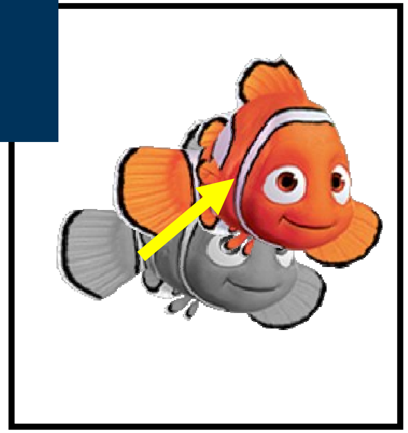
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Learning for Tracking and Lessons Learned from it

Helmut Grabner

Outline

Computer Vision: Tracking



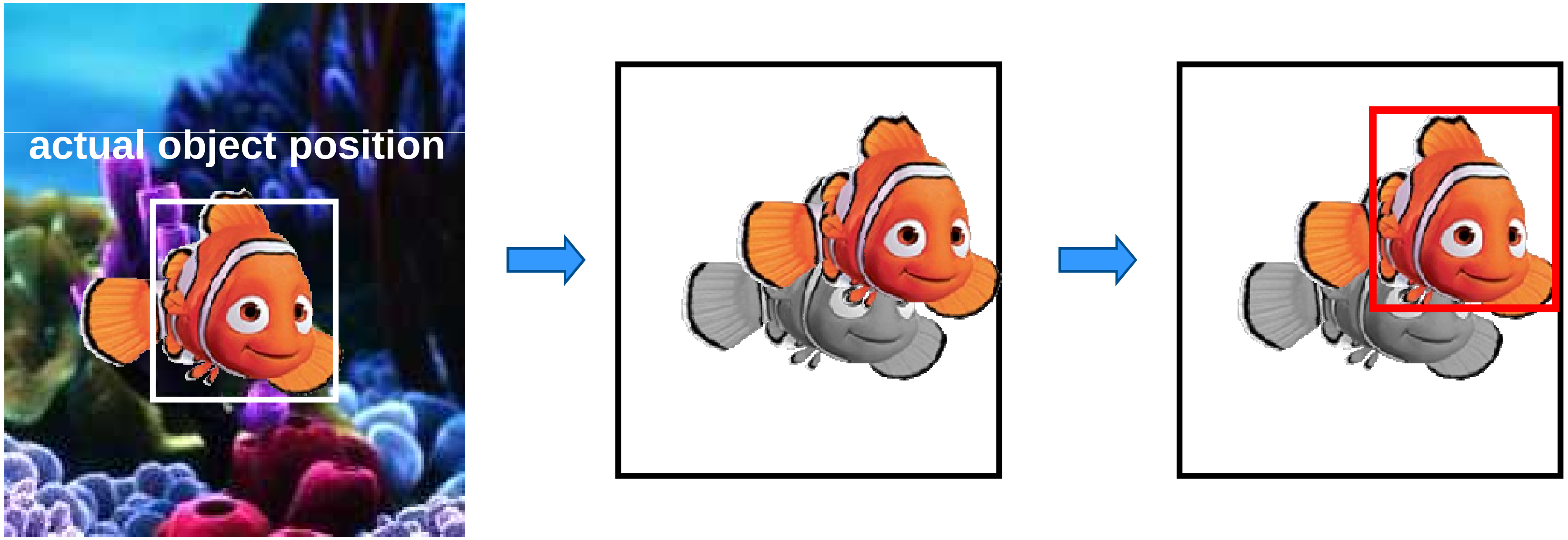
ON-LINE

Machine learning

Lessons Learned

Tracking by fast (re-) detection

Time t | **from time t to t+1** | **„find“ again**



Tracking Cues

- Object Appearance
- Background

Object/Background discrimination

- Object Boundary
- Motion

[Grabner et al. VideoProc.CVPR 2006]

Tracking Requirements (model free tracking)

- Adaptive

- Robu

And of course,

REAL TIME!

- Generality

PART I

On-line Boosting based Tracking

CVPR'06, BMVC'06

Boosting and Vision

- Boosting

  [Freund and Schapire, JCSC, 1997]

- On-line boosting

  [Oza and Russel, AIS, 2001]

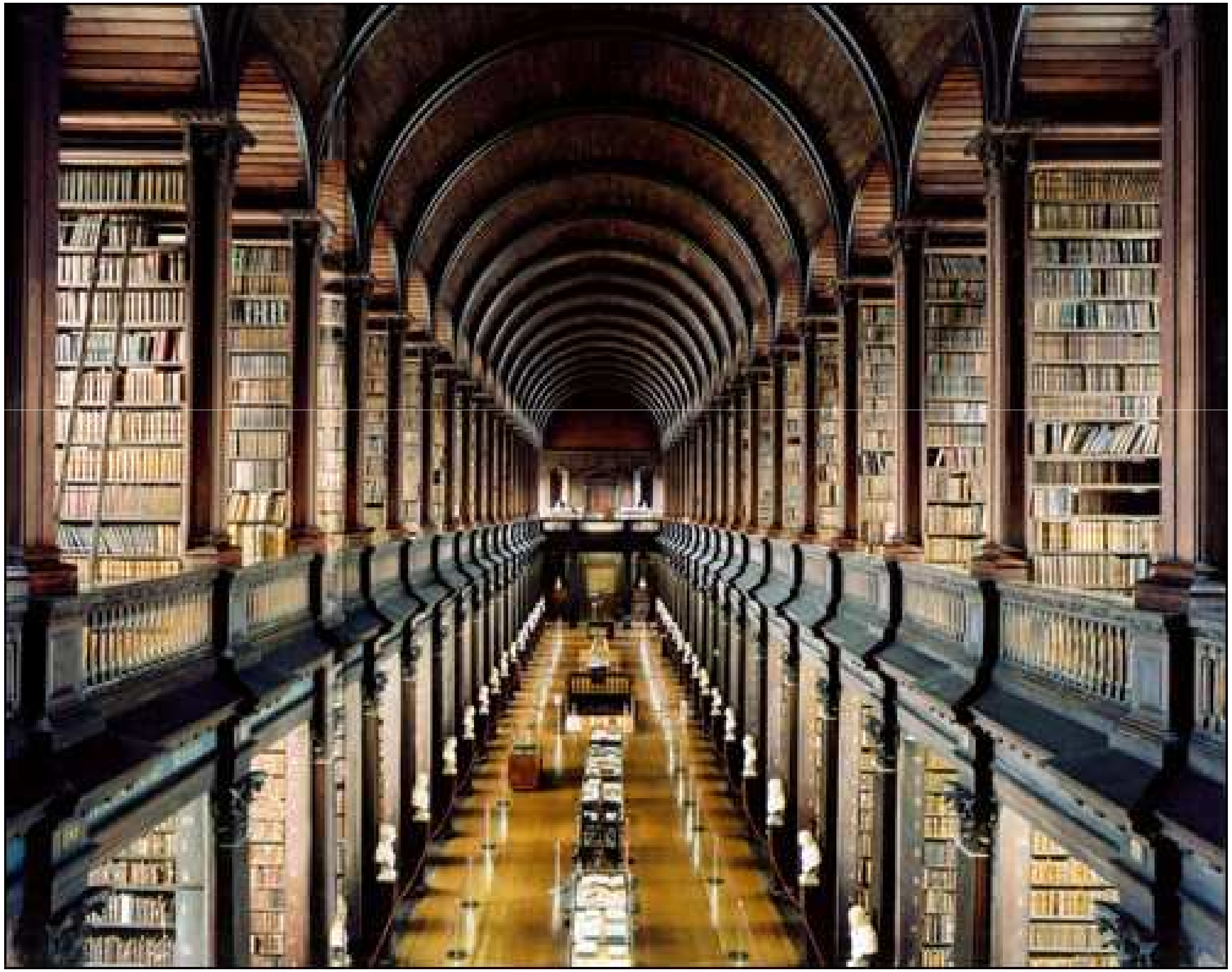
- Boosting for Feature Selection

  [Tieu and Viola. CVPR 2000], [Viola and Jones, CVPR 2001]

- **On-line Boosting for Feature Selection**

  [Grabner and Bischof, CVPR 2006]

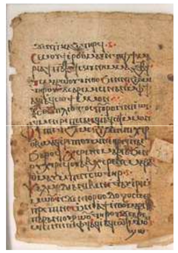
Off-line learning



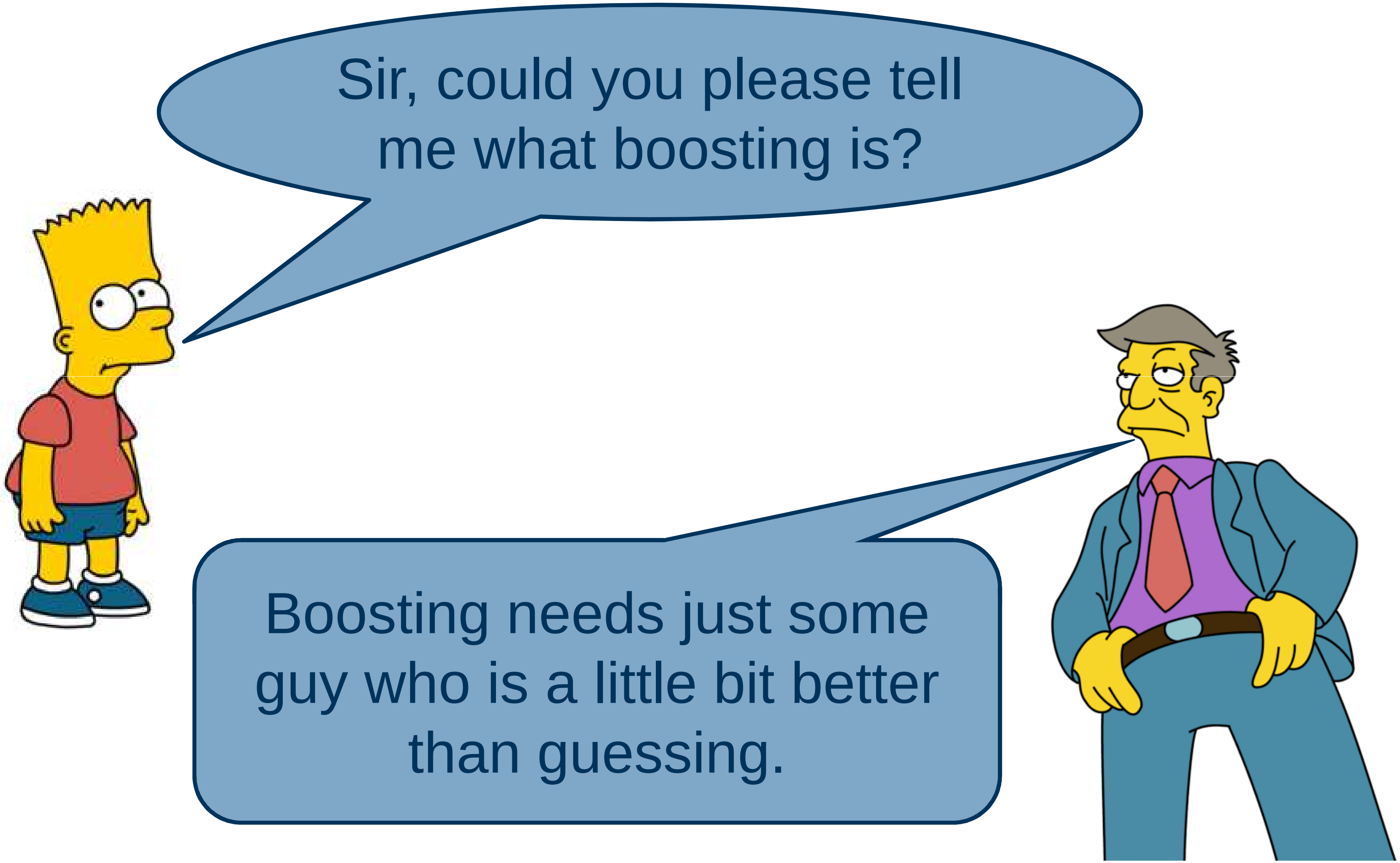
On-line learning

Learning Algorithm

Labeled Information



Teacher


Sir, could you please tell me what boosting is?
Boosting needs just some guy who is a little bit better than guessing.

Off-line boosting

Strong classifier

Weak classifier

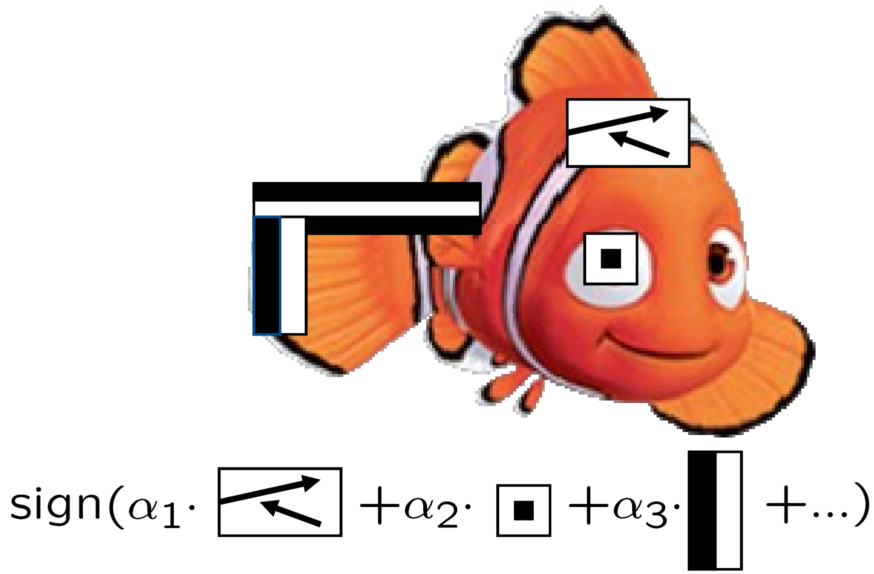
$$H(\mathbf{x}) = \mathrm{sign}\left(\sum_{n=1}^{N} \alpha_n \cdot h_n(\mathbf{x})\right)$$

Reweighting the training examples

Boosting for Feature Selection

- **Combination** of **Simple Image Features** for distinguishing two classes

- Features = weak classifier
- Boosting to select a subset (strong classifier)



On-line Boosting

$$H_t^{on} \leftarrow \mathsf{update}\left(H_{t-1}^{on}, (\mathbf{x}_t, y_t)\right)$$

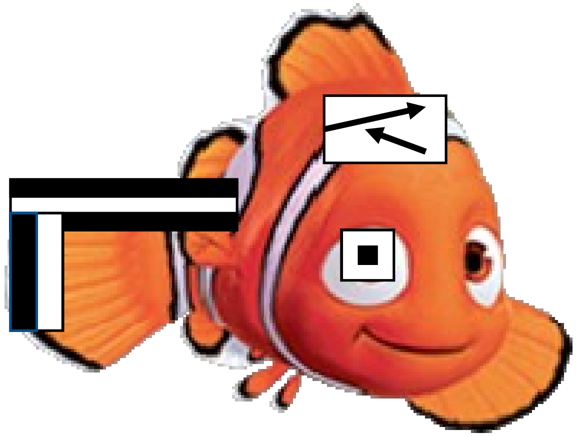
On-line Boosting

Converges to the off-line result!

On-Boosting for Feature Selection

REPLACE:
Off-line Boosting ⇨ On-line Boosting

- **Combination** of **Simple Image Features** for distinguishing two classes



- Features = weak classifier
- Boosting to select a subset (strong classifier)

$$\text{sign}(\alpha_1 \cdot \boxed{\,} + \alpha_2 \cdot \boxed{\,} + \alpha_3 \cdot \boxed{\,} + \ldots)$$

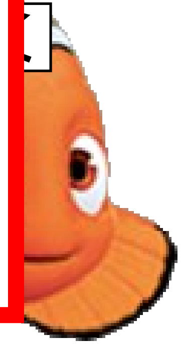
On-Boosting for Feature Selection

REPLACE: Boosting

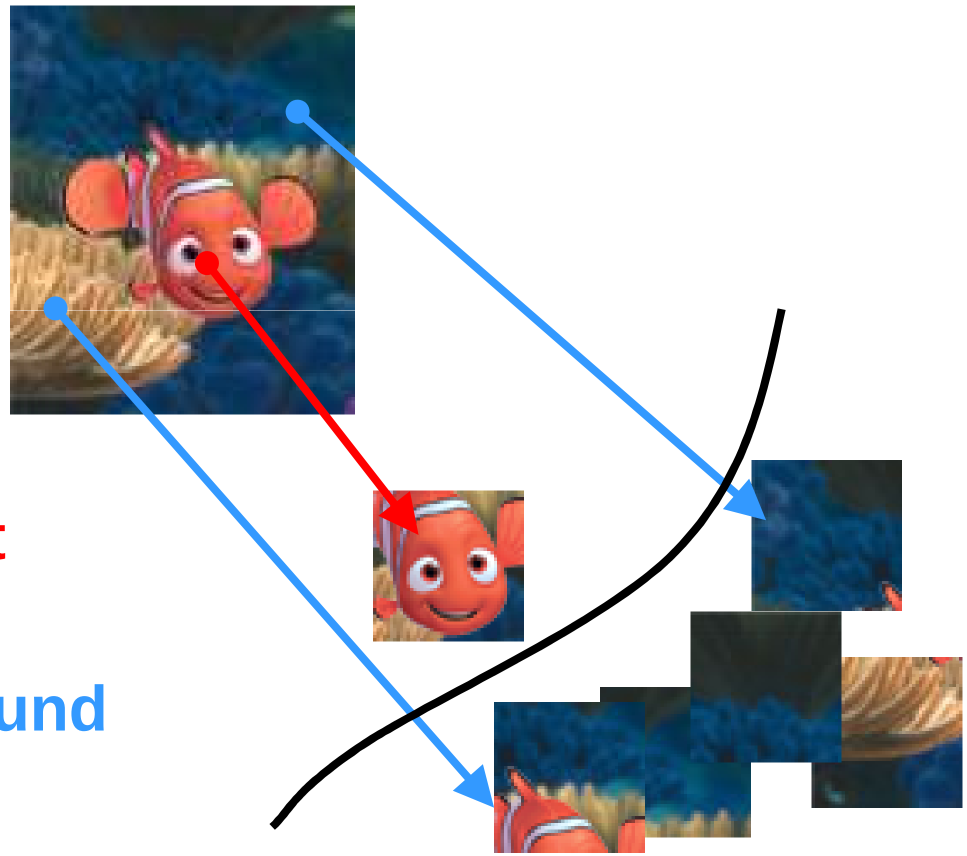
- Co
  Image
  distingu
- Feature
- Boosting to select a subset (strong classifier)

$\text{sign}(\alpha_1 \cdot \square + \alpha_2 \cdot \square + \alpha_3 \cdot \square + \ldots)$

General approach for on-line feature selection.



