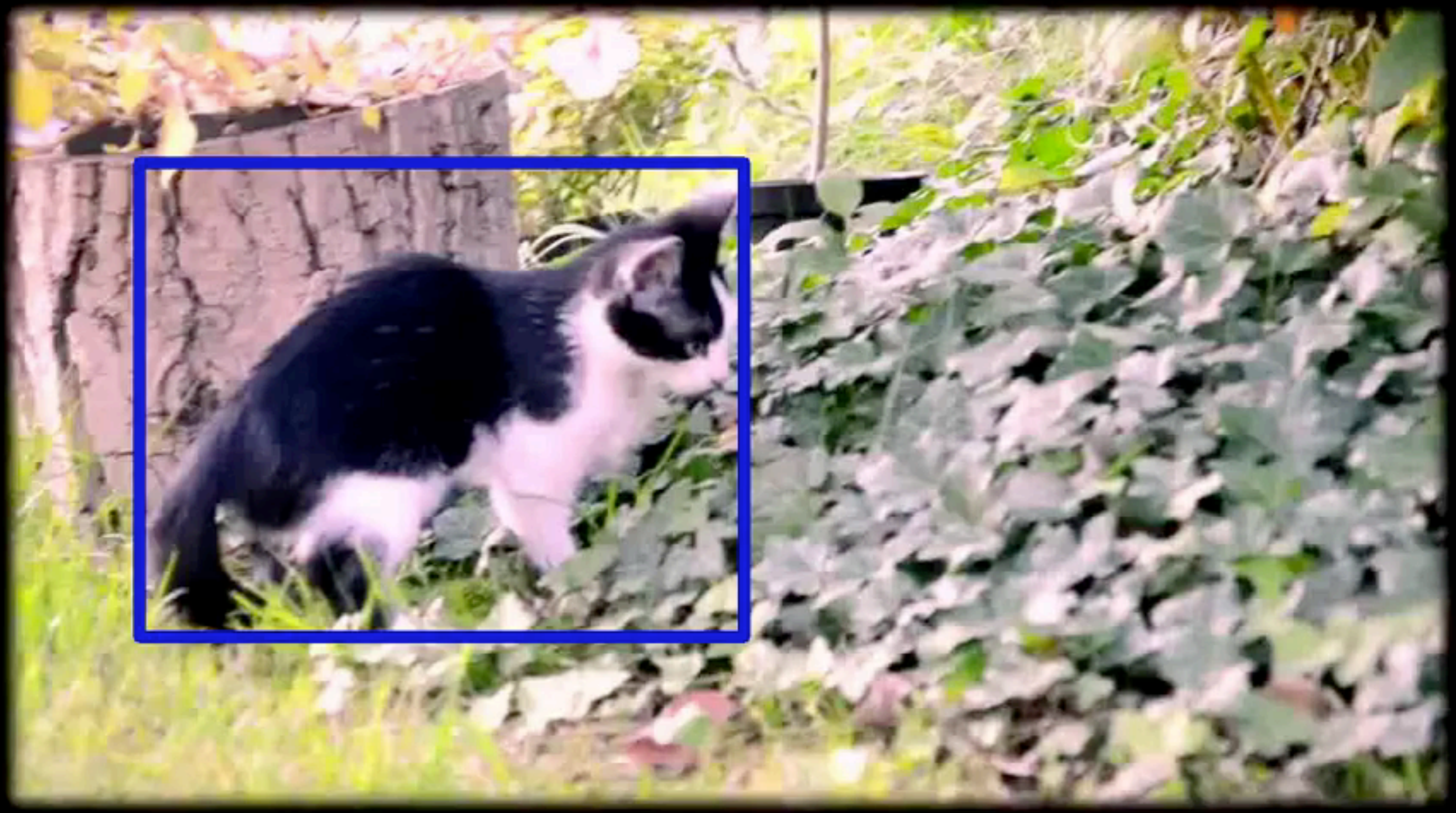
Still-image Detection

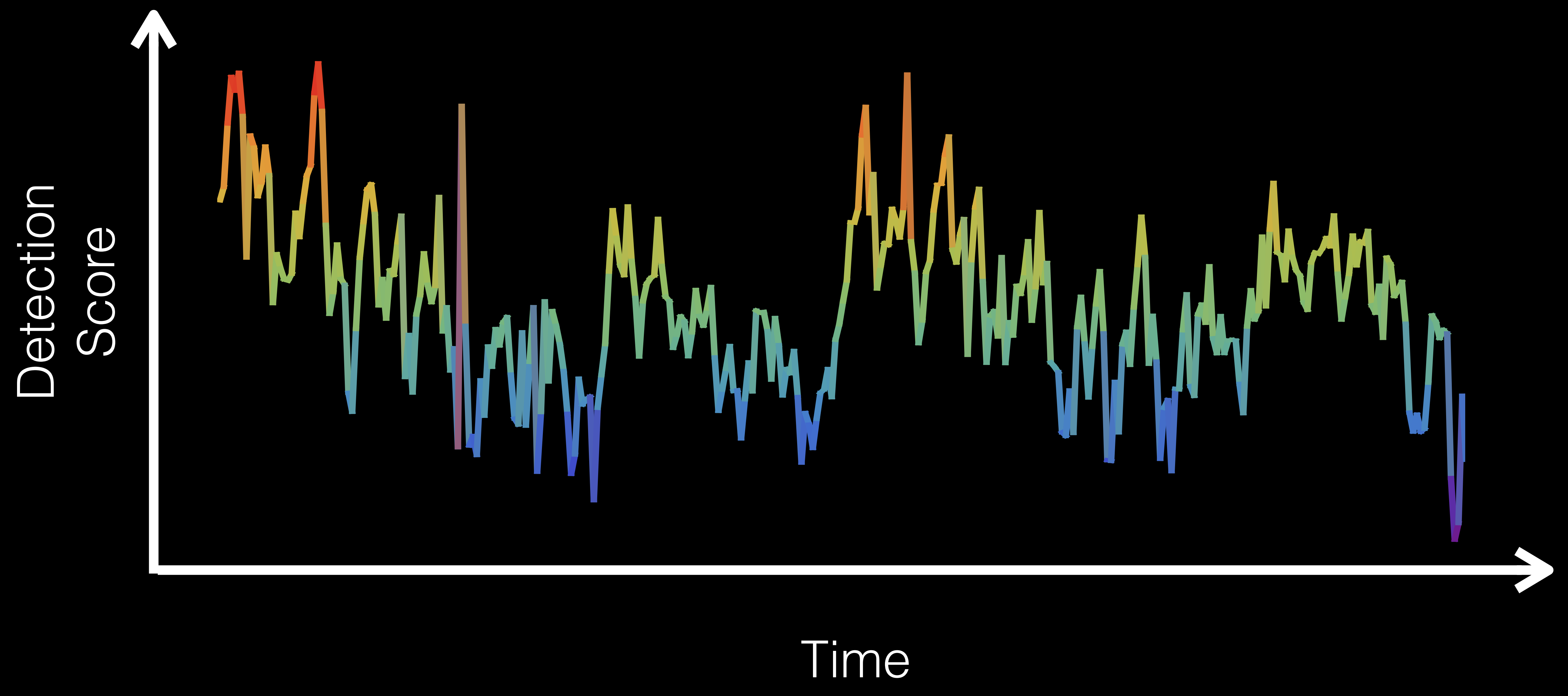




Still-image Detection: Limitation I

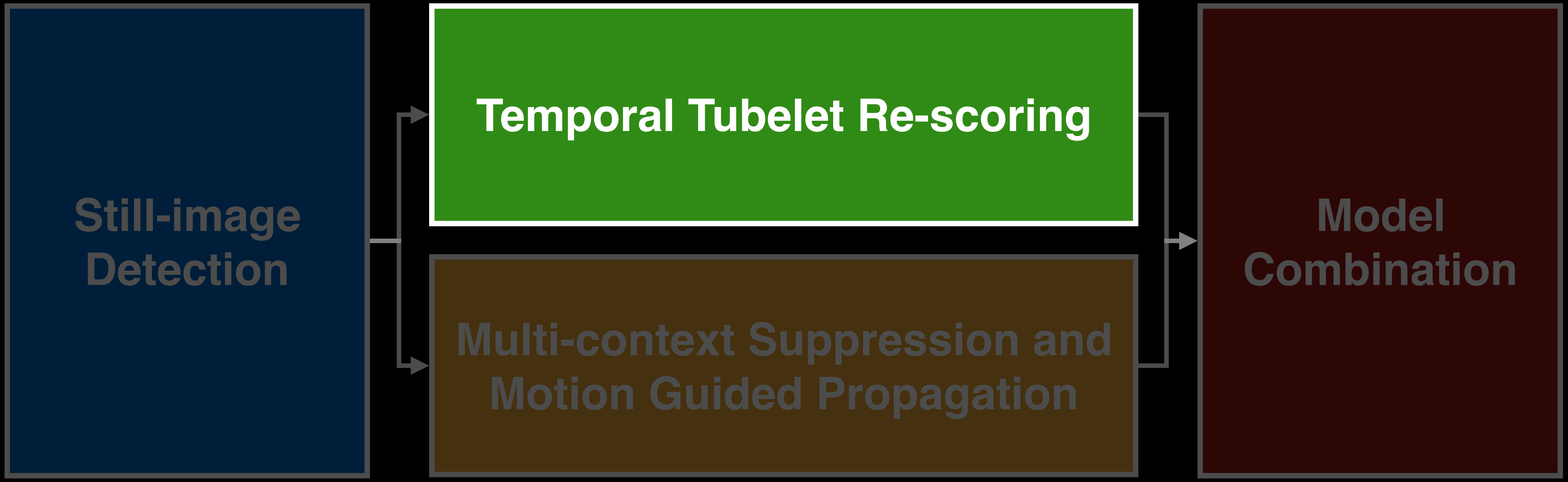
Large Temporal Variations



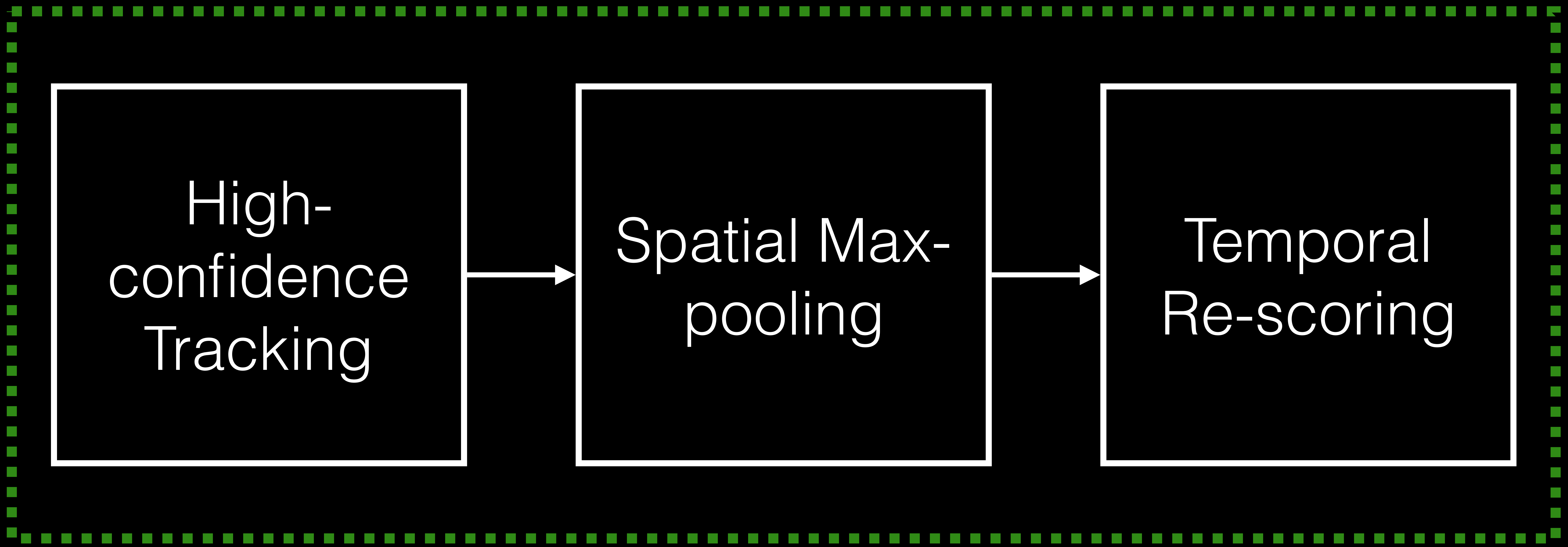


Solution - Tubelets

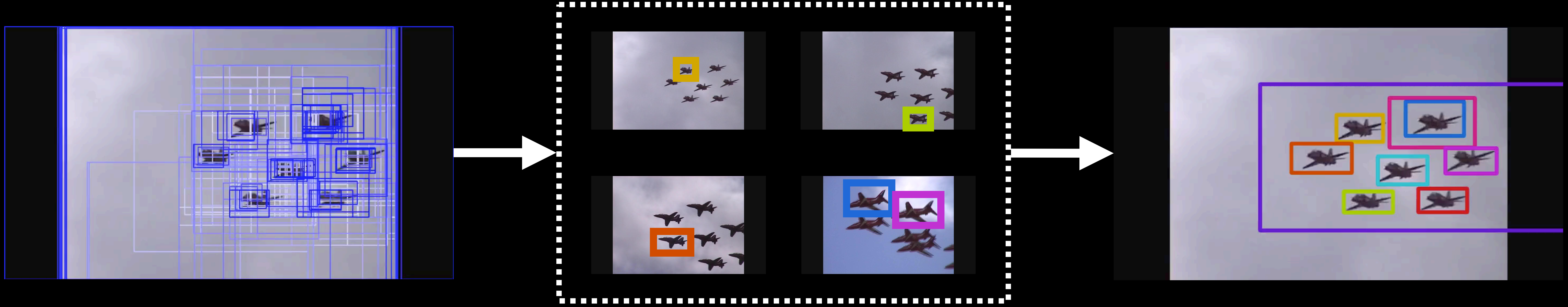
Proposed Framework



Temporal Tubelet Re-scoring



High-confidence Tracking



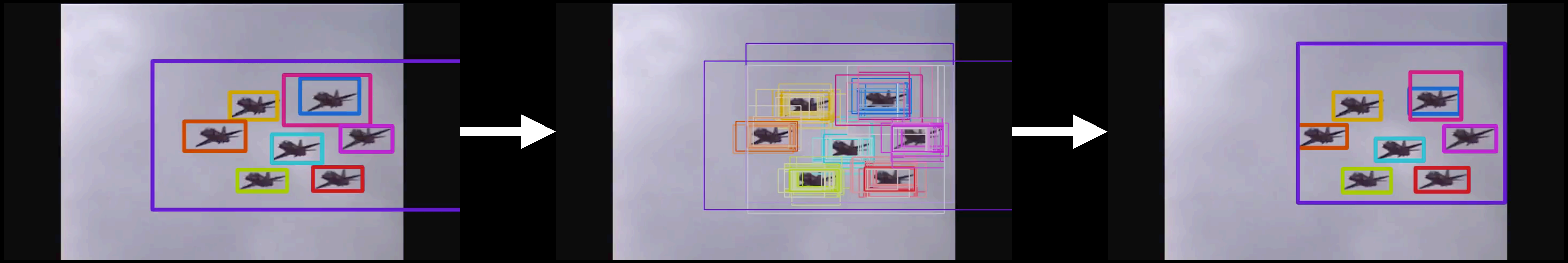
- Obtain detection results from still-image detectors
- Choose high-confidence detections as starting points (anchors) for tracking
- Obtain tubelets, which are bounding box sequences generated from tracking algorithms [1]

[1] Wang, Lijun et al. Visual Tracking with Fully Convolutional Networks. ICCV 2015