Tracking as Classification

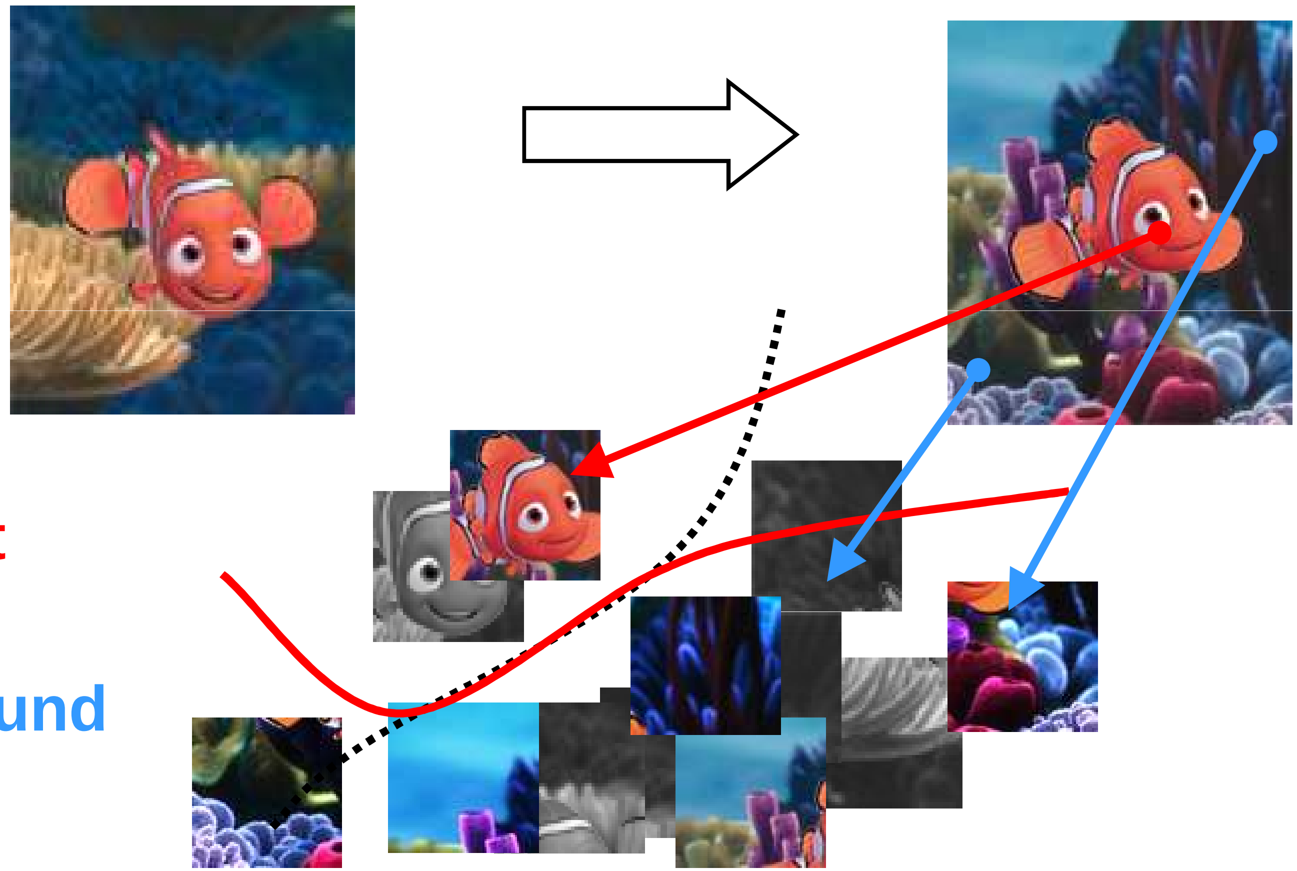


object

vs.

background

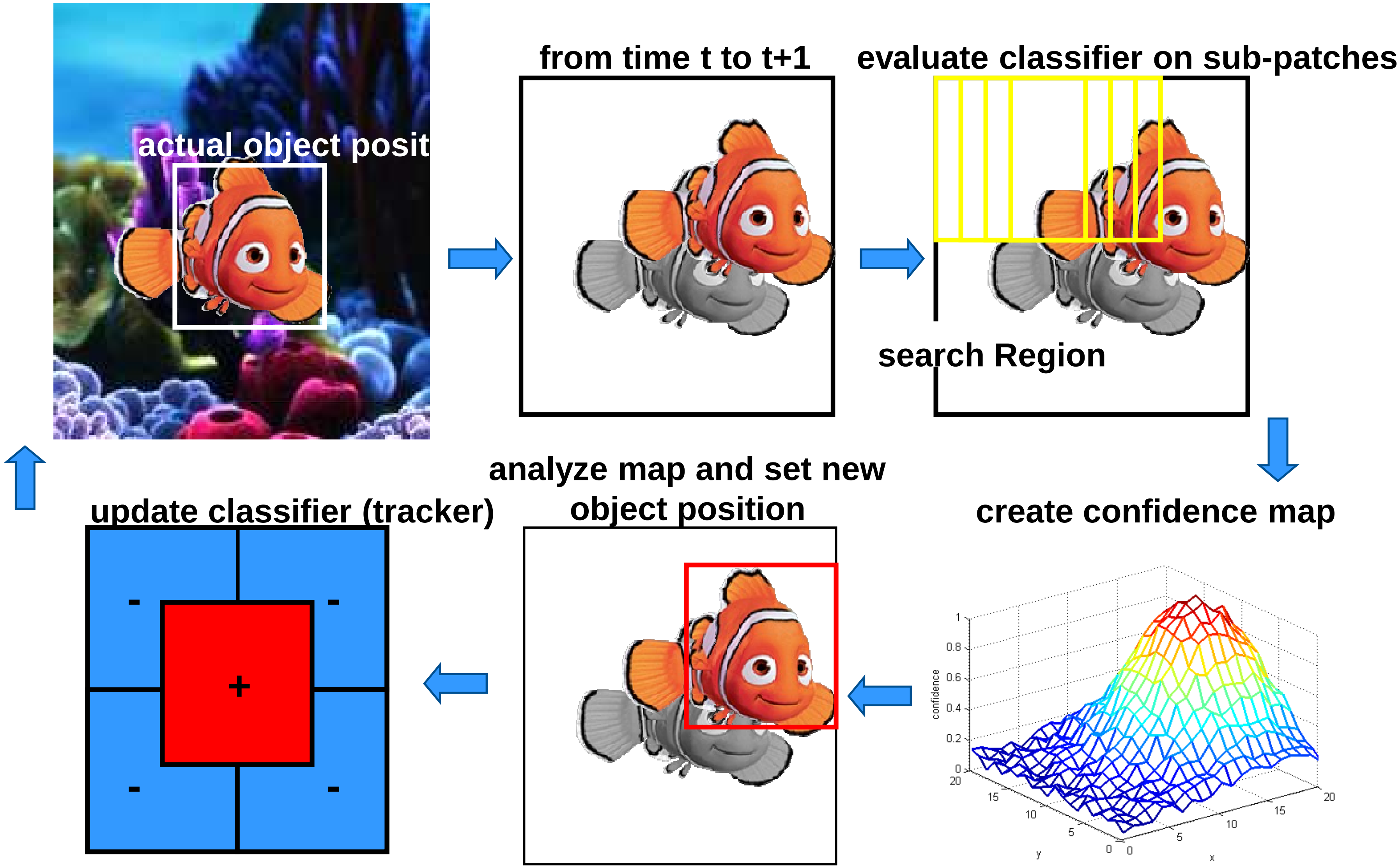
Tracking as Classification



object

vs.

background


actual object posit
from time t to t+1
evaluate classifier on sub-patches
search Region
create confidence map
1
0.8
0.6
0.4
0.2
0
confidence
20
15
10
5
0
y
0
5
10
15
20
x
analyze map and set new object position
update classifier (tracker)
-
-
+
-
-

Object Detector

Fixed Training set
General object detector

Off-line Boosting for Feature Selection

Object Tracker

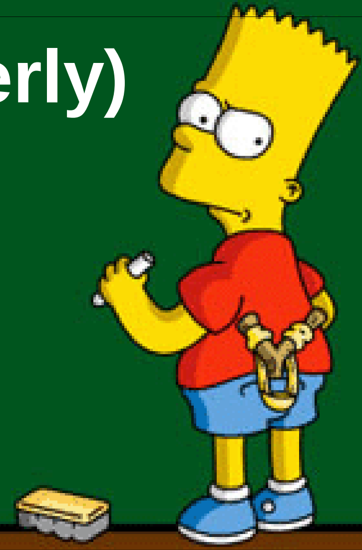
On-line update
Object vs. Background

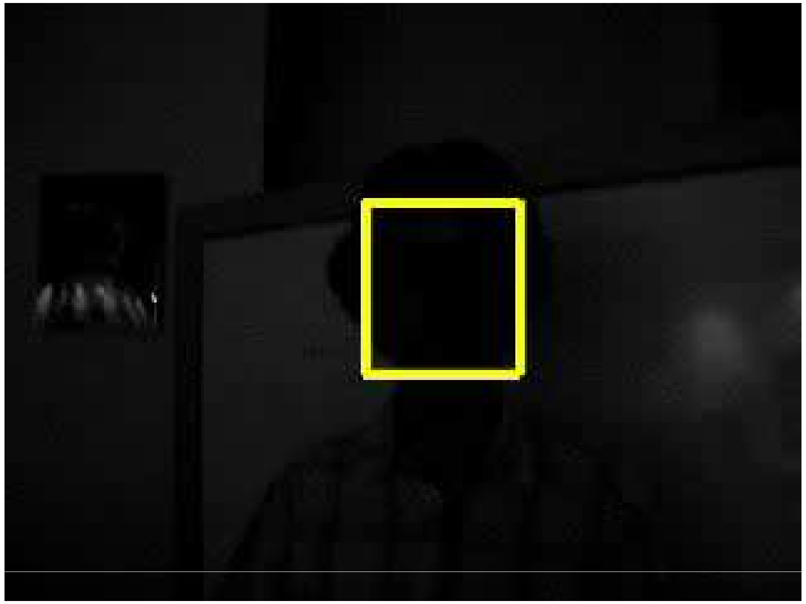
On-Line Boosting for Feature Selection

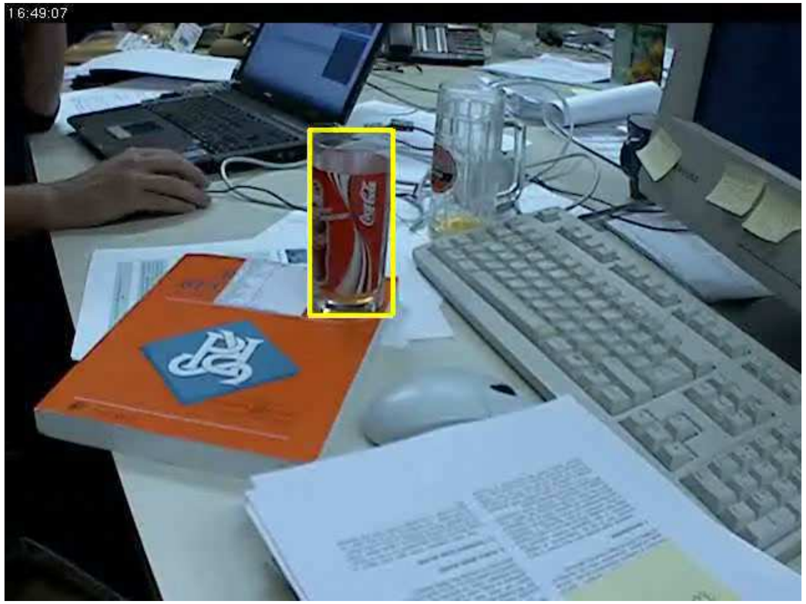
LESSON LEARNED 1

Tracking is a simple task!

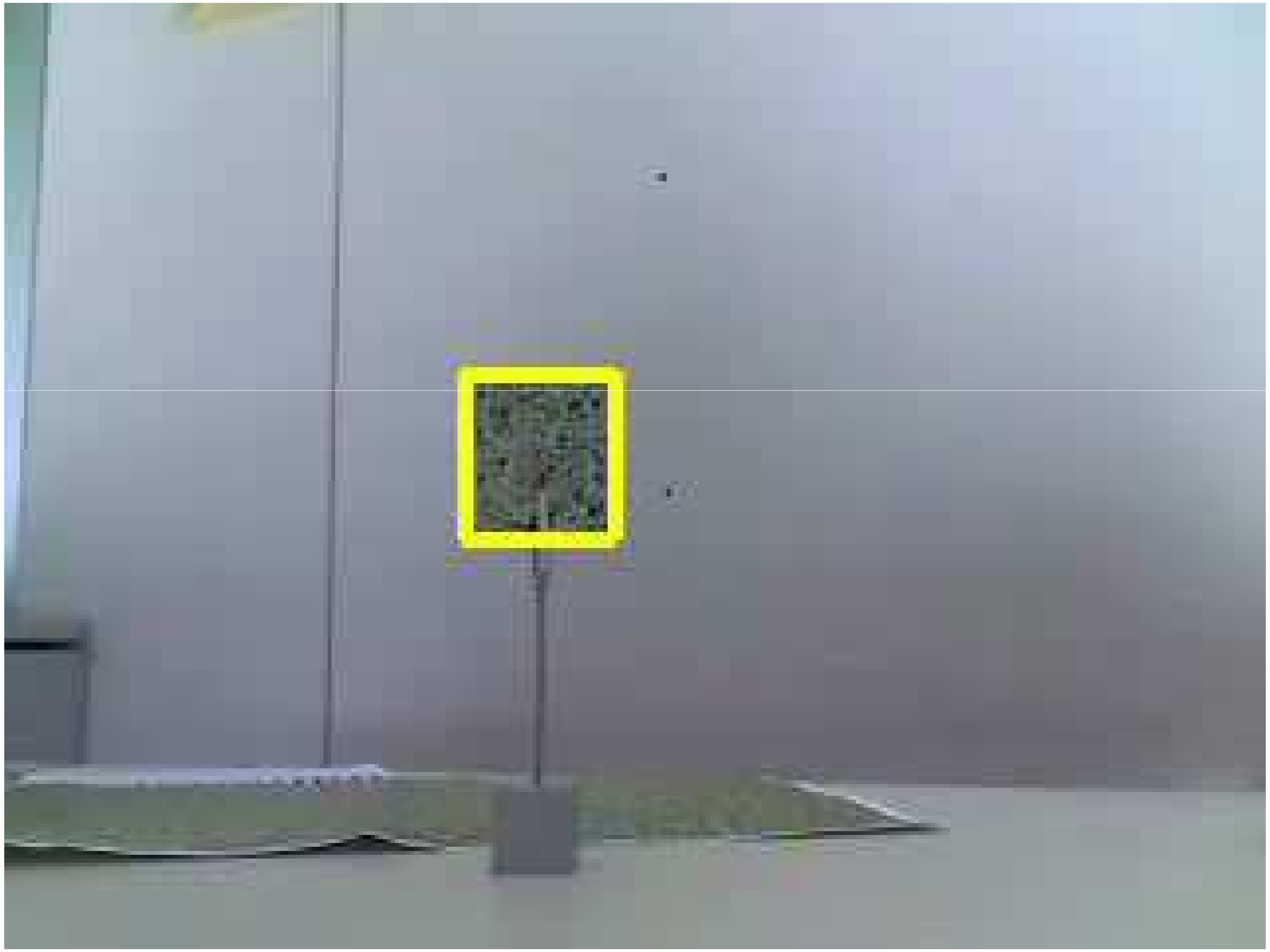
(When formulating it properly)