Spatial Max-pooling: Why?

- The detection scores on the tracked tubelets are not satisfactory
  - Boxes from tracked tubelets and those from still-image detection have **different statistics**
  - Tracked box locations are not optimal due to **tracking failures**
- Neighboring high-confidence detections are utilized to improve tubelet detection scores, which is called **spatial max-pooling**

Spatial Max-pooling



- Still-image detection results that have **large overlaps with tubelet boxes** are chosen for each tubelet

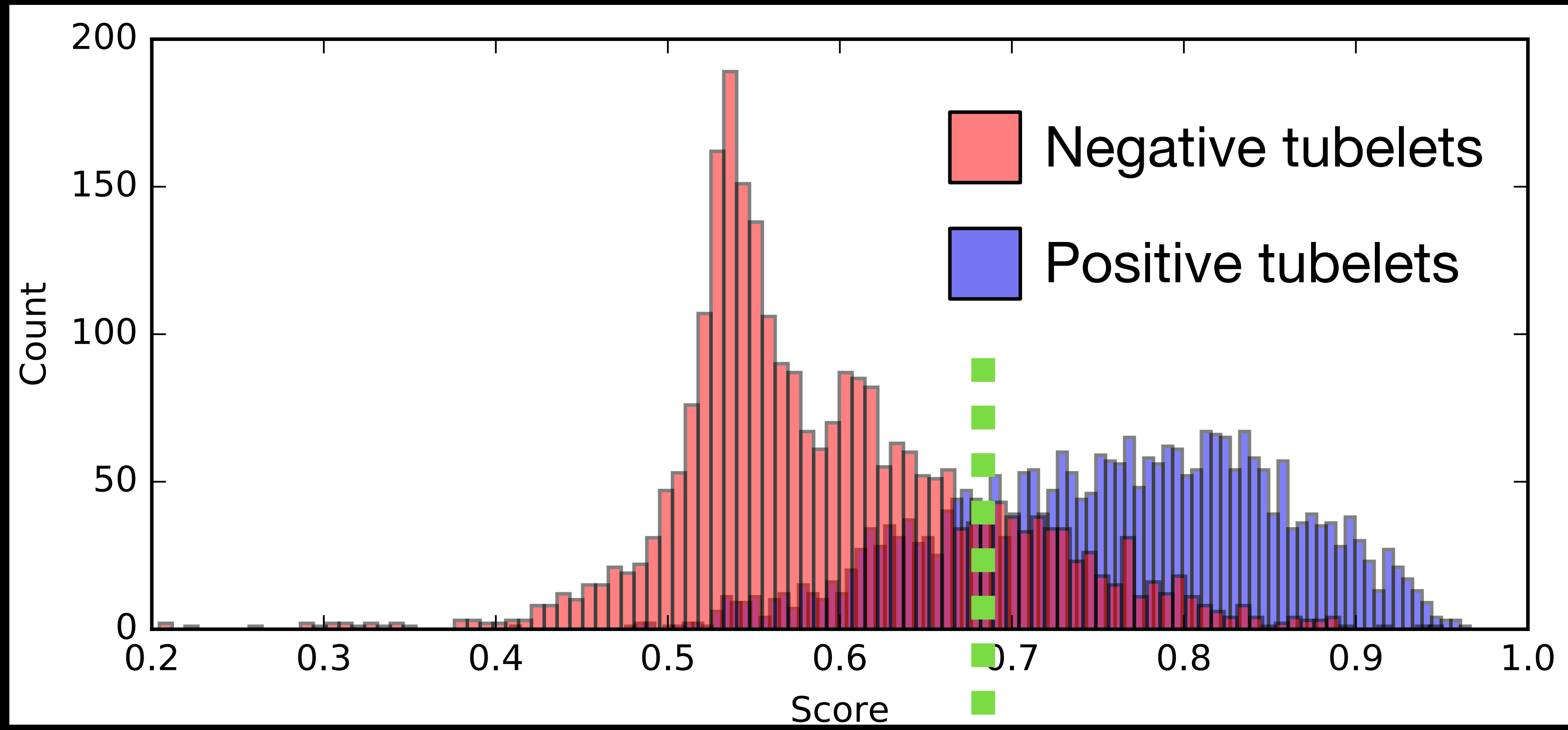
- Only detections with **maximum detection scores** are left after spatial max-pooling

- Use the **Kalman Filter** to smooth the bounding box locations.

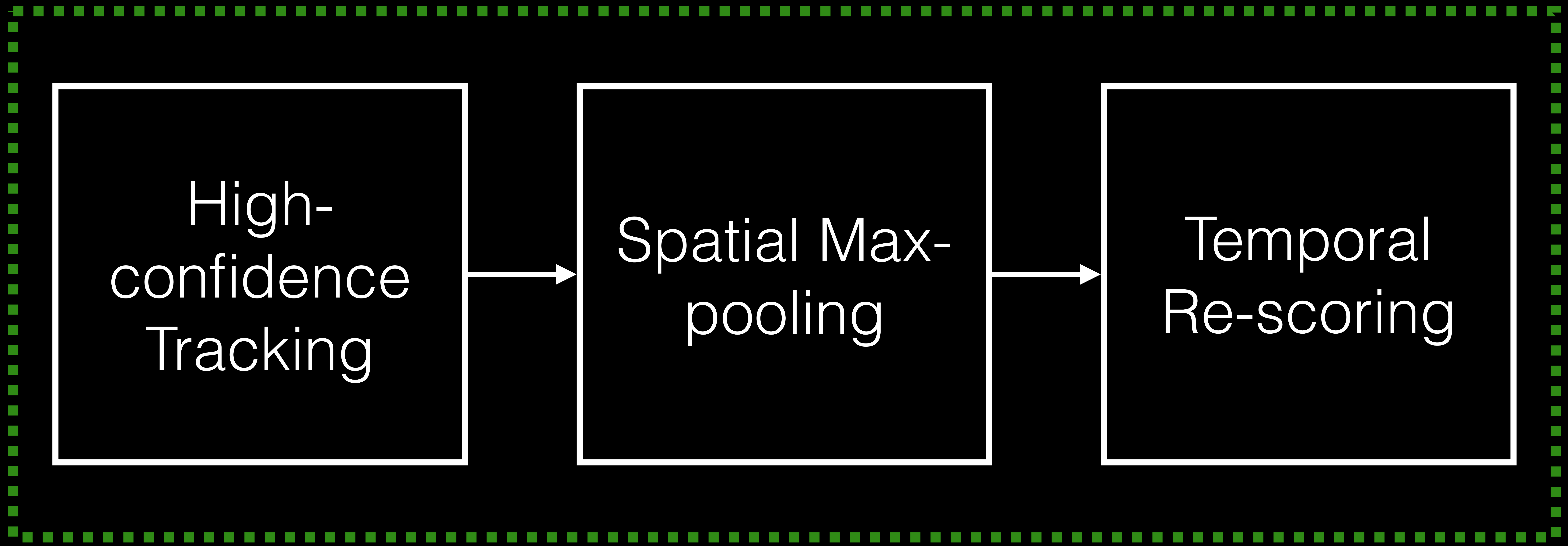
Temporal Re-scoring

- **Tubelet Classification**. Classify tubelets based on statistics of detection scores (mean, median, top-k). A linear classifier is learnt based on the statistics.

- **Tubelet Re-scoring**. Map detection scores of positive tubelets to [0.5, 1], negative ones to [0, 0.5].