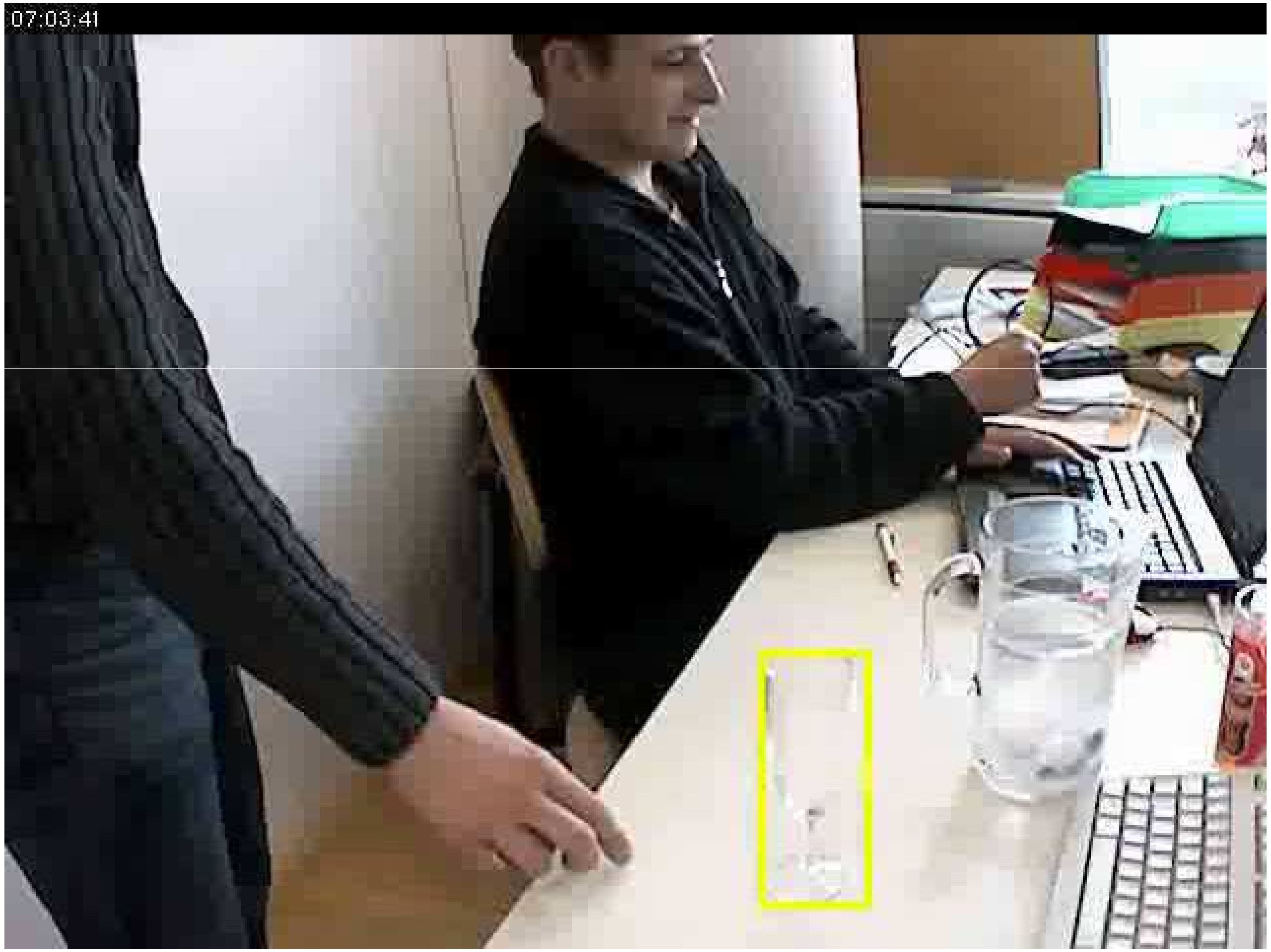



16:49:07

"Simple tracking"



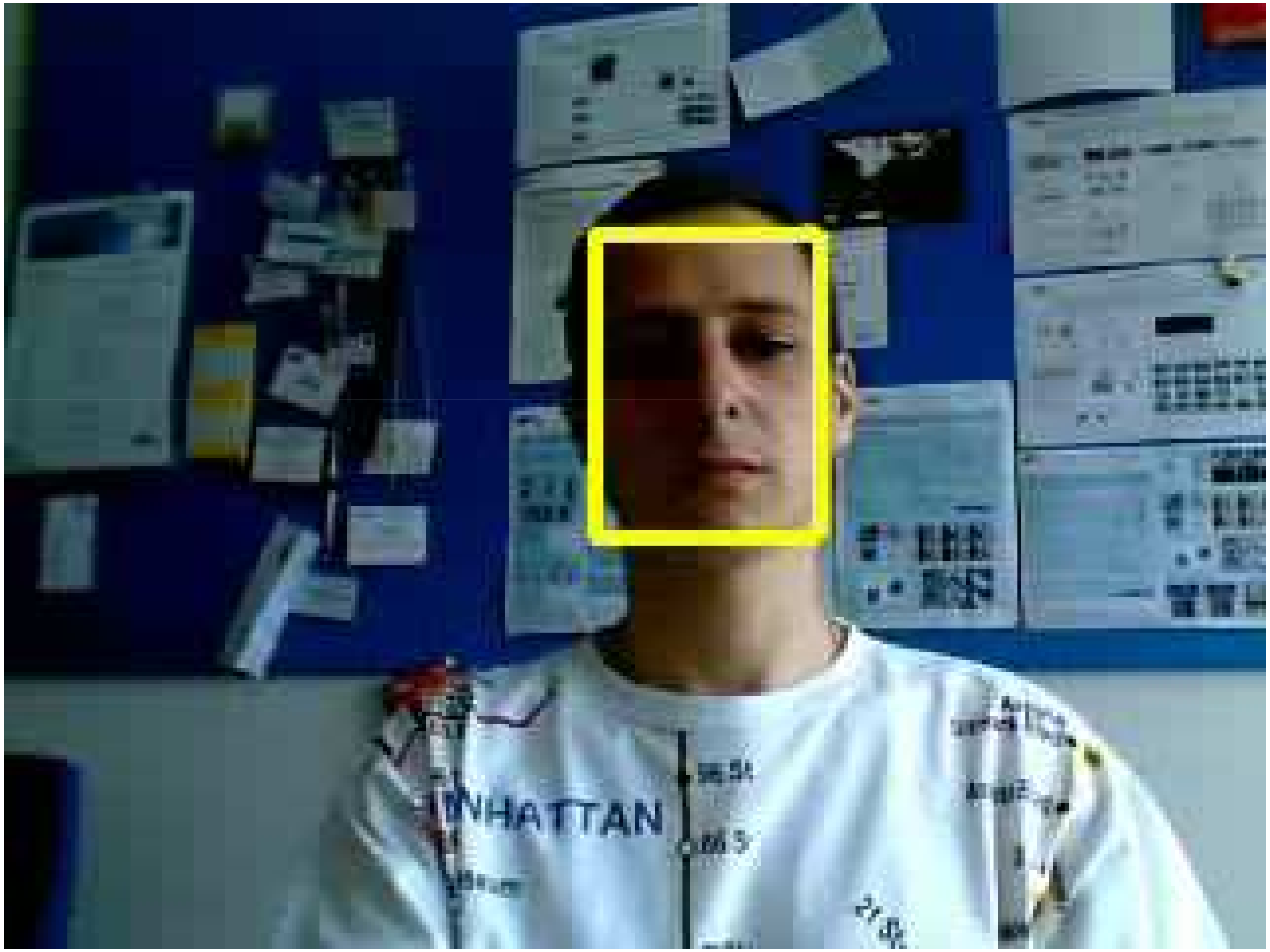
“Tracking the Invisible”



Tracking Solved ☺

Does it fail?
If yes, when?

When does it fail…

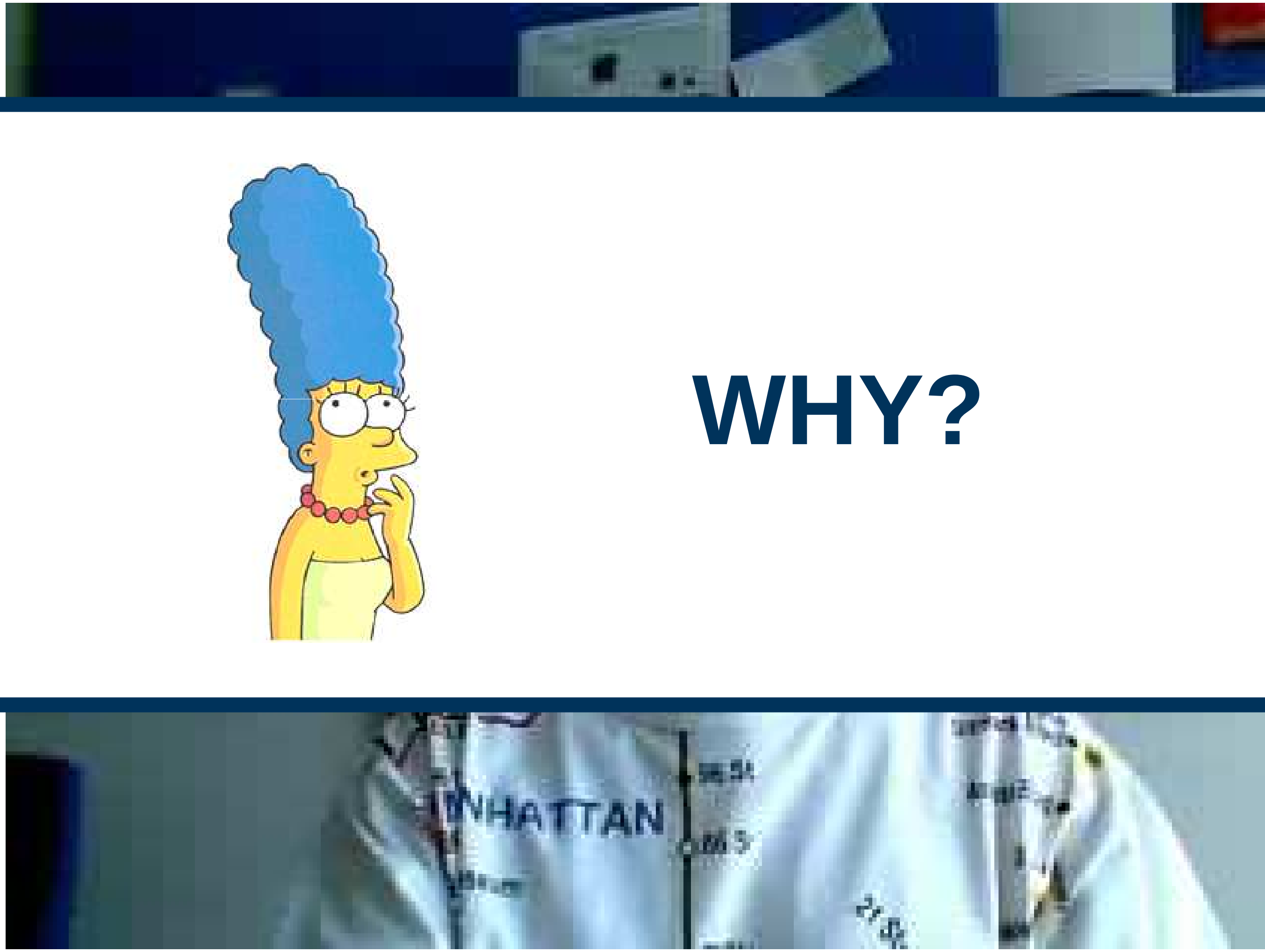


When does it fail…

Often, all too often!

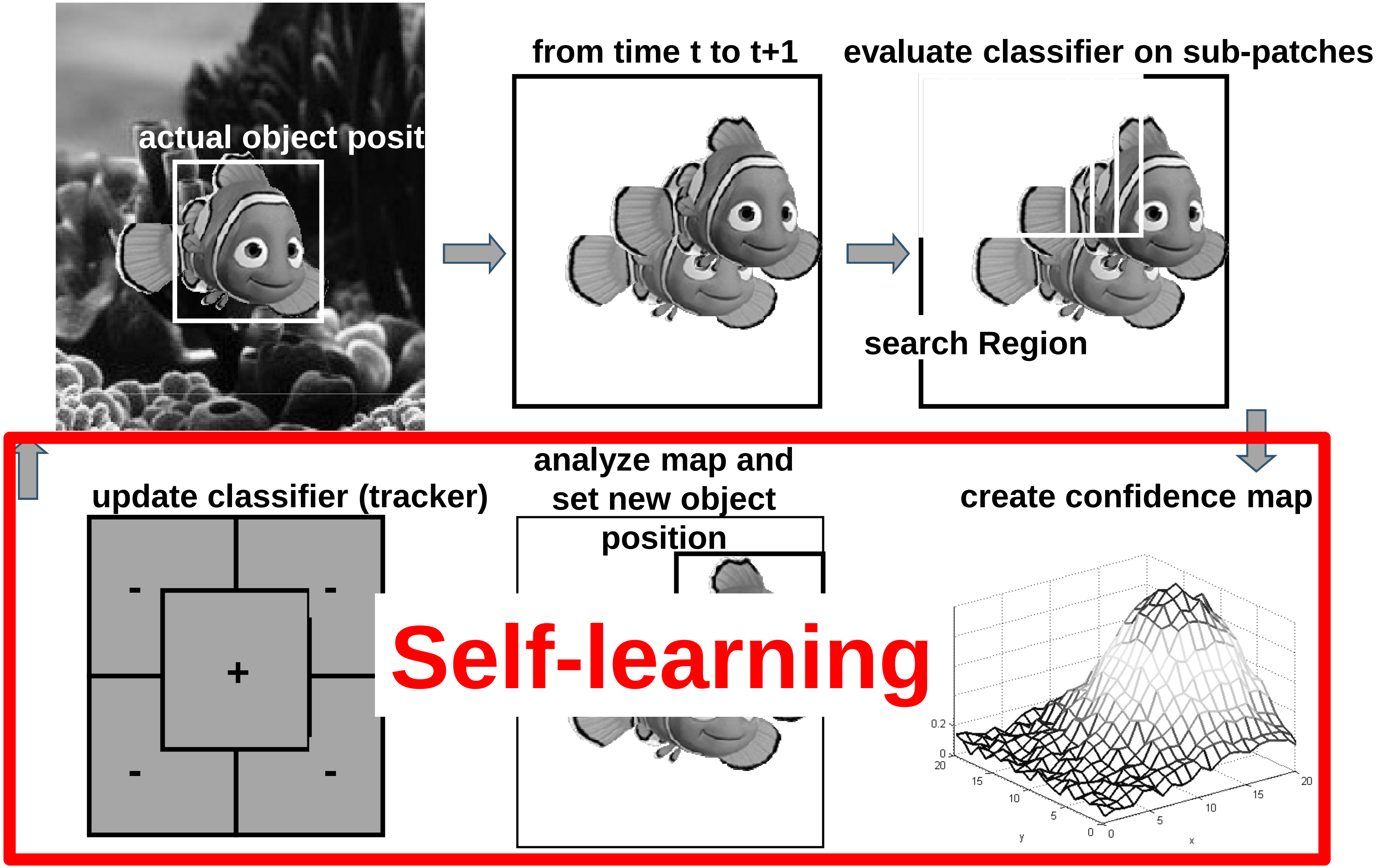
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

When does it fail…



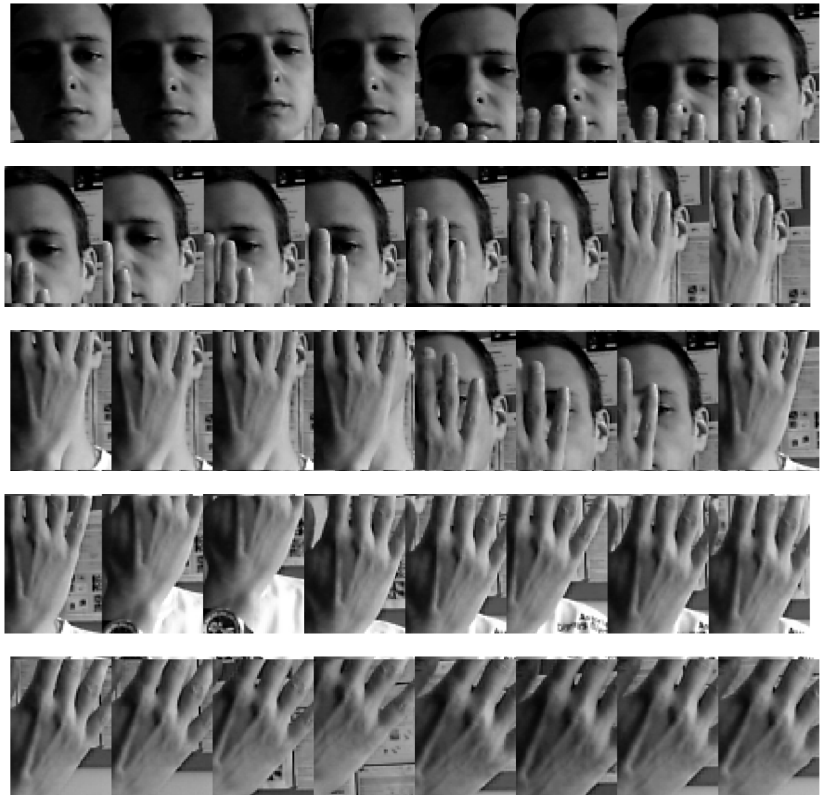
WHY?