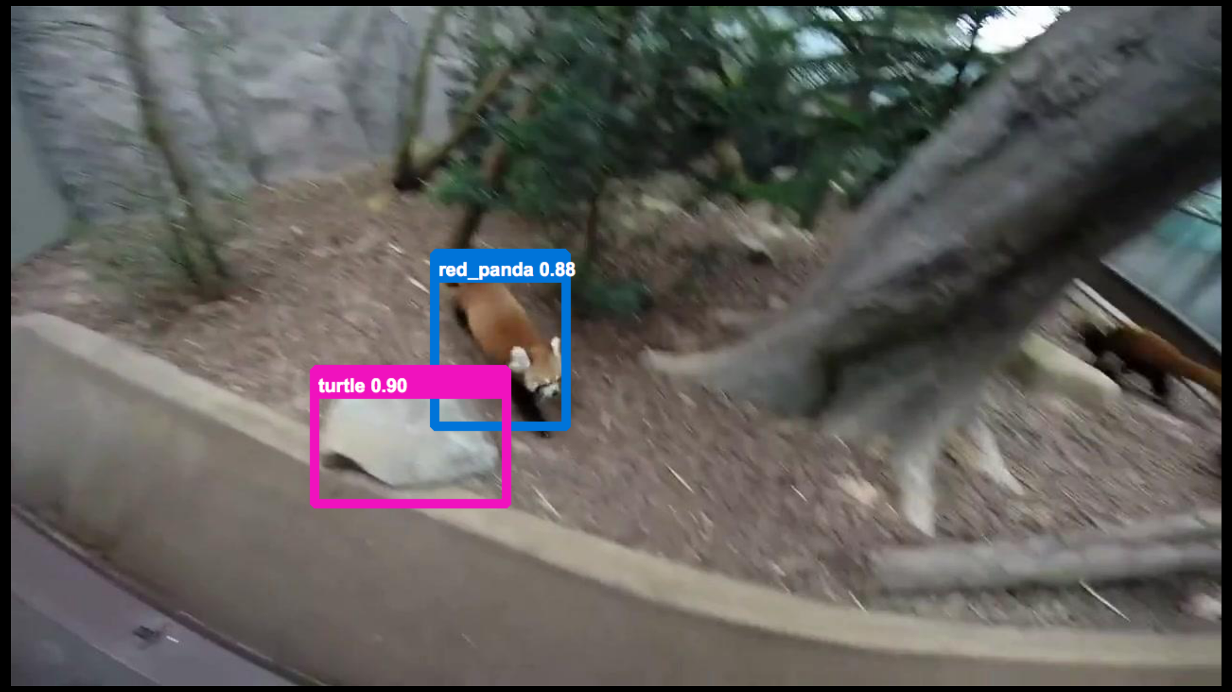
Temporal Tubelet Re-scoring



Still-image Detection: Limitation II

Ignored Context

red panda turtle



red panda turtle

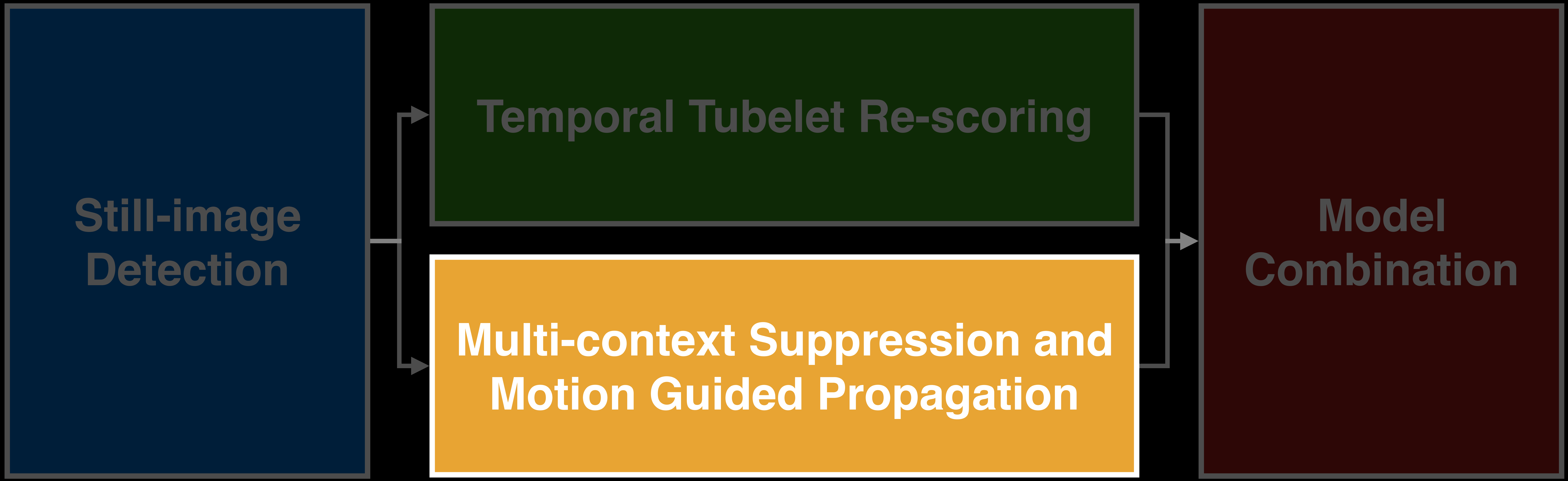
red panda

red panda

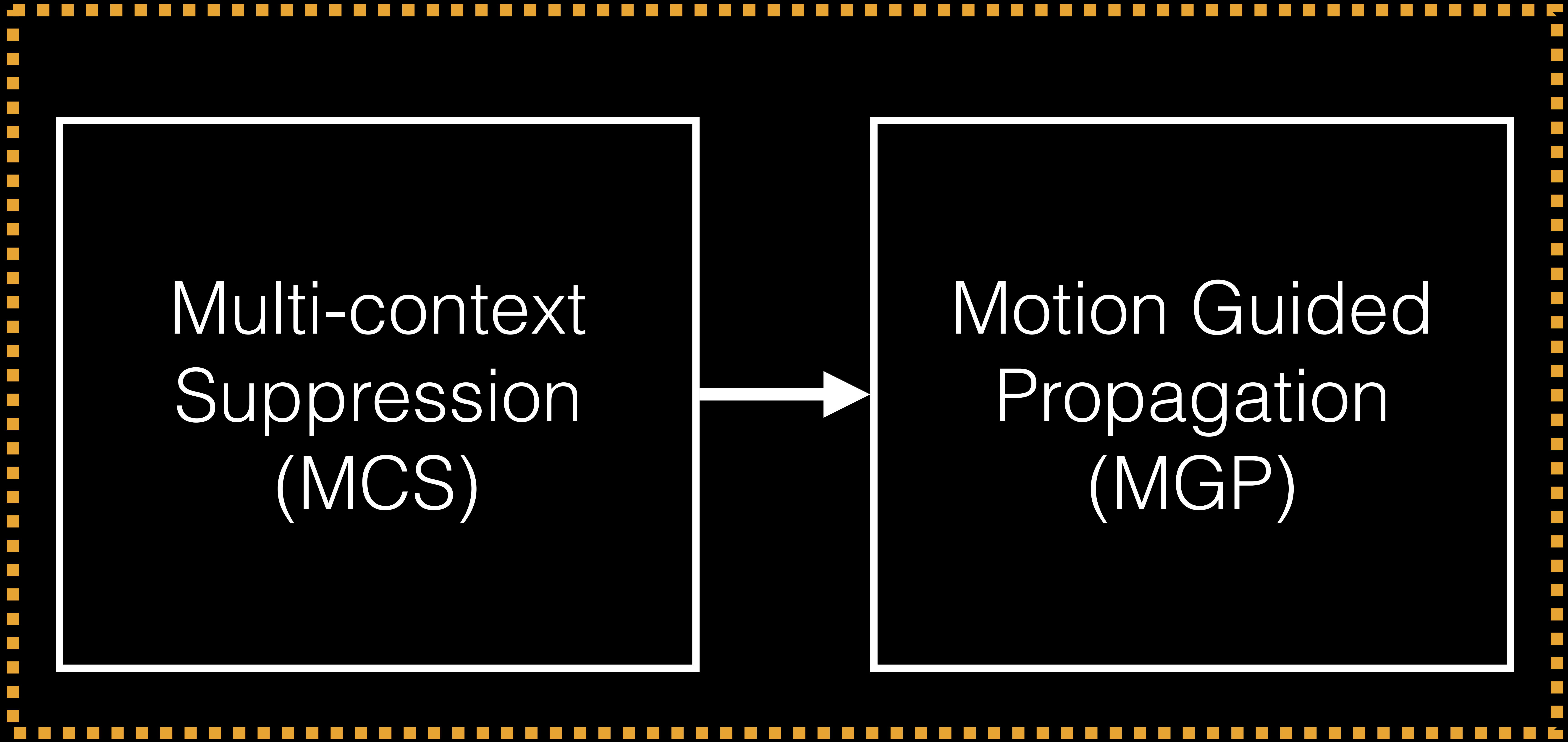
red panda

red panda

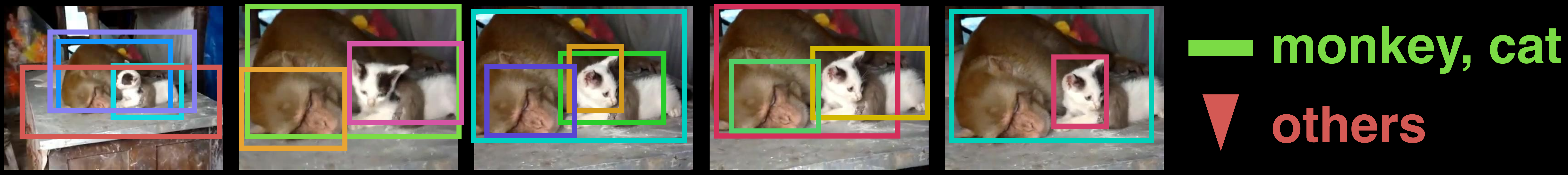
Proposed Framework



Multi-context Suppression and Motion Guided Propagation

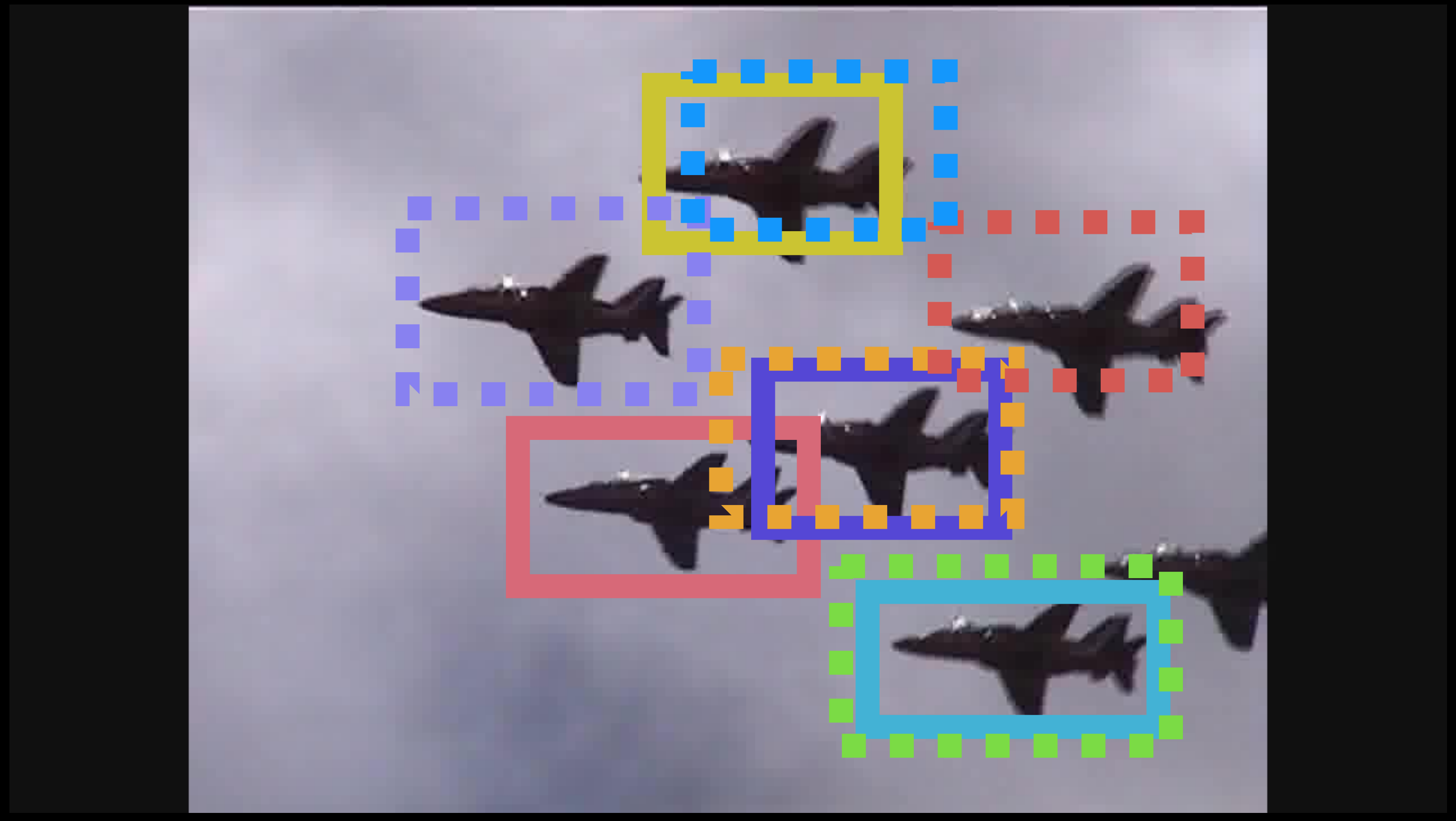


Multi-context Suppression (MCS)

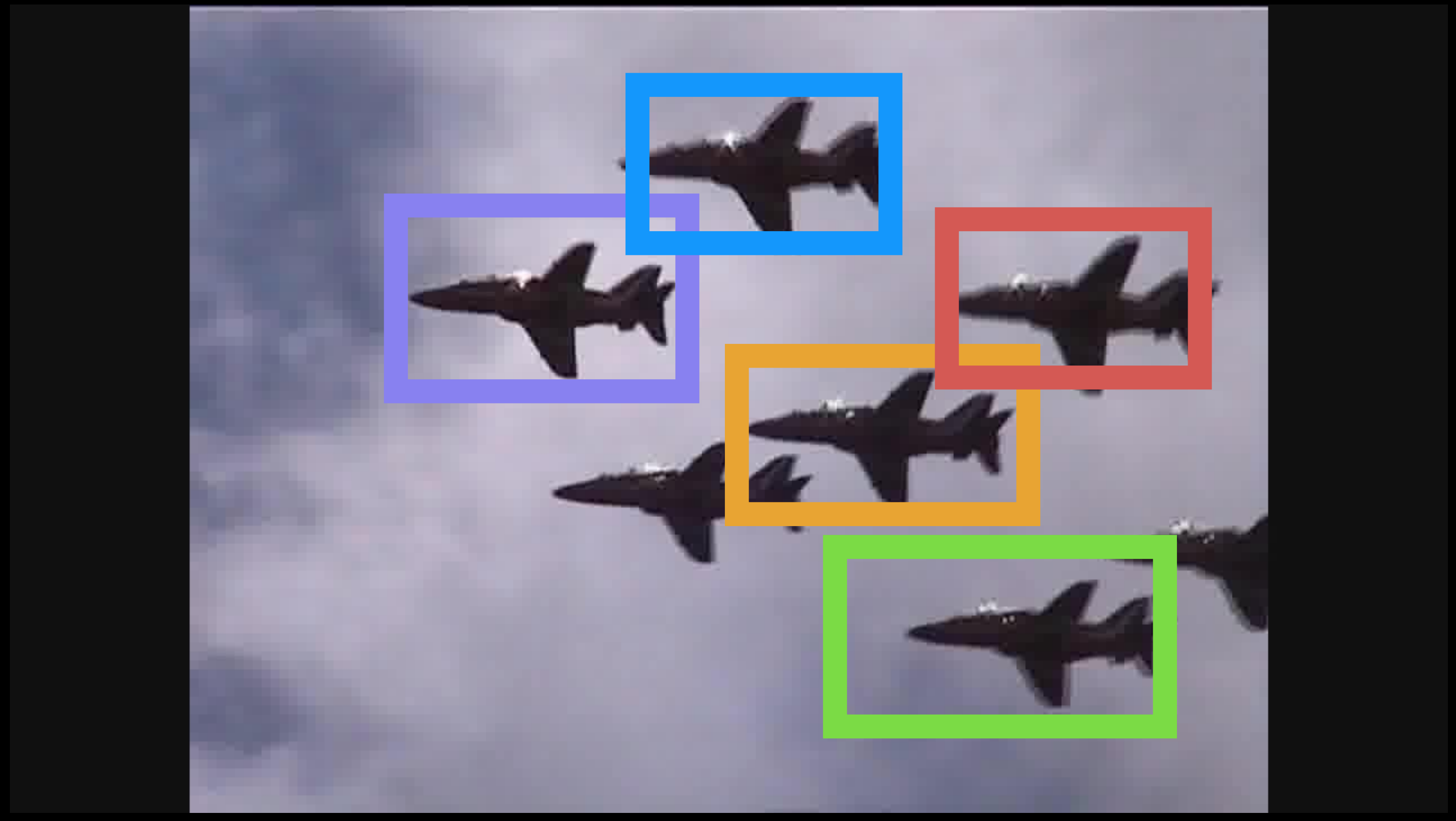


- **Sort** all detection scores of all proposals in a video in **descending order**
- The classes of the **high rankings** are denoted as the confident classes
- The scores of **classes with low rankings** are suppressed, while the scores of confident classes remain unchanged