2009/08/18, Southampton | H. Grabner, Tracking for Learning and Lessons Learned from it - ETH-Zurich, Computer Vision Lab | 29

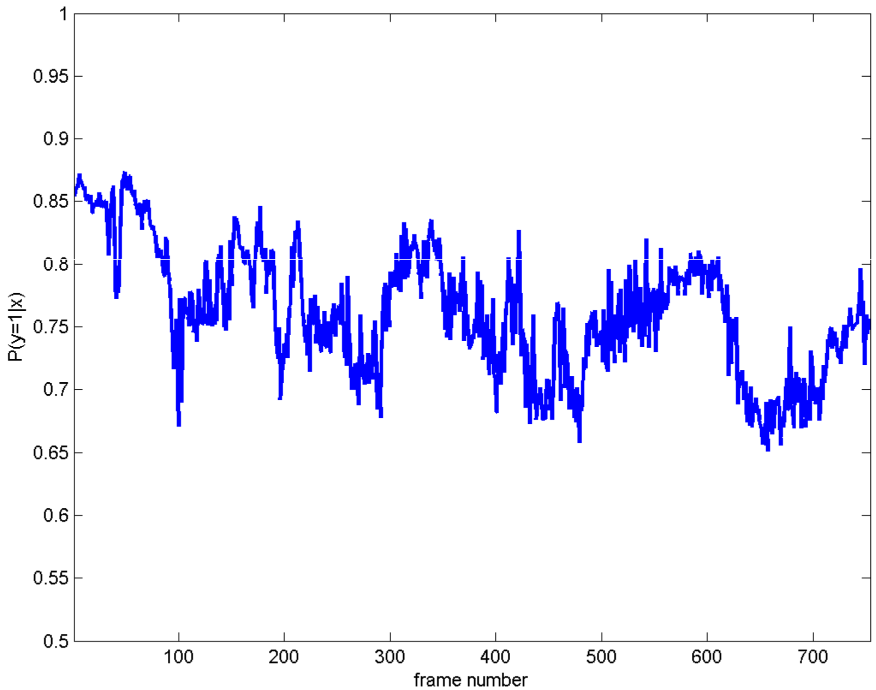

actual object posit
from time t to t+1
evaluate classifier on sub-patches
search Region
update classifier (tracker)
analyze map and
set new object
position
create confidence map
-
-
+
-
-
Self-learning
0.2
0
20
15
10
5
0
y
0
5
10
15
20
x

Drifting due to self-learning policy

Tracked Patches



Confidence



Lesson learned 2

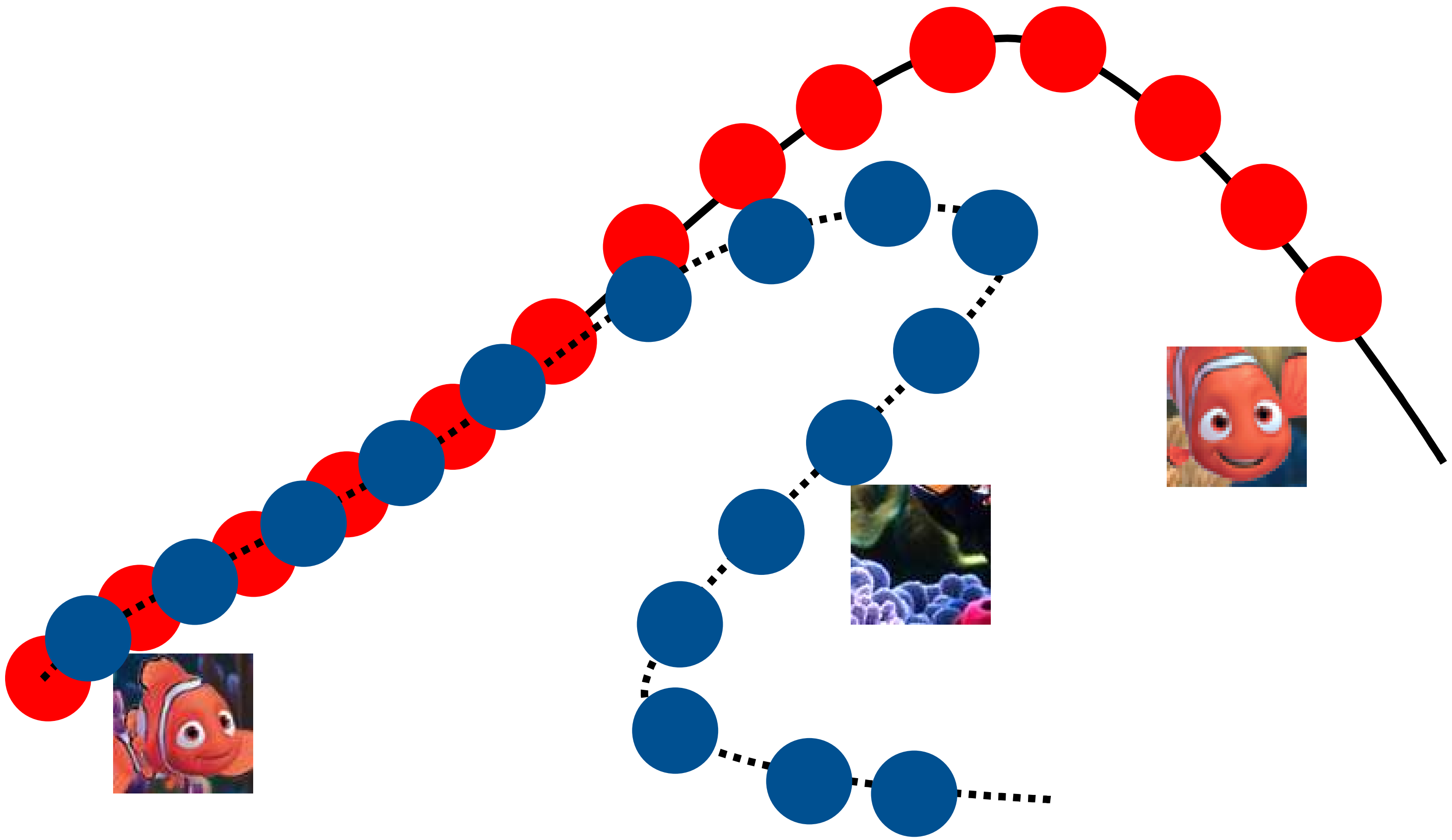
Self-learning → drifting!

PART II

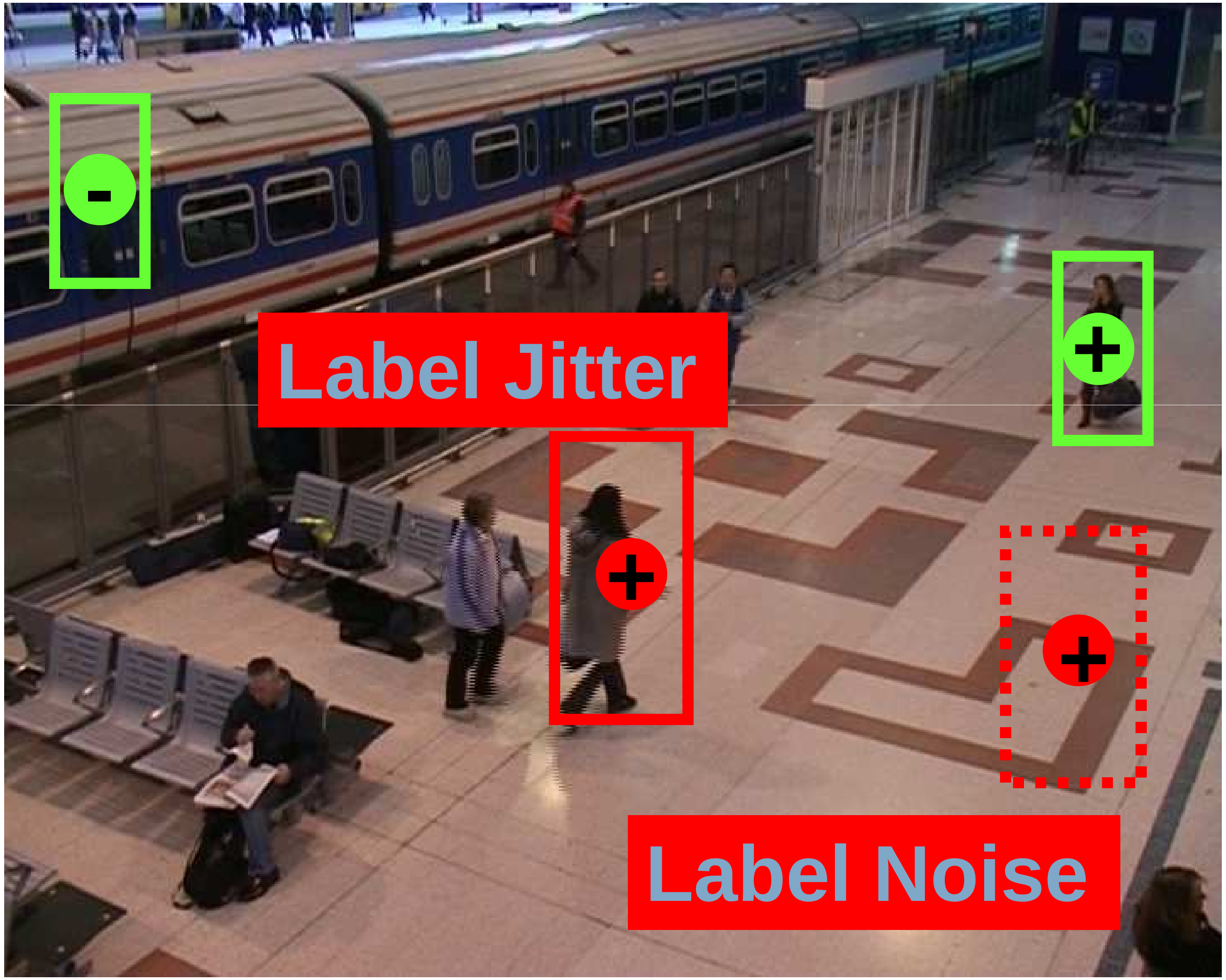
Semi-Supervised On-line Boosting for Tracking

ECCV'08

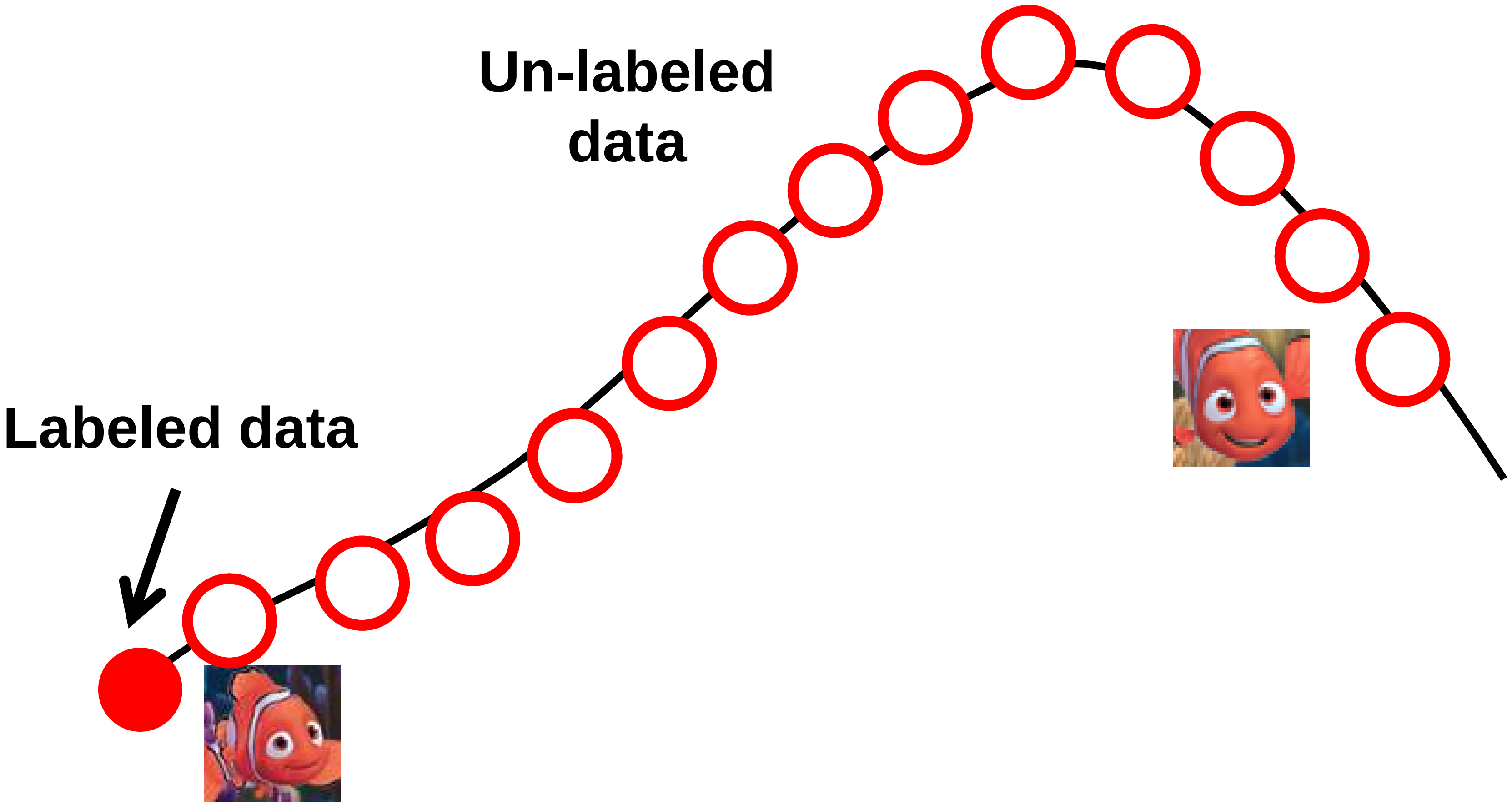
Review: Supervised Tracking



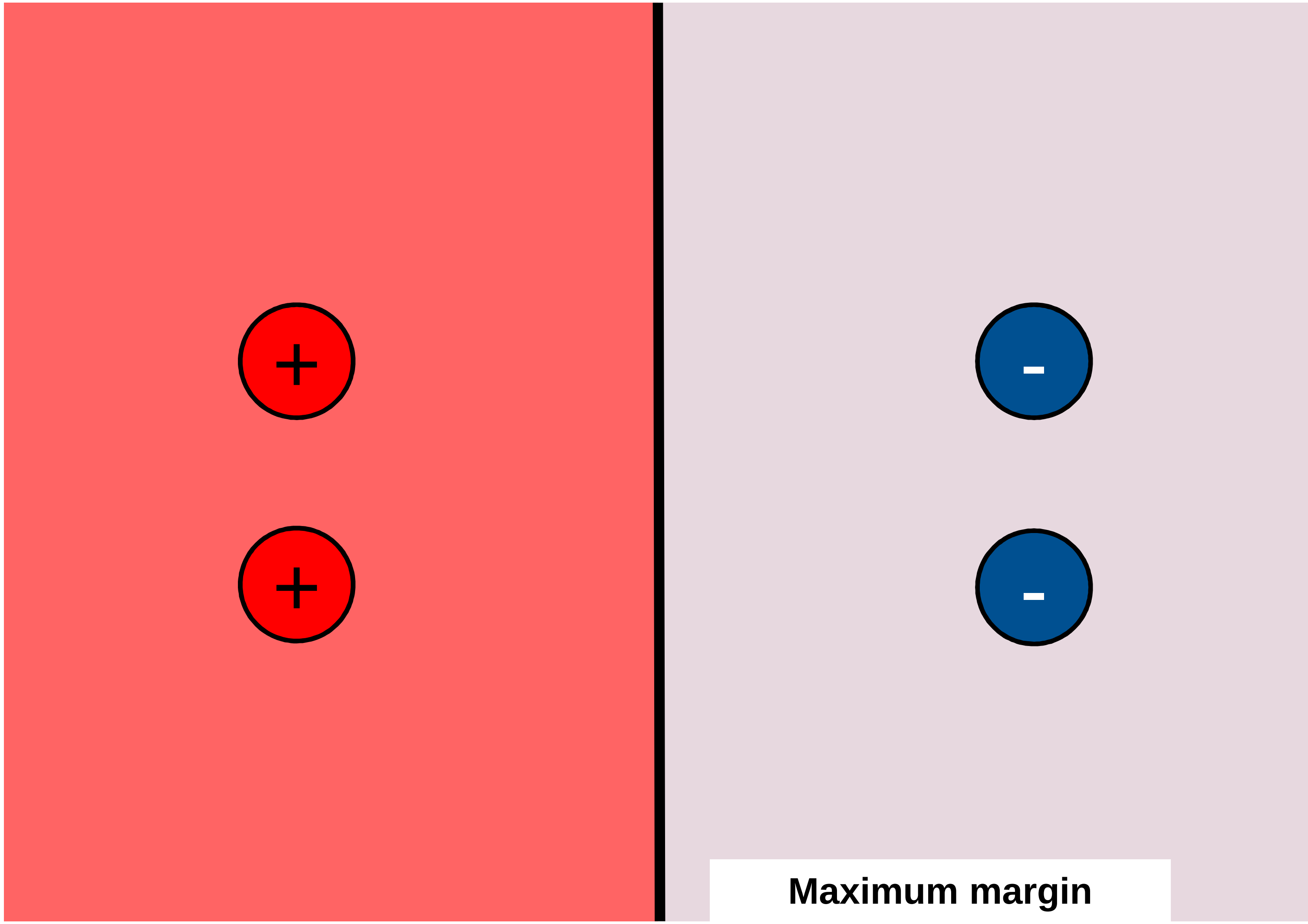
Problems of…



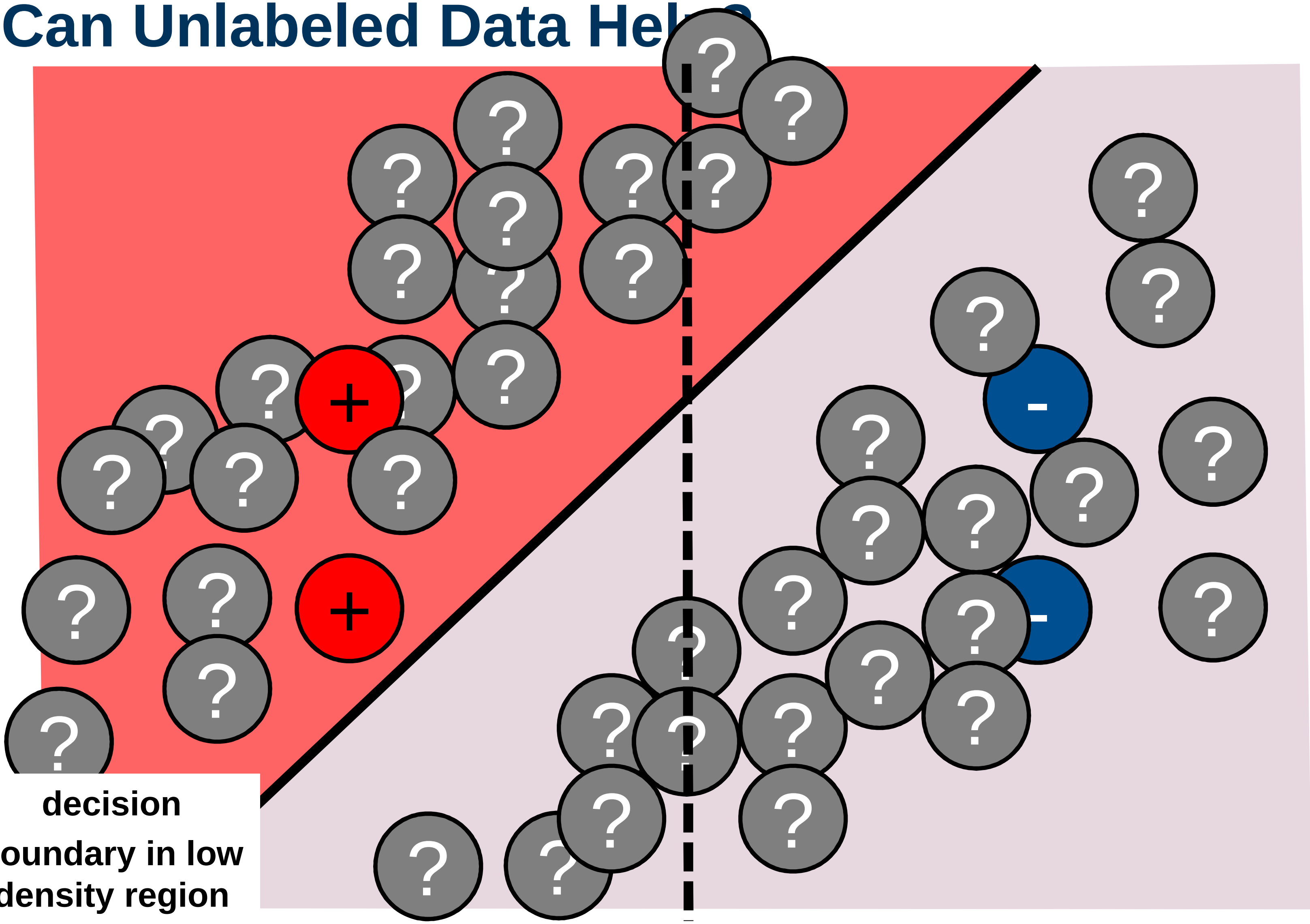
Semi-Supervised Tracking



Supervised learning



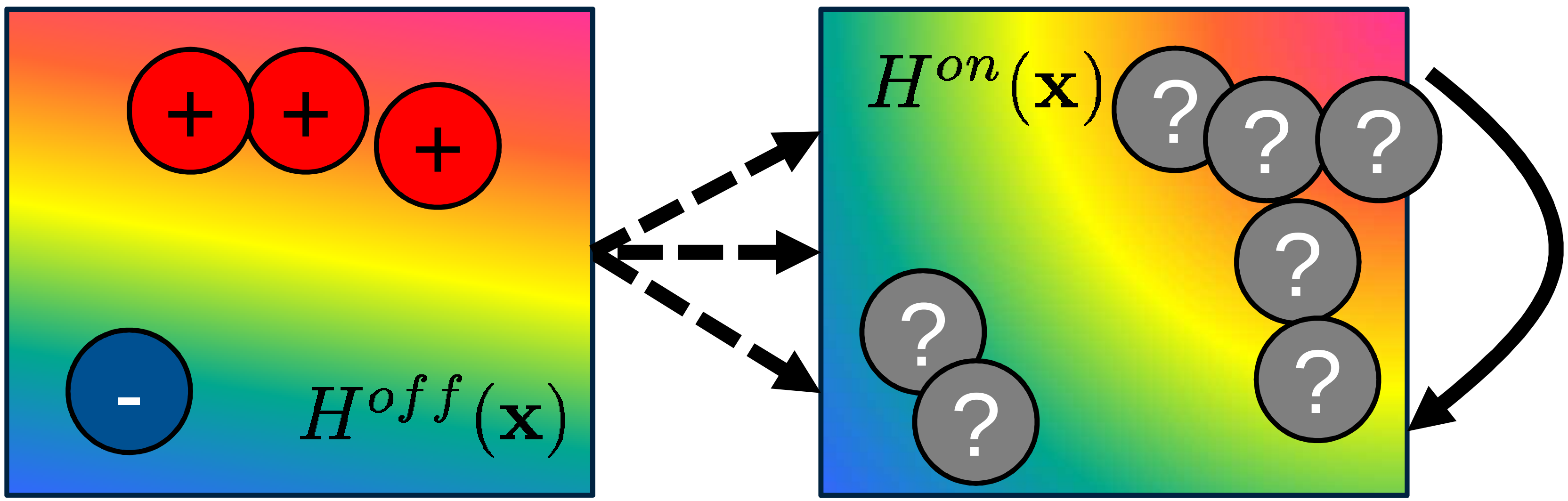
Can Unlabeled Data Help?



decision boundary in low density region

Semi-Supervised On-line Boosting

Prior



Semi-Supervised On-line Boosting

fix

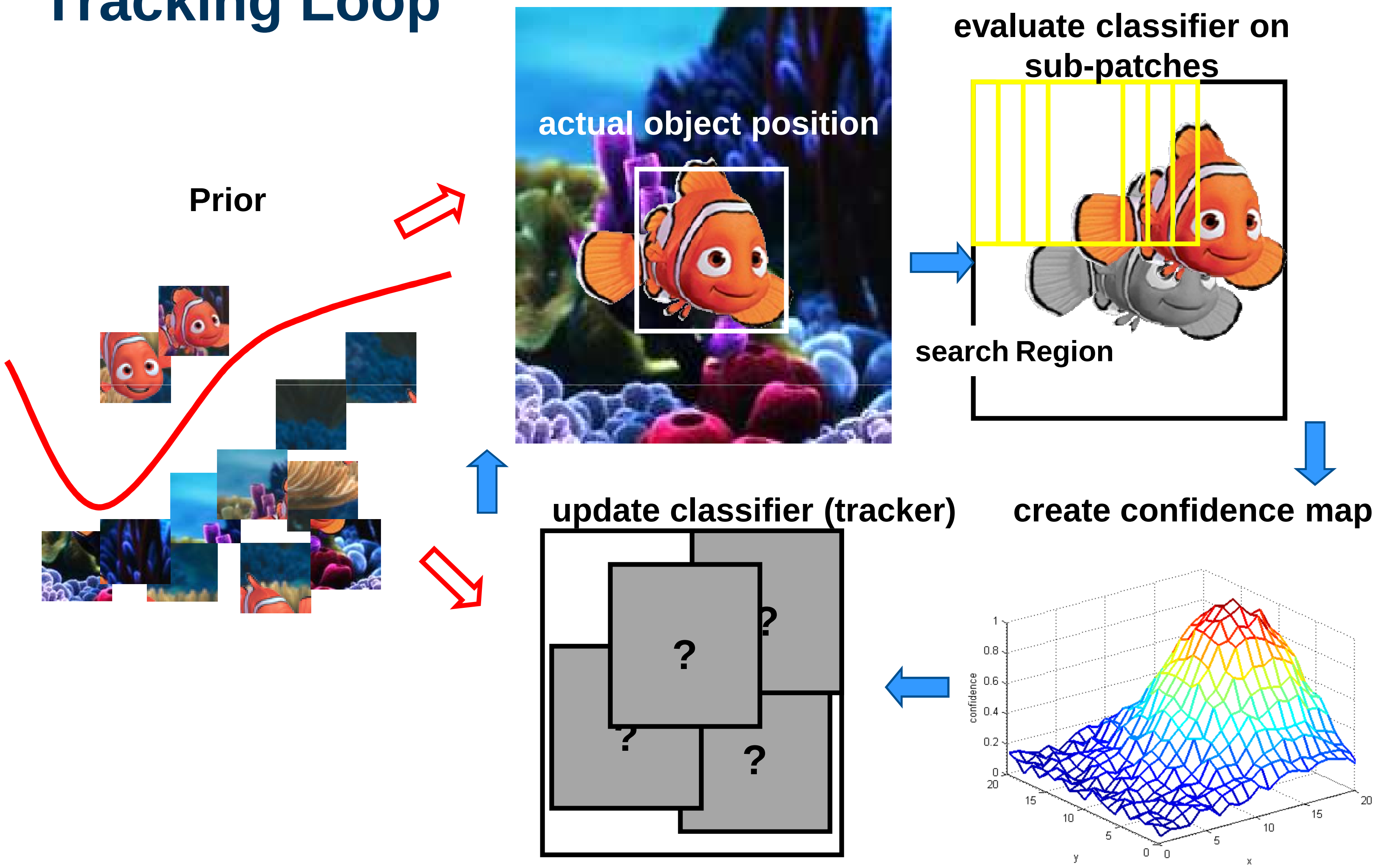
“stable”

dynamic

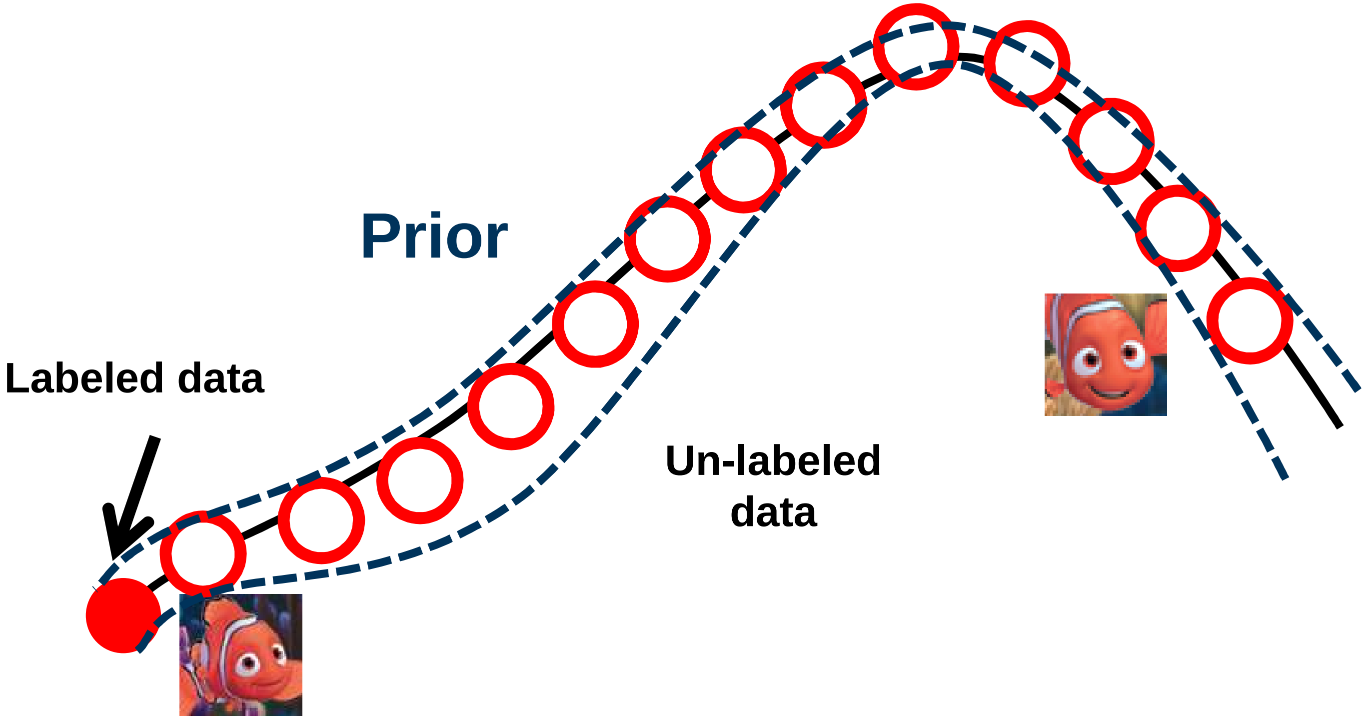
Nobody is perfect!
But, be a honest Teacher!

H^{off} (Prior) can be wrong with low confidence.

Tracking Loop



Object Detector	Our approach	Object Tracker
Fixed Training set General object detector	Fixed Prior for updating an Adaptive on-line classifier	On-line update Object vs. Background



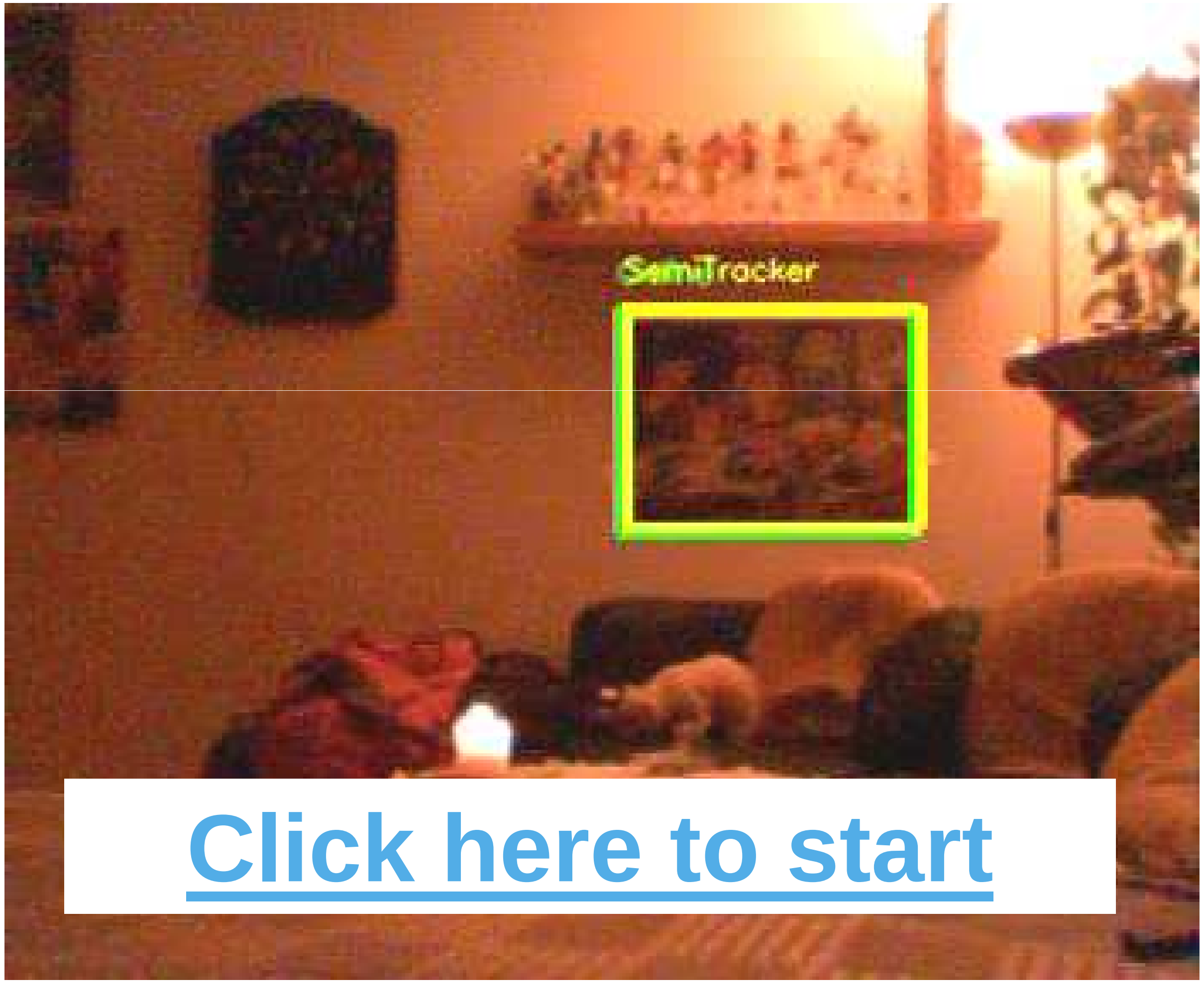
LESSON LEARNED 3

On-line Semi-supervised learninig $\rightarrow$ limited drifting.