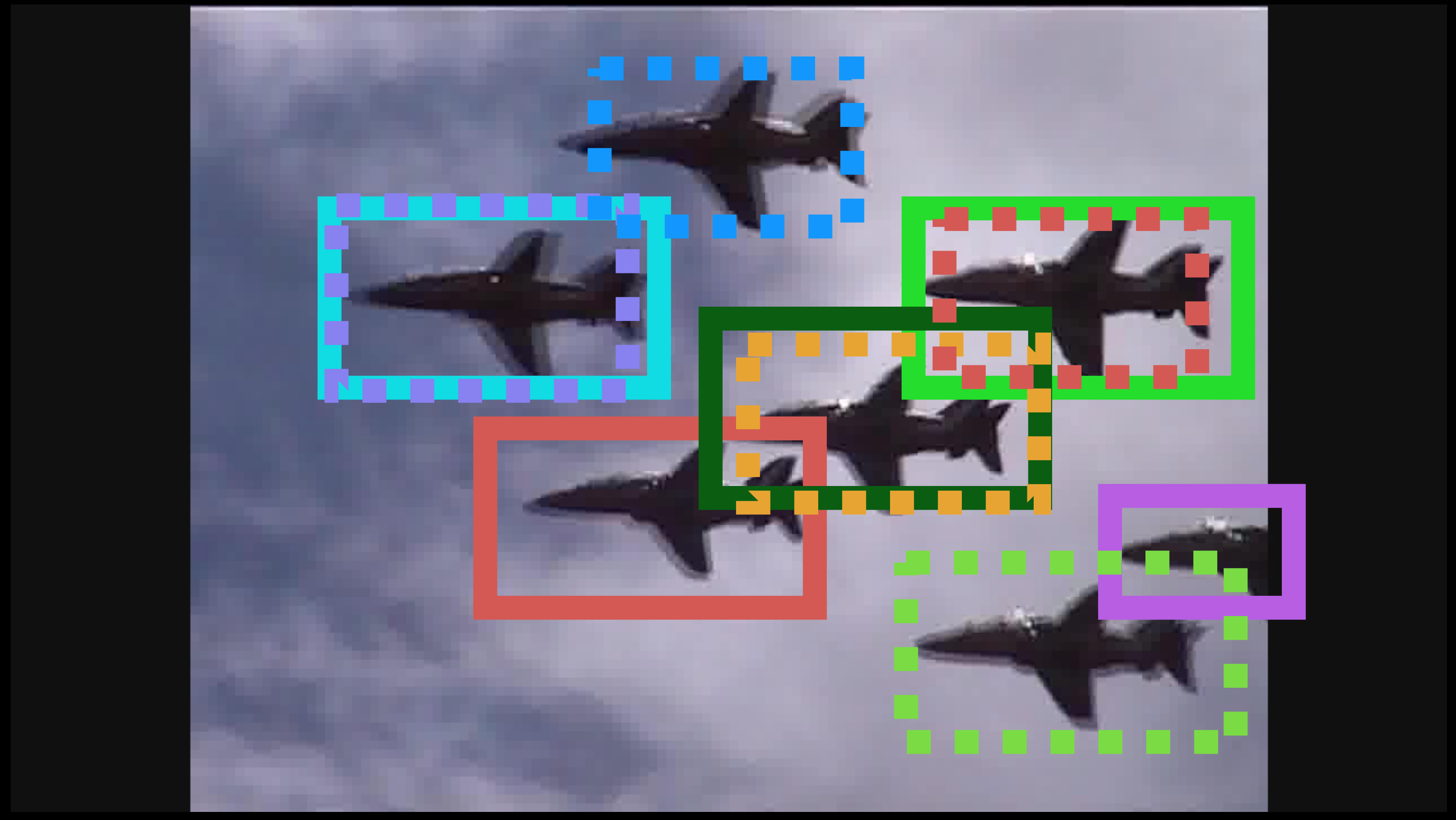
Motion Guided Propagation (MGP)



Frame t-1



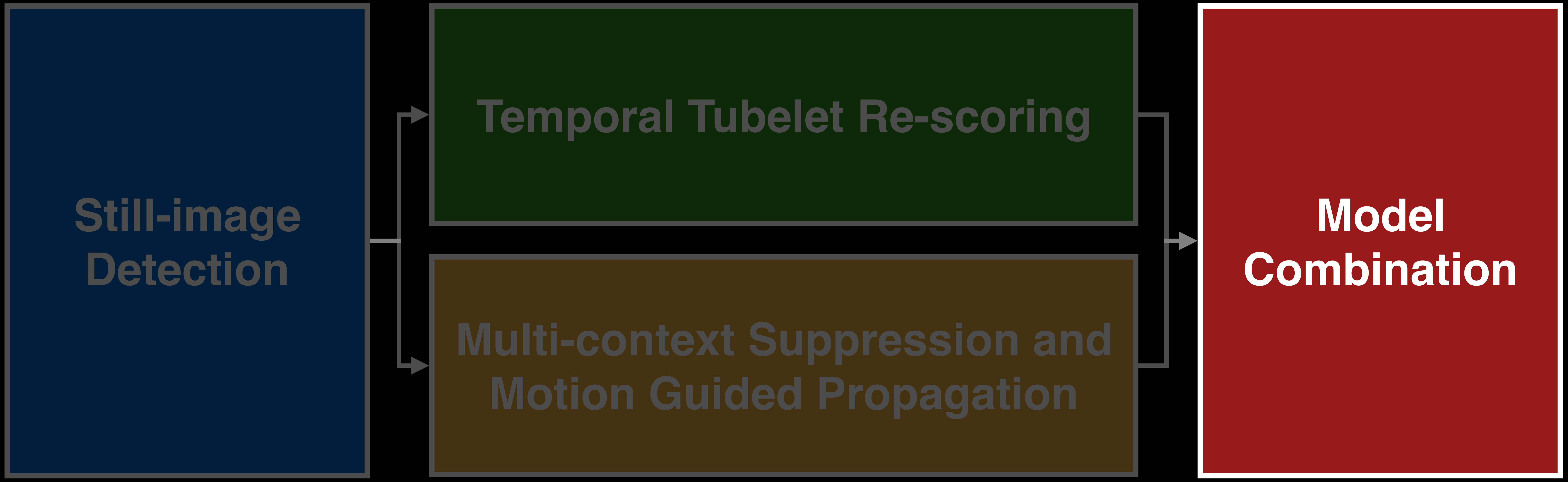
Frame t



Frame t+1

- In each frame, some objects are **not found by detector**. However, detections on adjacent frames are **complementary** to each other.
- Detections are **propagated to adjacent** frames. Optical flow is used for guiding the propagation.
- Propagation results in redundant boxes, which can be **easily handled** by non-maximum suppression (NMS)

Proposed Framework

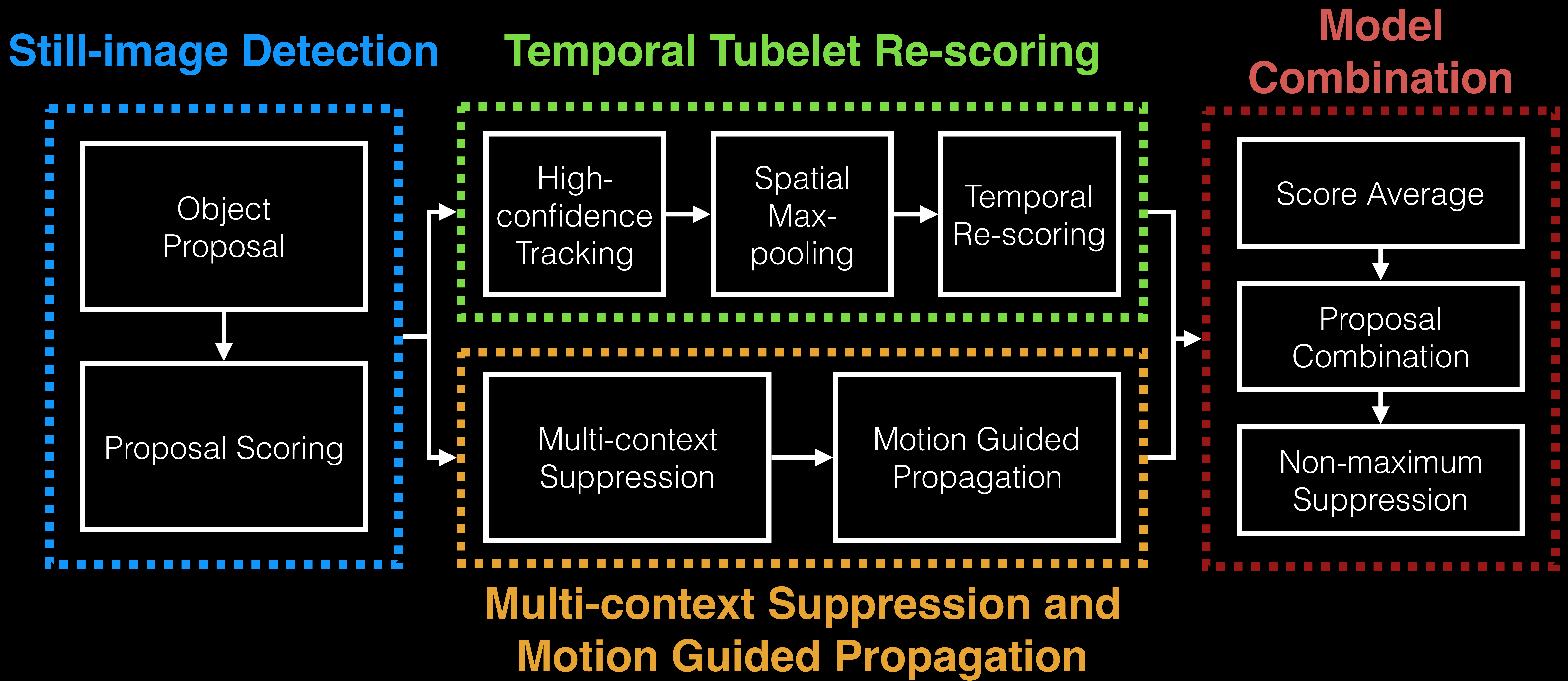


Model Combination

- Two groups of proposals:
  - 1) Proposals from CRAFT [1]: scores from CRAFT
  - 2) Selective Search + EdgeBox: scores from DeepID-net [2]
- Given a group of proposals, their detection scores can be obtained by averaging several models.
- NMS is used for combining multiple groups of proposals

[1] J. Yan, et al. CRAFT Objects from Images, axiv preprint.
[2] W. Ouyang, et al. Deepid-net: Deformable deep convolutional neural networks for object detection. CVPR, 2015.