Occlusions

Object disapearance

Long term tracking (1h)

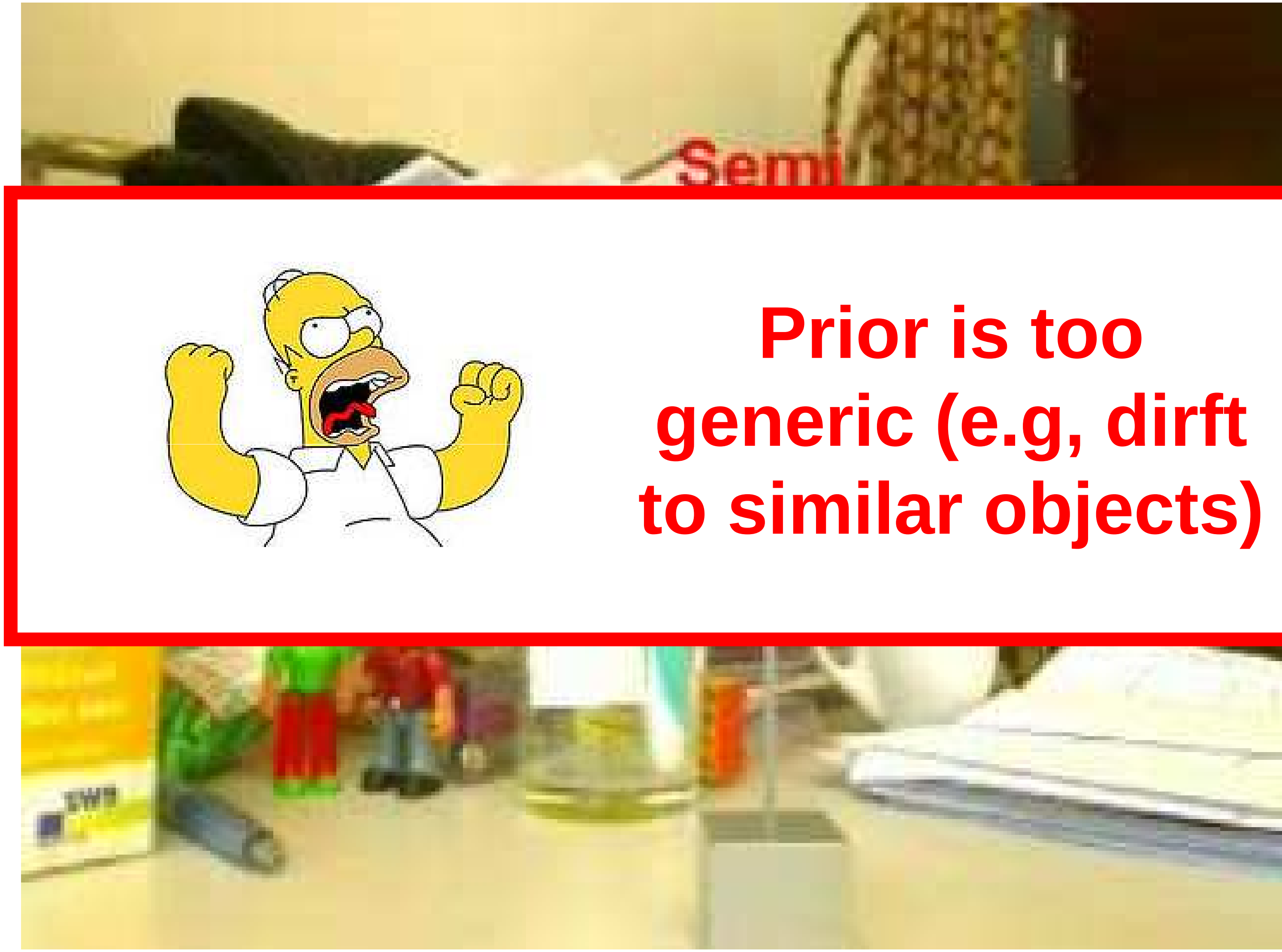


Click here to start

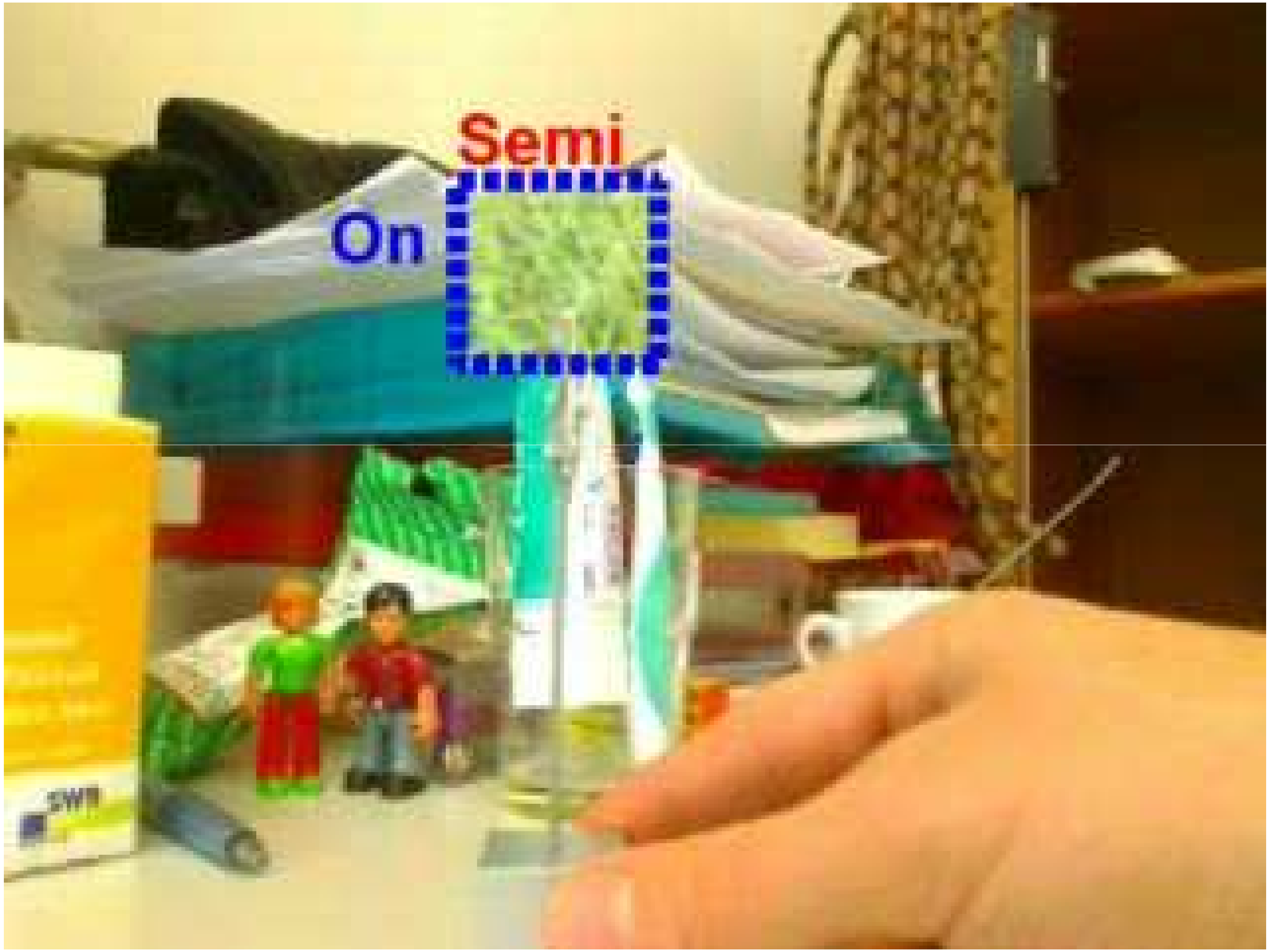
Tracking Solved ☺

Does it fail?
If yes, when?


Semi
On



Prior is too generic (e.g, dirft to similar objects)


Semi
On

Prior restricts too much (e.g., partial occlusions)

Lesson learned 4

Prior is essential in semi-supervised learning.

(c.f., Stability Plasticy Dilemma)

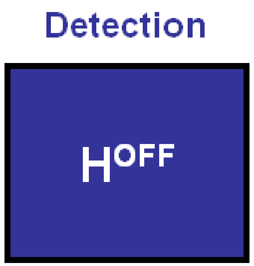
PART III

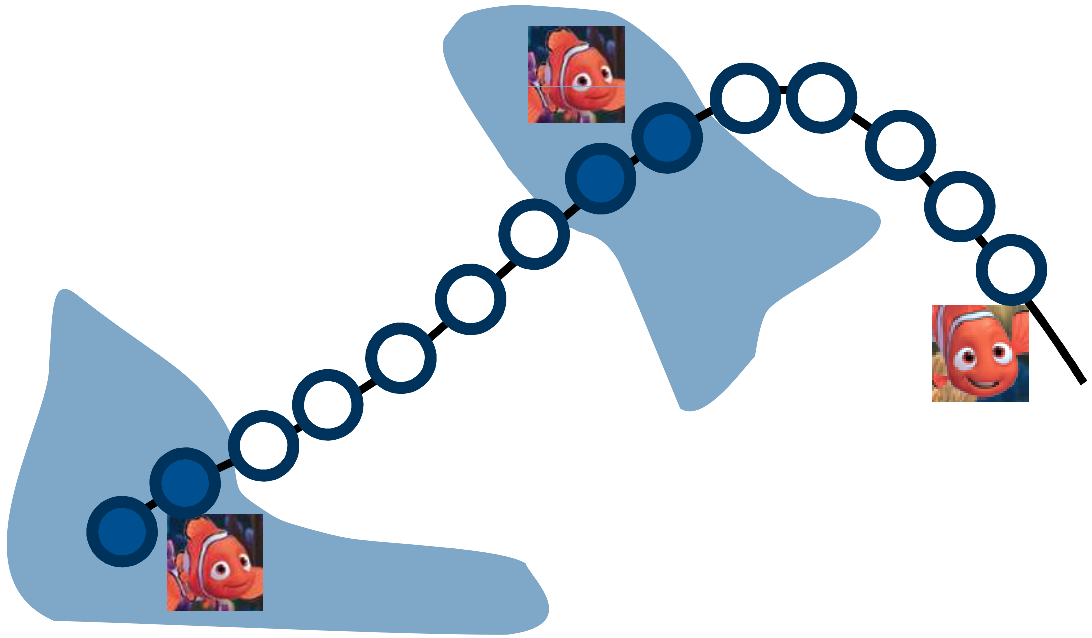
Beyond Semi-Supervised Tracking

ICCV'09 WS on On-line Learning for Computer Vision

Review: Detection

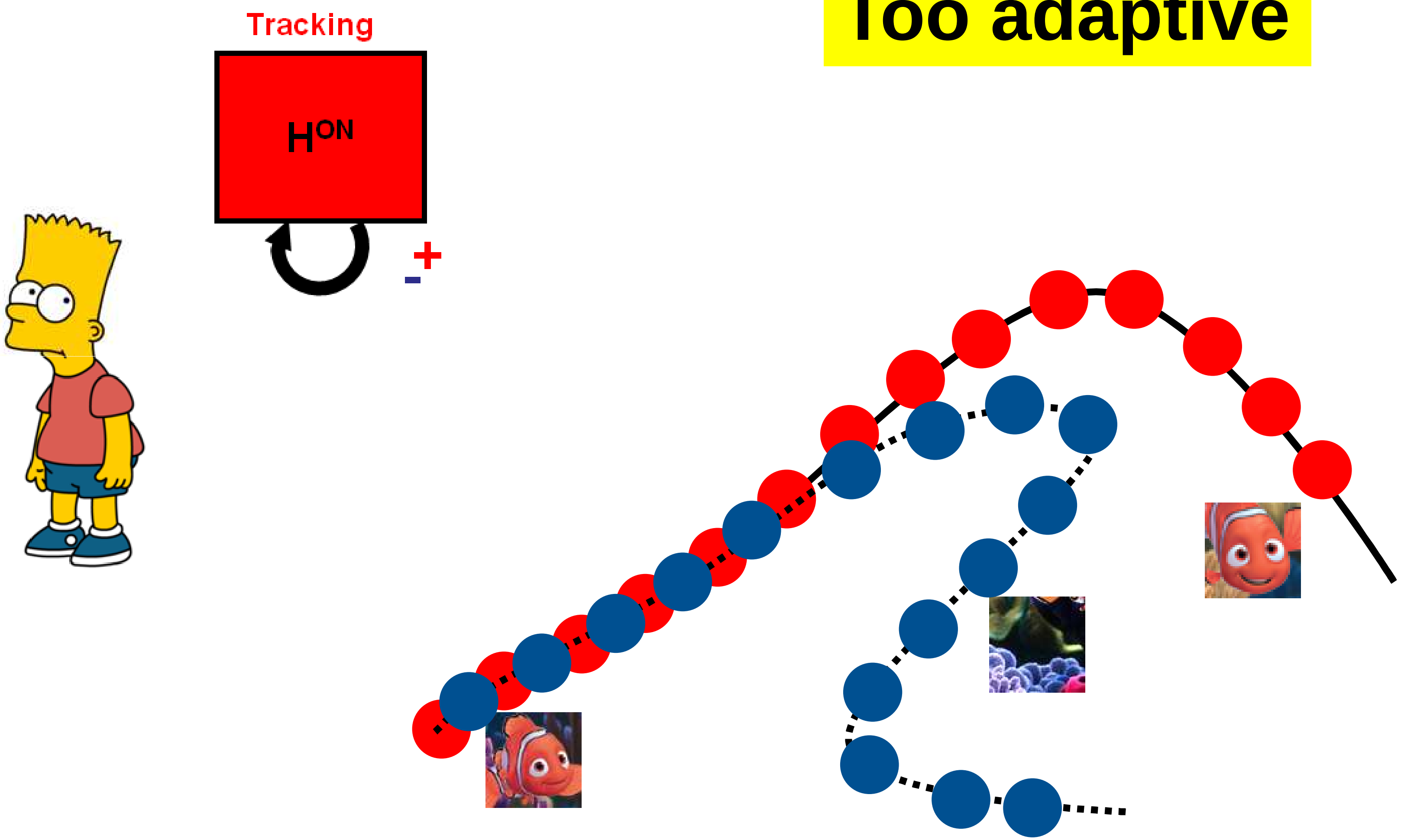
Non adaptive at all!





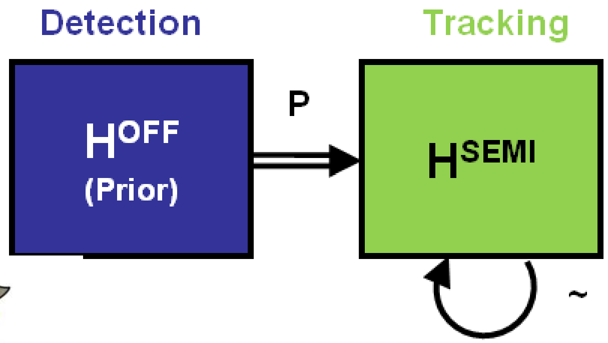
Review: Supervised Tracking

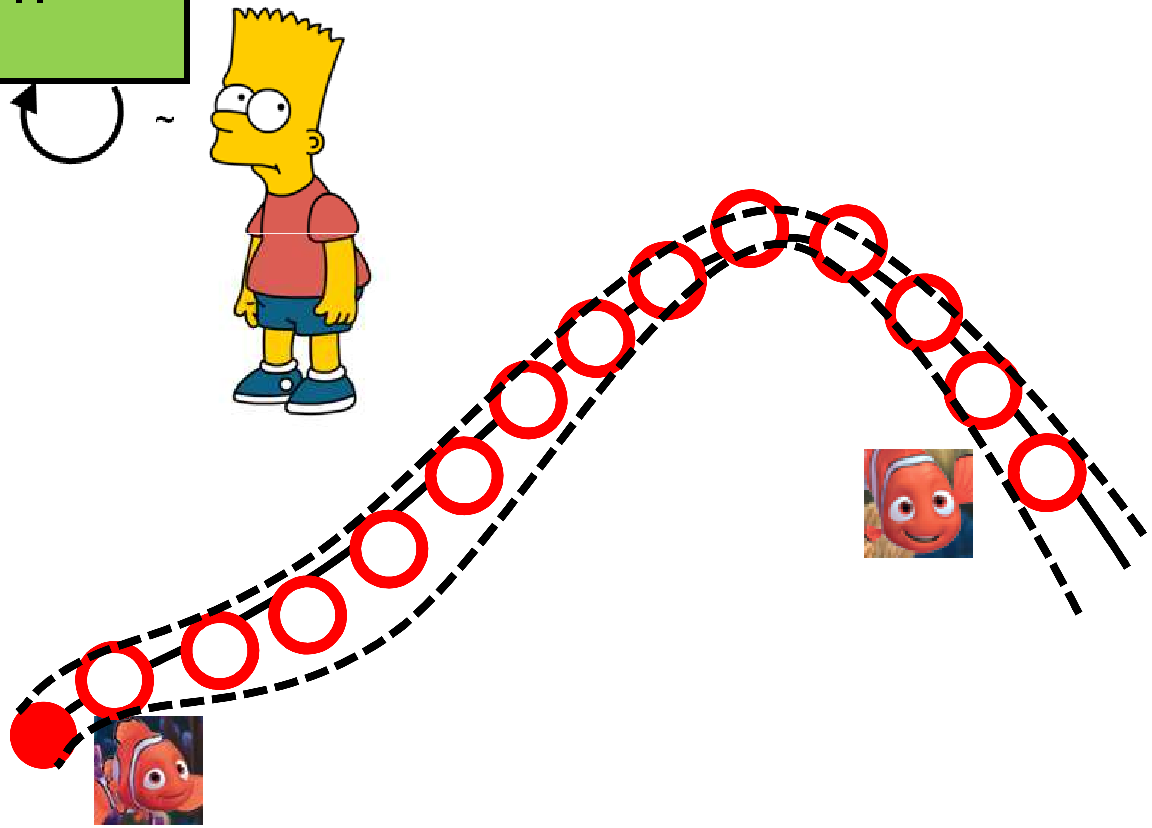
Too adaptive



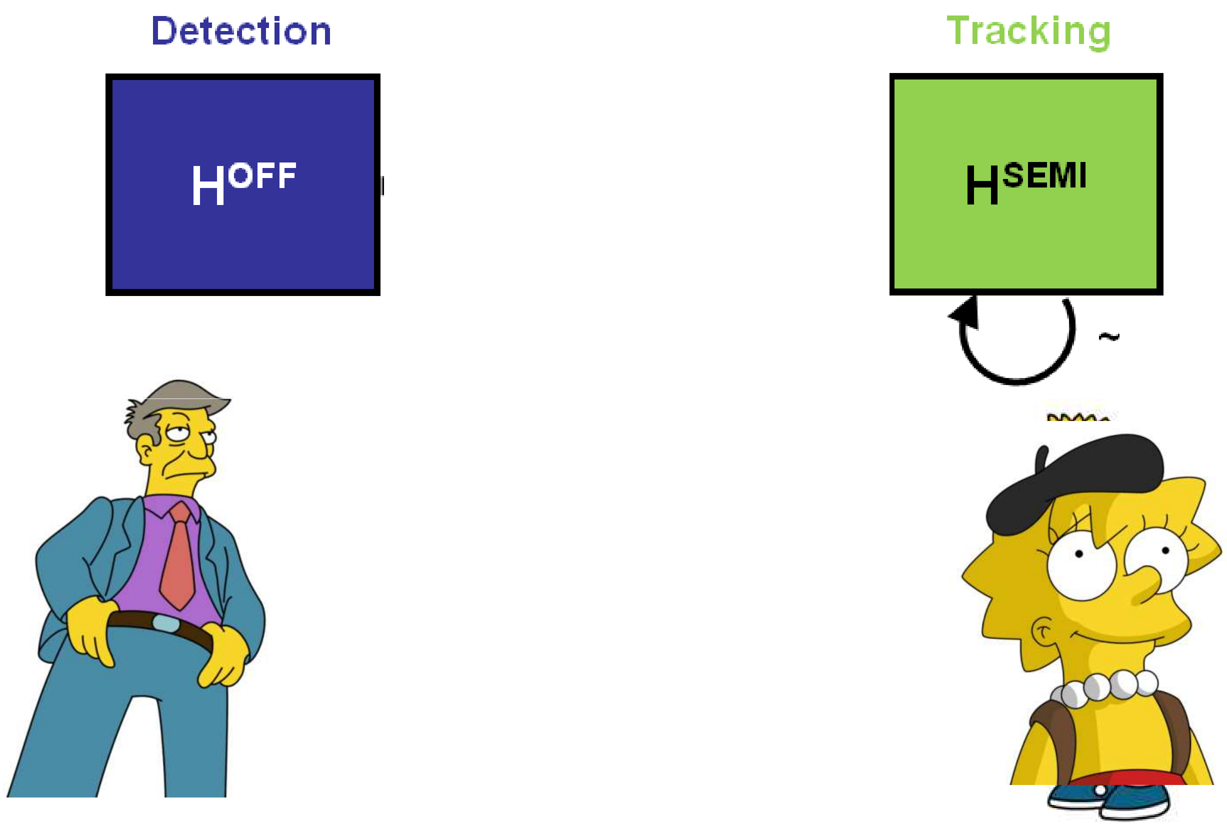
Review: Semi-Supervised Tracking

Limit drifting but too restrictive / general

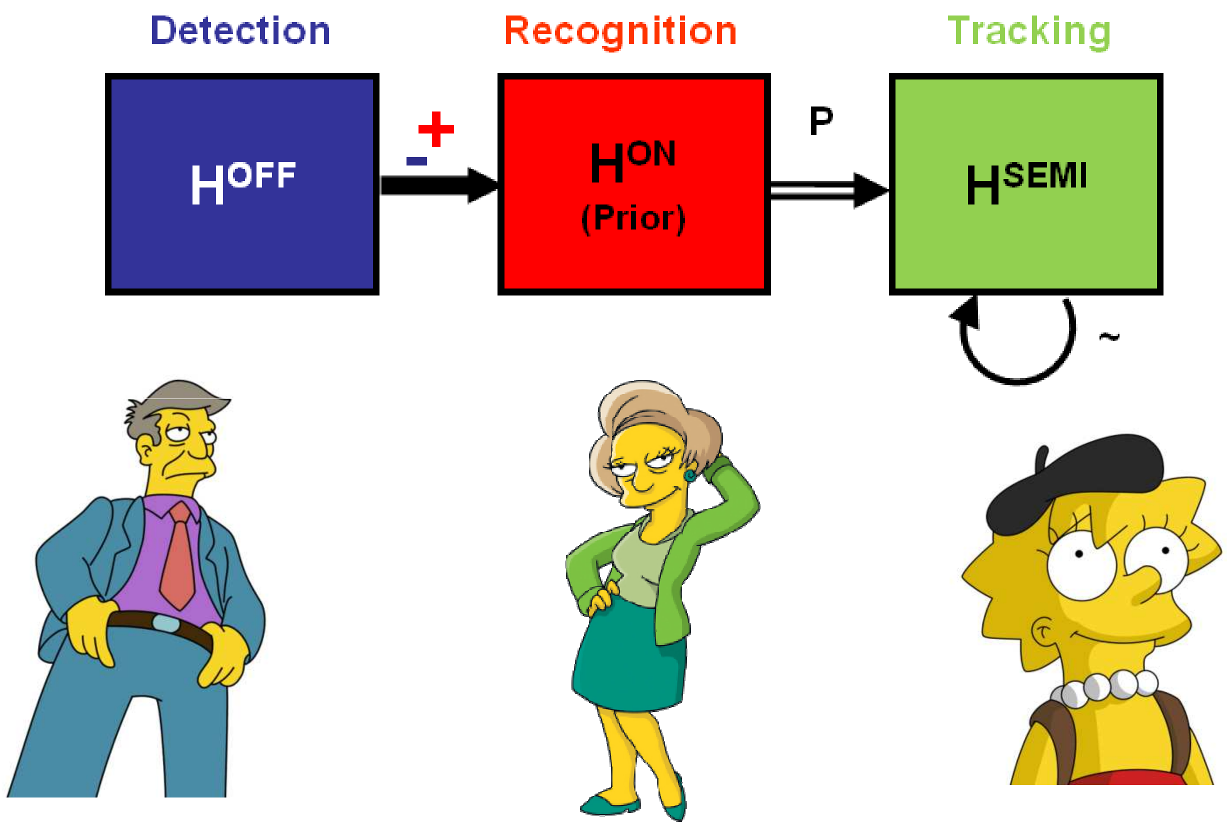




NEW PRINCIPLE: Active Sampling via Tracking

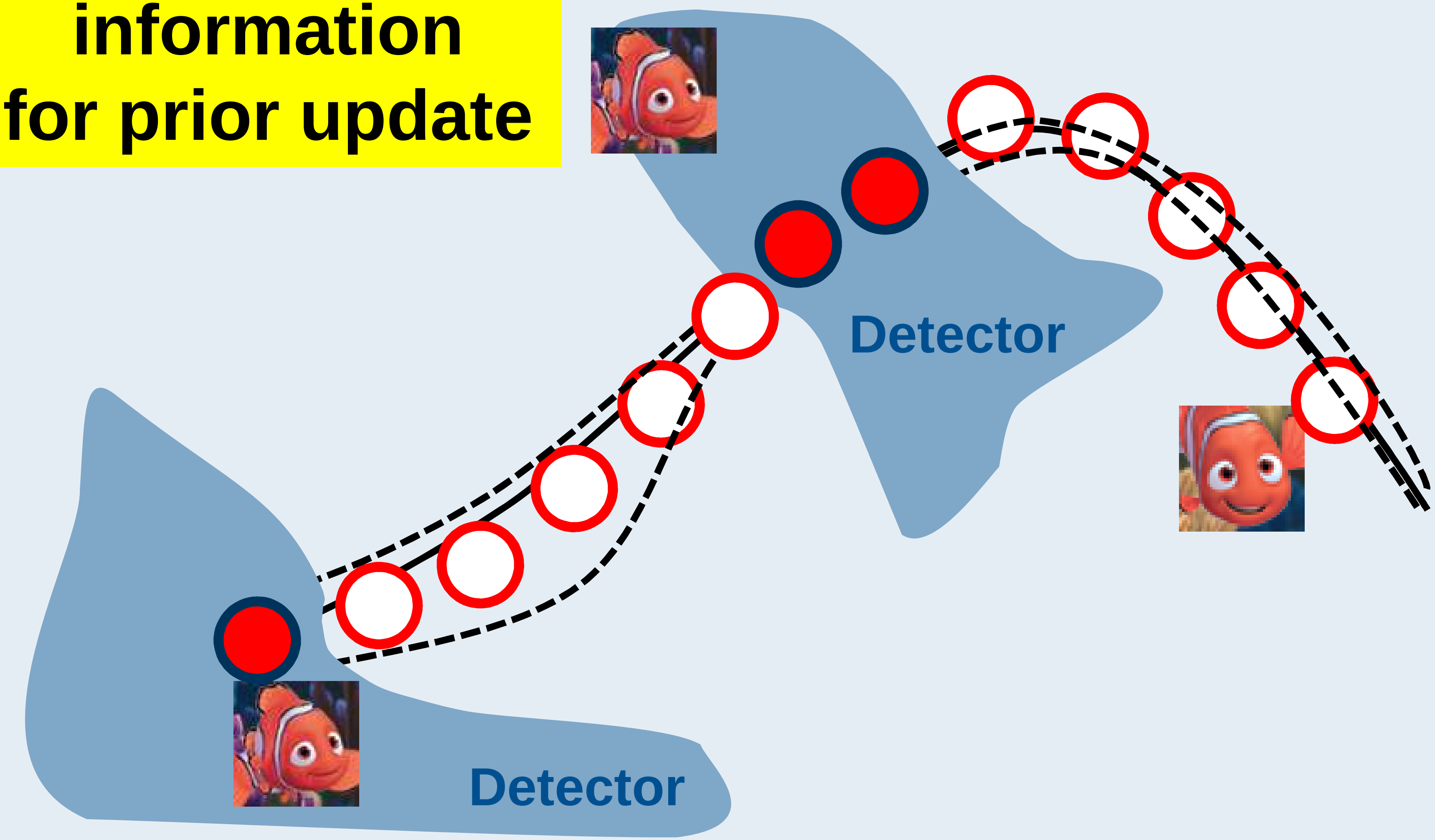


NEW PRINCIPLE: Active Sampling via Tracking

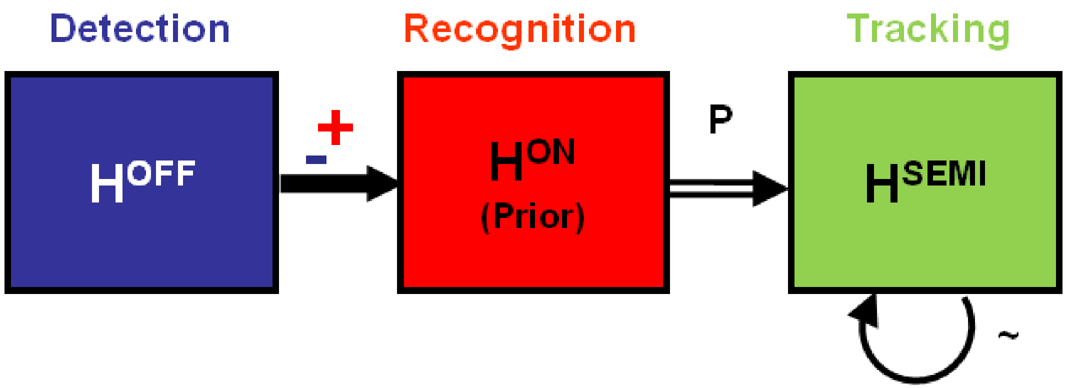


NEW APPROACH: Adaptive Prior

Additional information for prior update



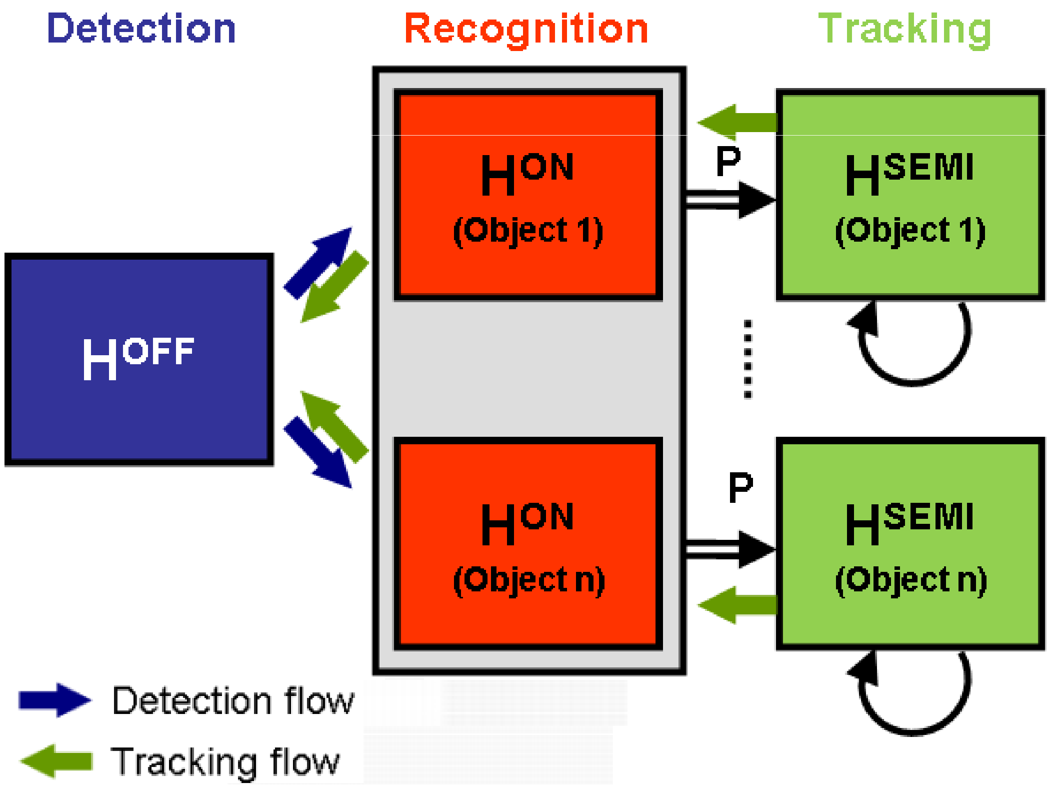
Specializing (Simplifying)