Proposed Framework



Component Analysis

Training Data Configuration

CNN Training Data

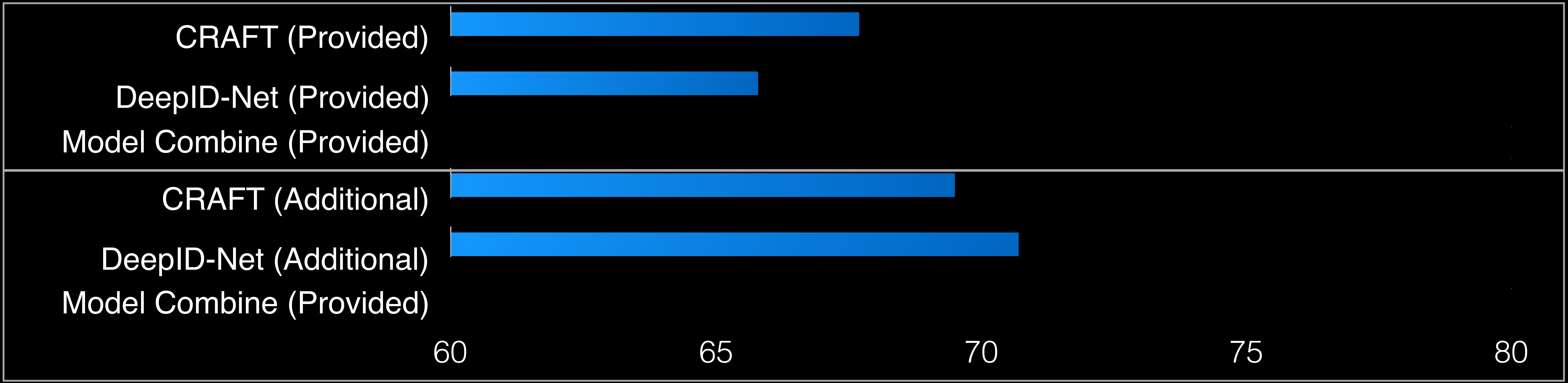
DET:VID Ratio	1:0	3:1	2:1	1:1	1:3
MeanAP / %	49.8	56.9	**58.2**	57.6	57.1

SVM Training Data

DET Positive	✅	✅	❌	❌	❌	✅
VID Positive	❌	✅	✅	✅	✅	✅
DET Negative	✅	✅	✅	✅	❌	✅
VID Negative	❌	❌	❌	✅	✅	✅
MeanAP / %	49.8	47.1	35.8	51.6	52.3	**53.7**

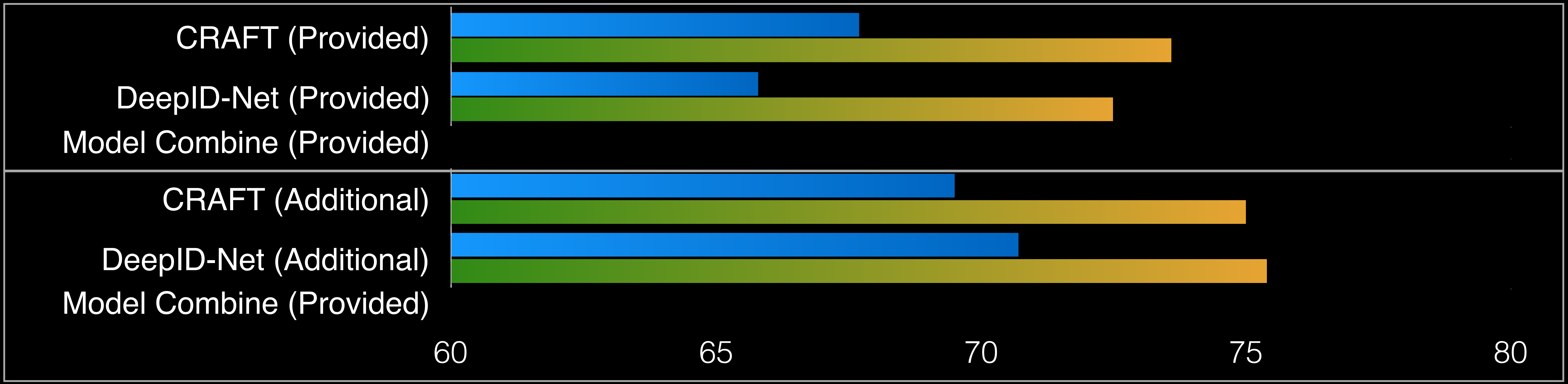
Framework Components

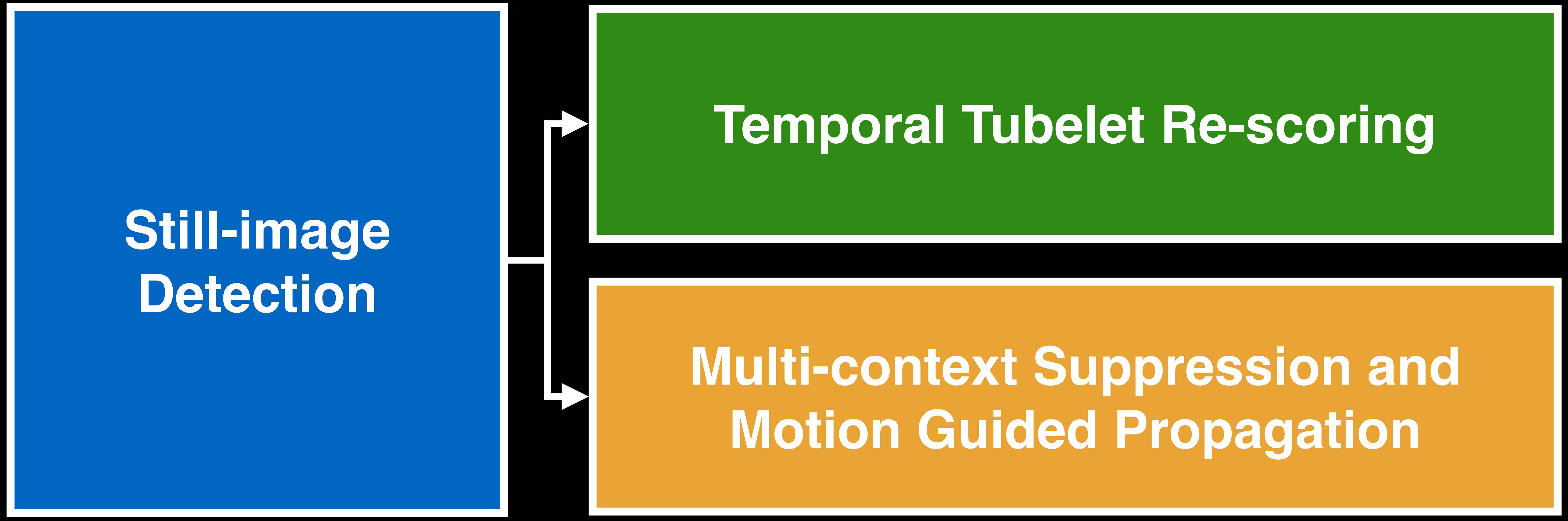
Framework Components



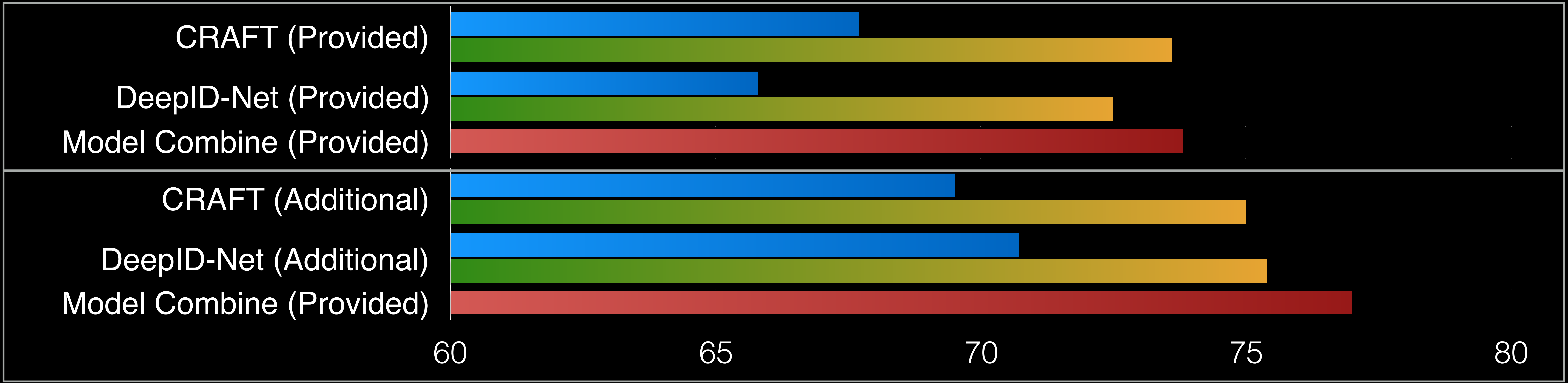
Still-image Detection

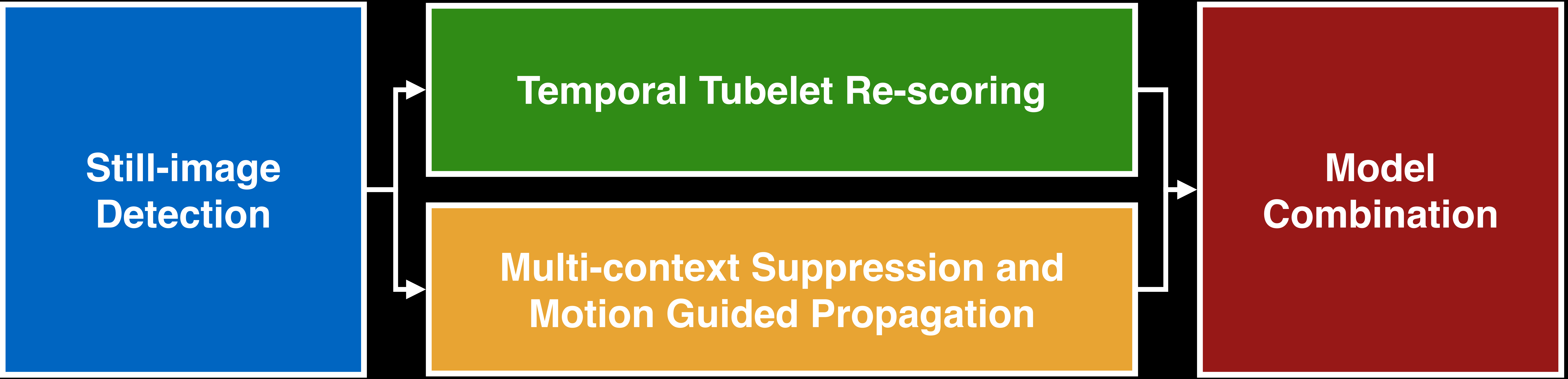
Framework Components





Framework Components





Results

Data	Model	Still-image	MCS+MGP +Rescoring	Model Combine	Test Set (official results)	Rank in ILSVRC 2015	#win
Provided	CRAFT [1]	67.7	73.6	73.8	67.8	#1	28/30
	DeepID-net [2,3,4]	65.8	72.5				
Additional	CRAFT [1]	69.5	75.0	77.0	69.7	#2	11/30
	DeepID-net [2,3,4]	70.7	75.4				

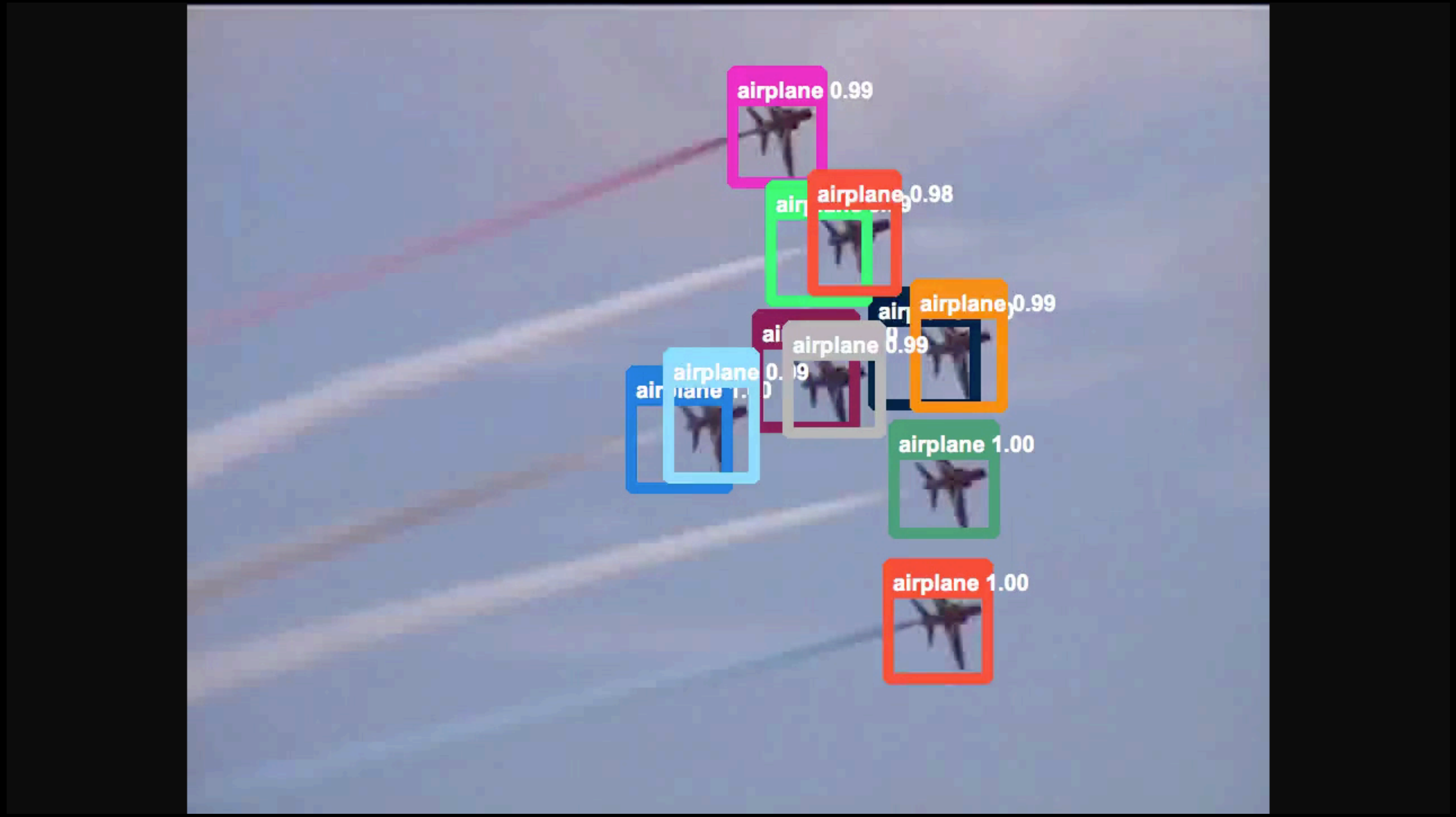
Validation set   Test set

[1] J. Yan, et al. CRAFT Objects from Images, axiv preprint.
[2] W. Ouyang, et al. Deepid-net: Deformable deep convolutional neural networks for object detection. CVPR, 2015.
[3] X. Zeng, et al. Window-Object Relationship Guided Representation Learning for Generic Object Detections , axiv preprint.
[4] W. Ouyang, et al. Factors in Finetuning Deep Model for object detection, axiv preprint.

Our Team in ILSVRC2015

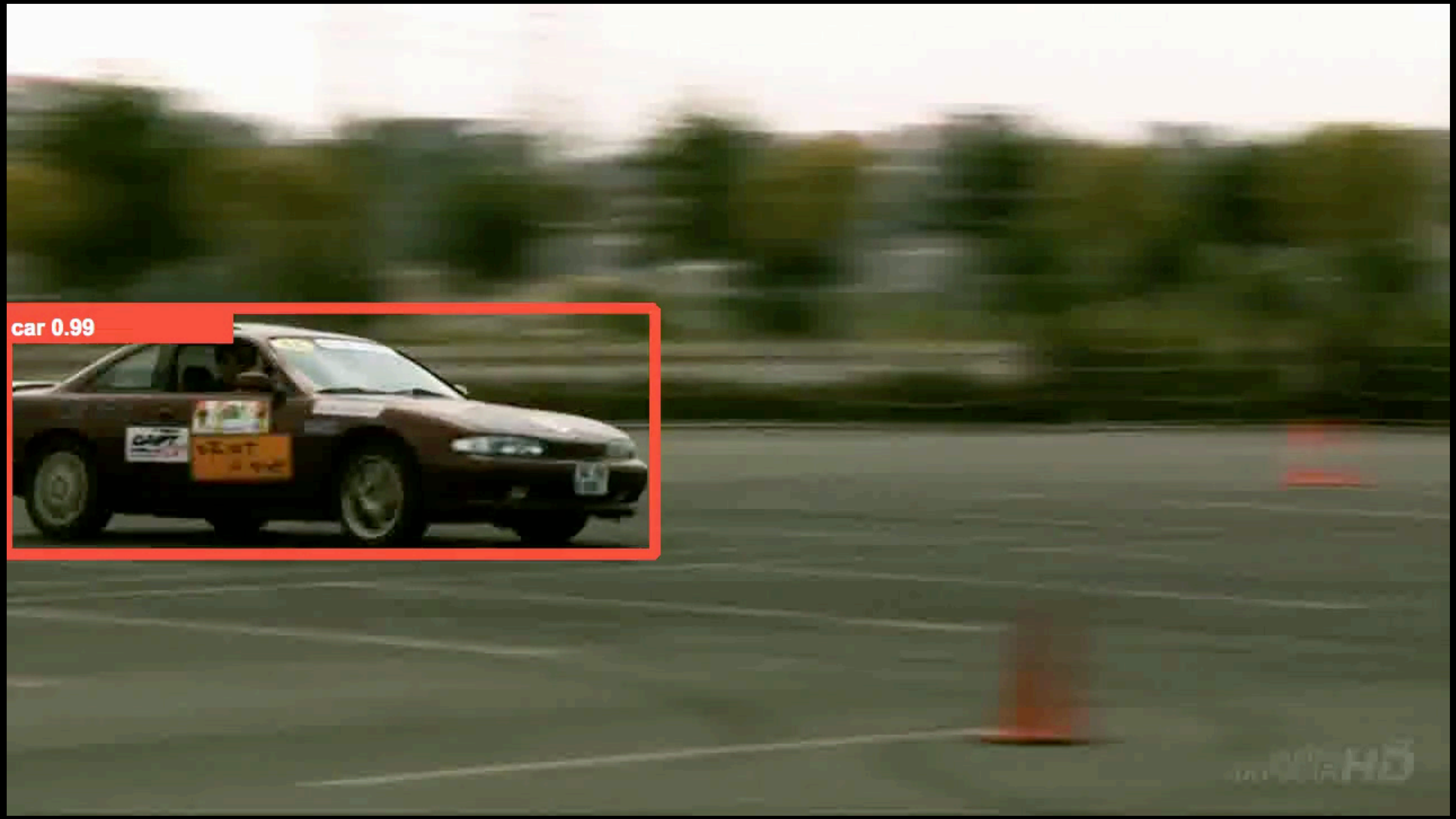
Team	Task	Track	Rank
CUimage	DET	Provided	#3
		Additional	#2
CUvideo	VID	Provided	#1
		Additional	#2

Results

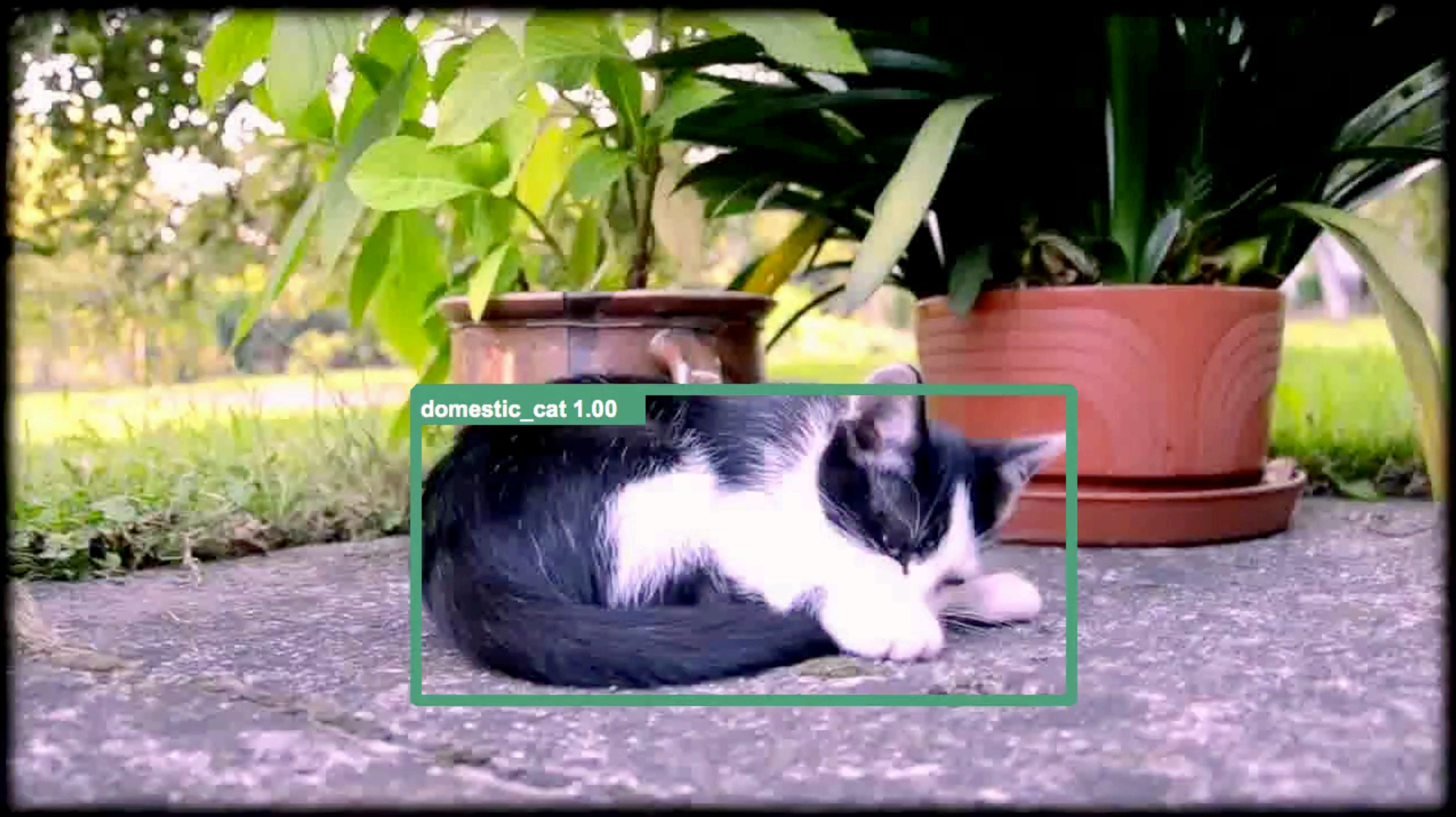

airplane 0.99
airplane 0.98
airplane 0.99
airplane 0.99
airplane 1.00
airplane 1.00

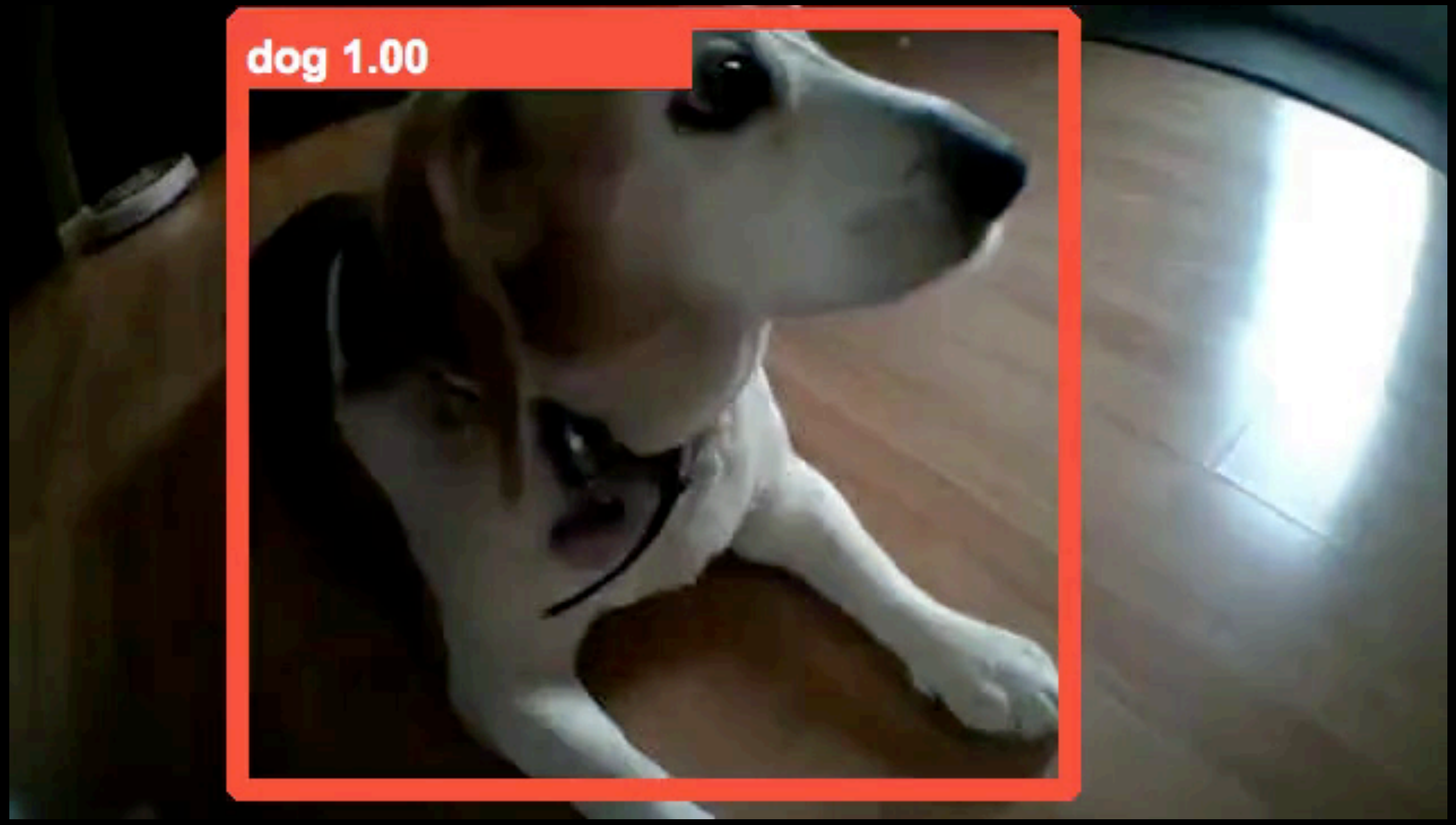

airplane 0.78
airplane 0.85
airplane 0.88
airplane 0.66
airplane 0.72

Results

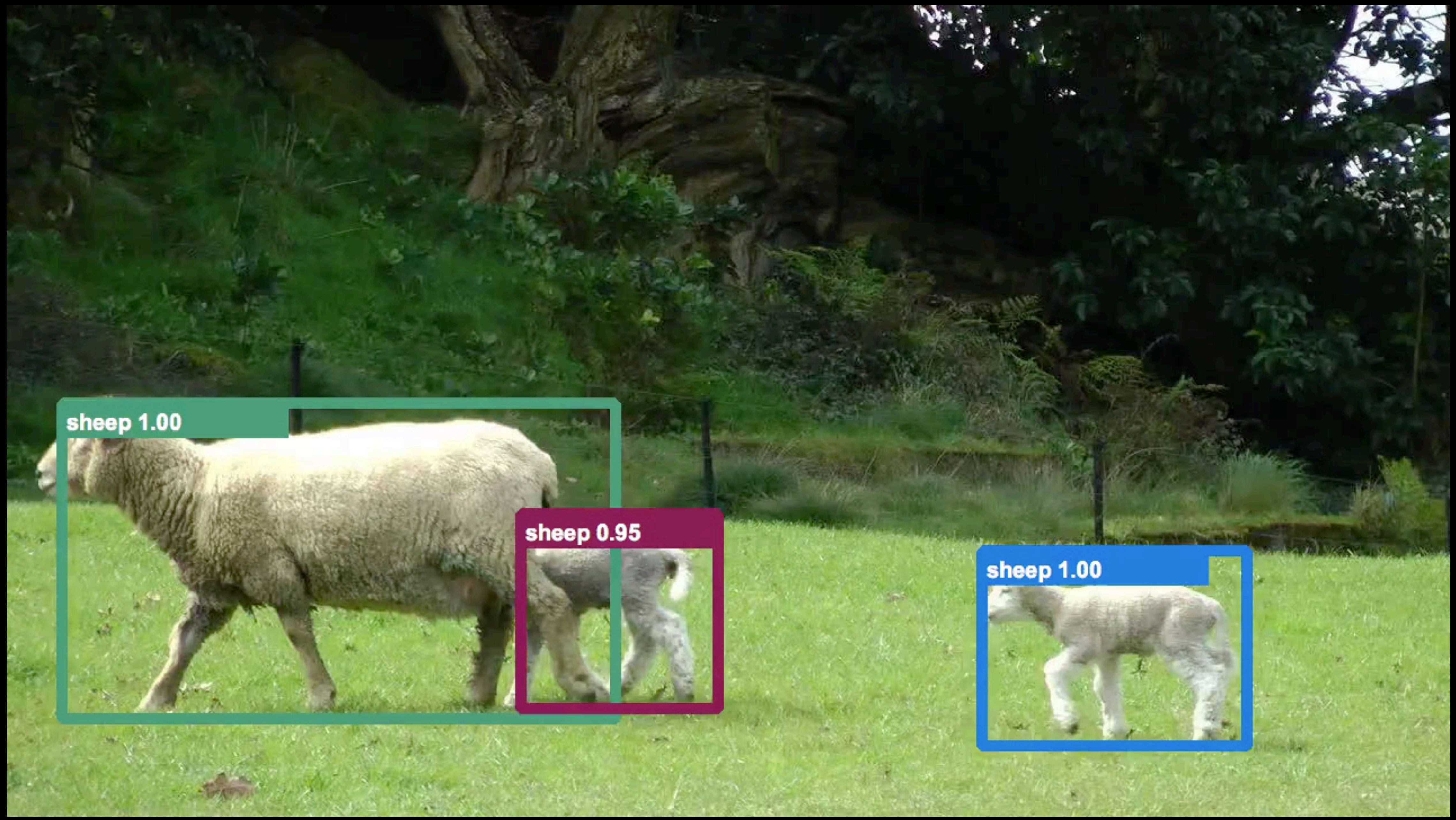


Results





Results



Results

Thank You!

Questions?