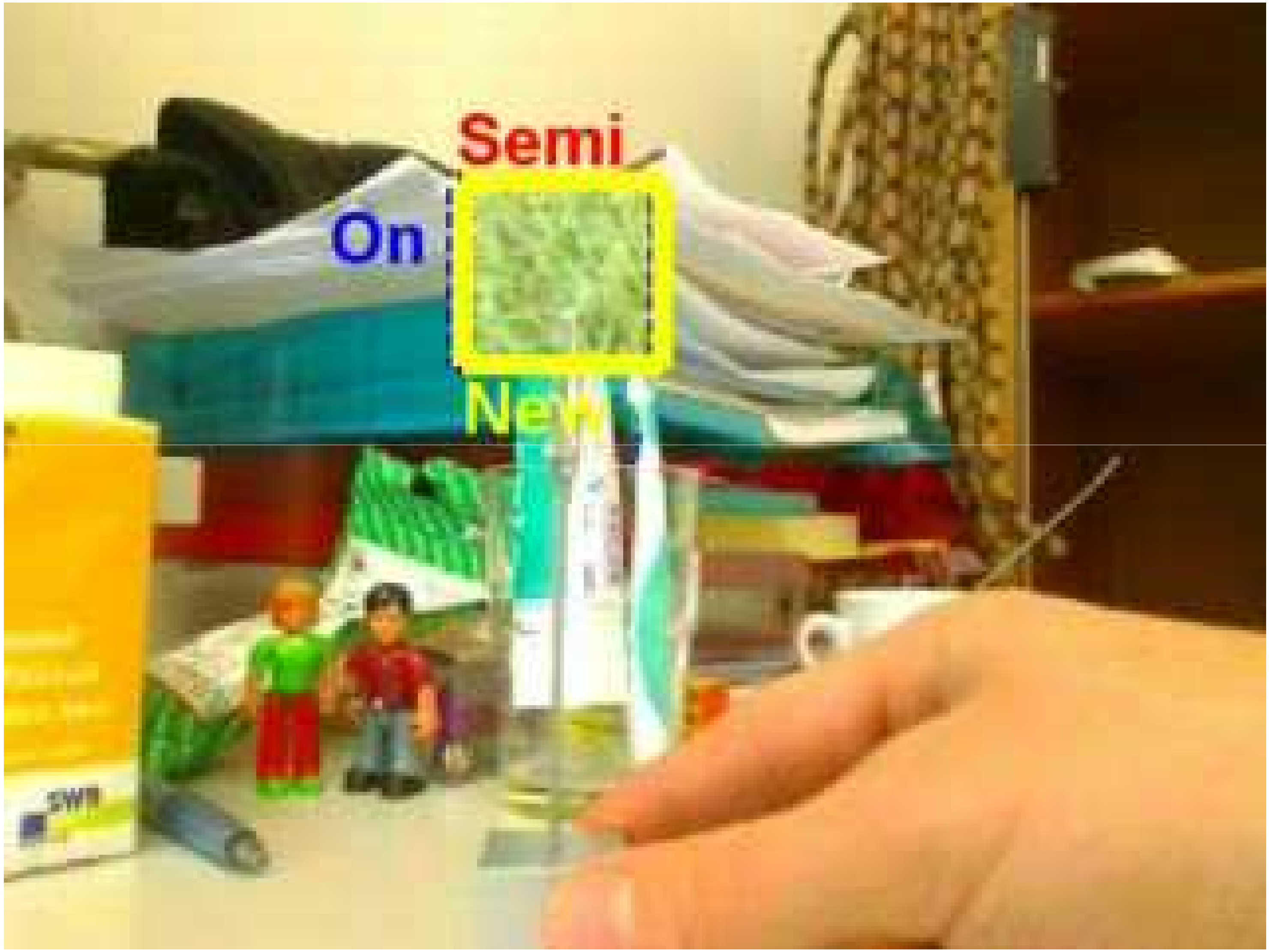
Updates	No	Few trustful	Many semi-supervised
Learning task	Object class **vs.** everything else	Particular objects **vs.** other objects and background	Current Object appearance **vs.** local surrounding
Applicable	Any time, everywhere	Current scene	Local neighborhood

Multiple classifier system

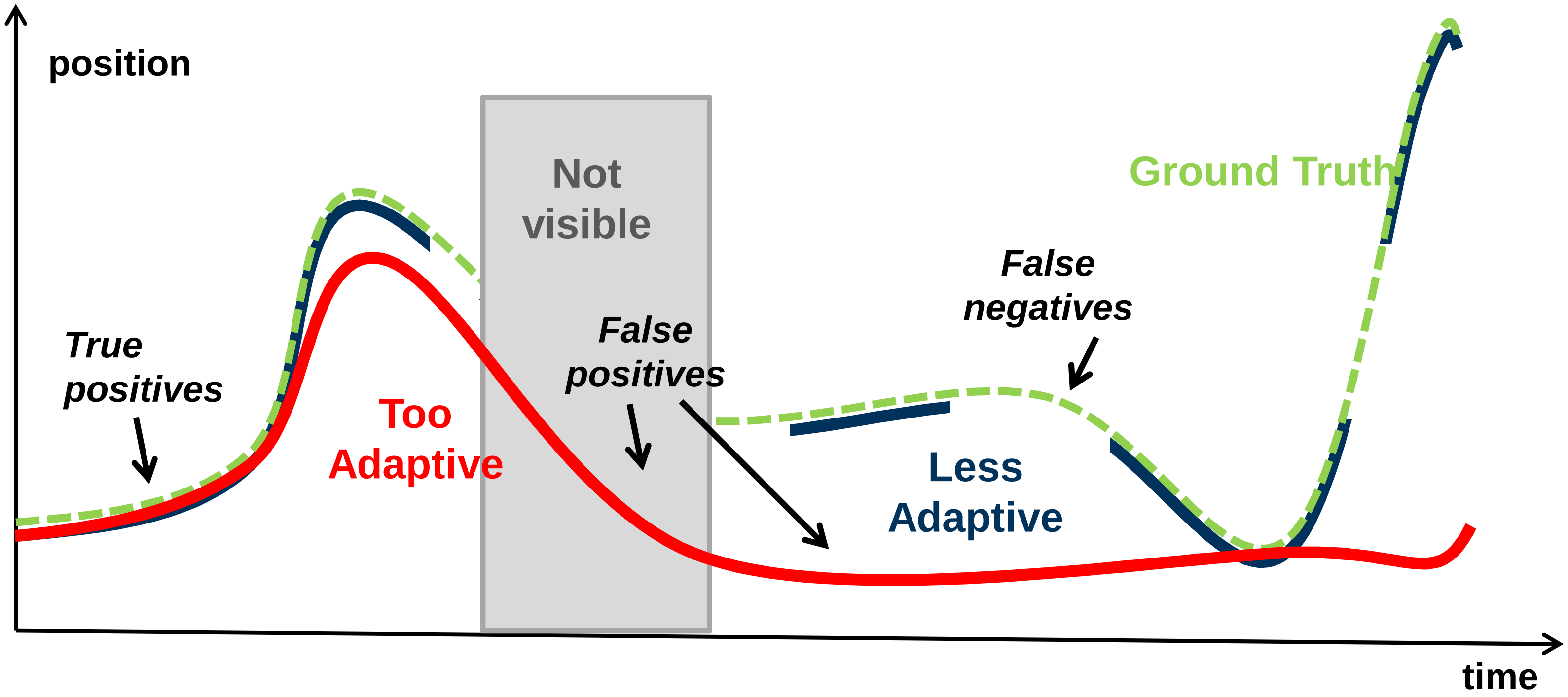
- `#include "vision.h"` use addition information, e.g., *multiple objects, background image*
- Information aggregation




Semi
On
New


Semi
On
New

Performance evaluation

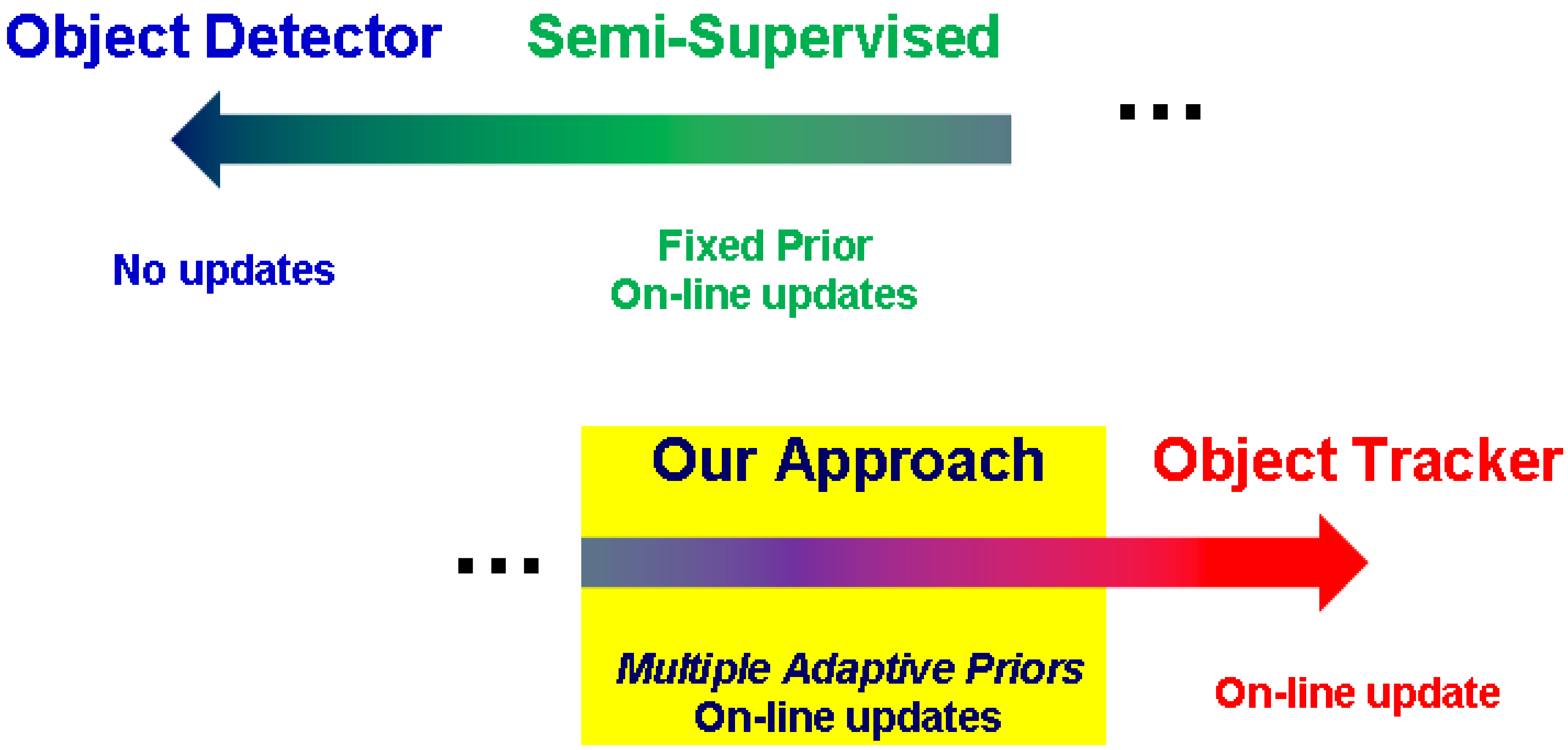


	On-line	Semi	Beyond Semi
recall	0.15	0.76	0.76
precision	0.89	0.32	0.99
f-measure	0.26	0.45	0.86

Implicit Occlusion handling

Really Long Term Tracking (24h)

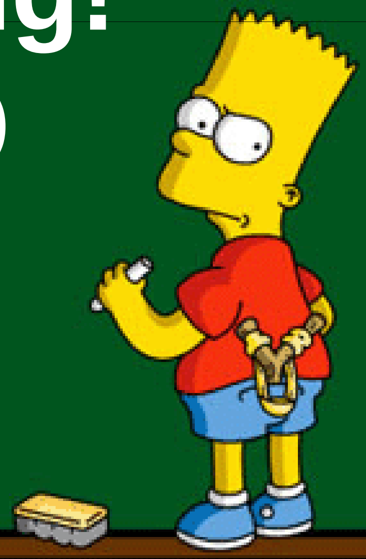
[Click here to start]


Object Detector
Semi-Supervised
...
No updates
Fixed Prior
On-line updates
Our Approach
Object Tracker
...
Multiple Adaptive Priors
On-line updates
On-line update

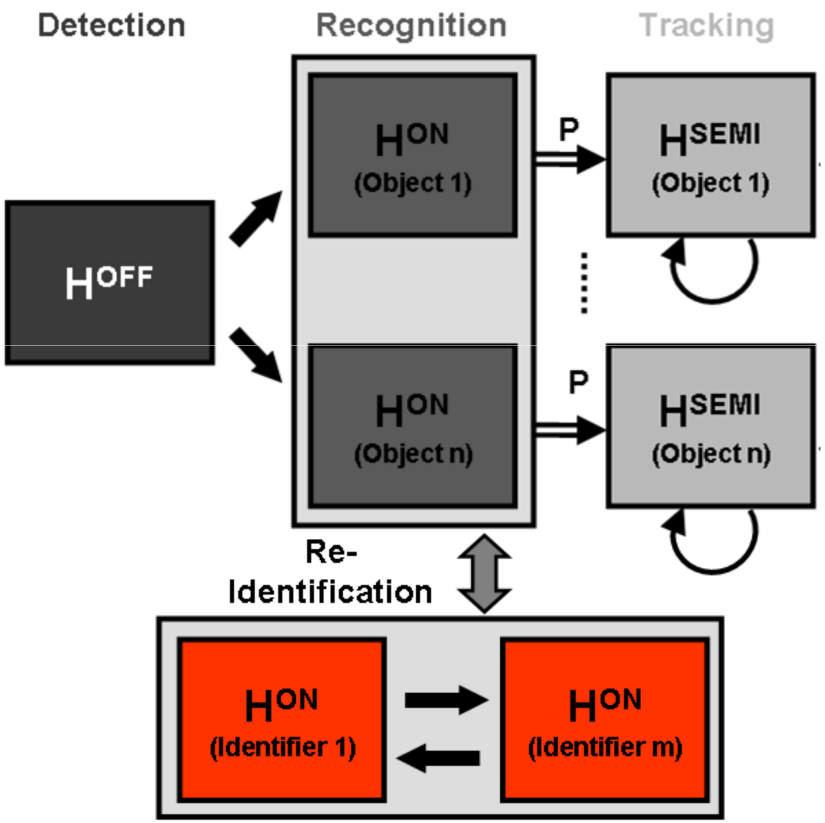
Lesson learned 5

Vision is more then pure Machine Learning!

(keep problems simple)

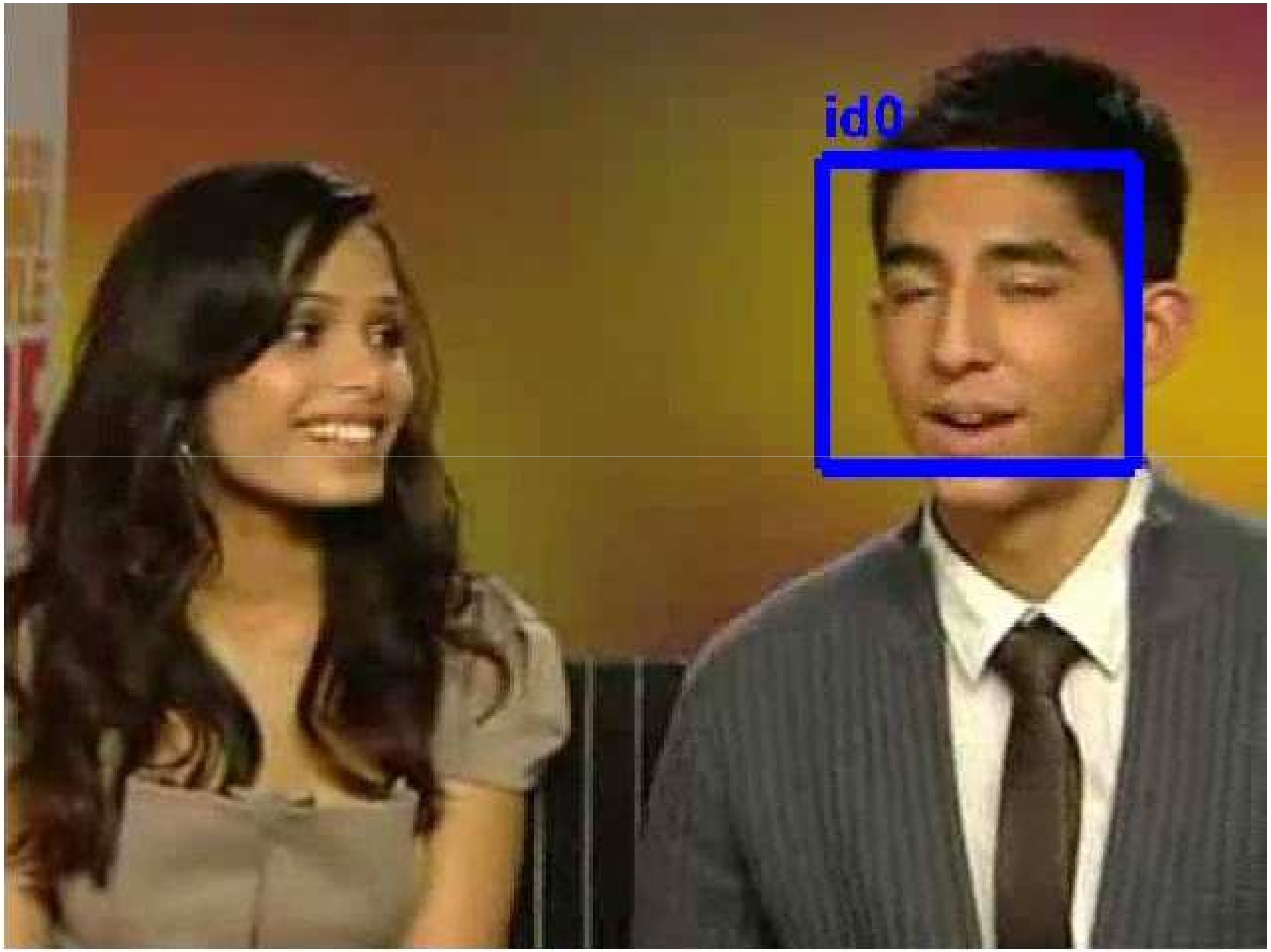


Extension 1: re-Identification

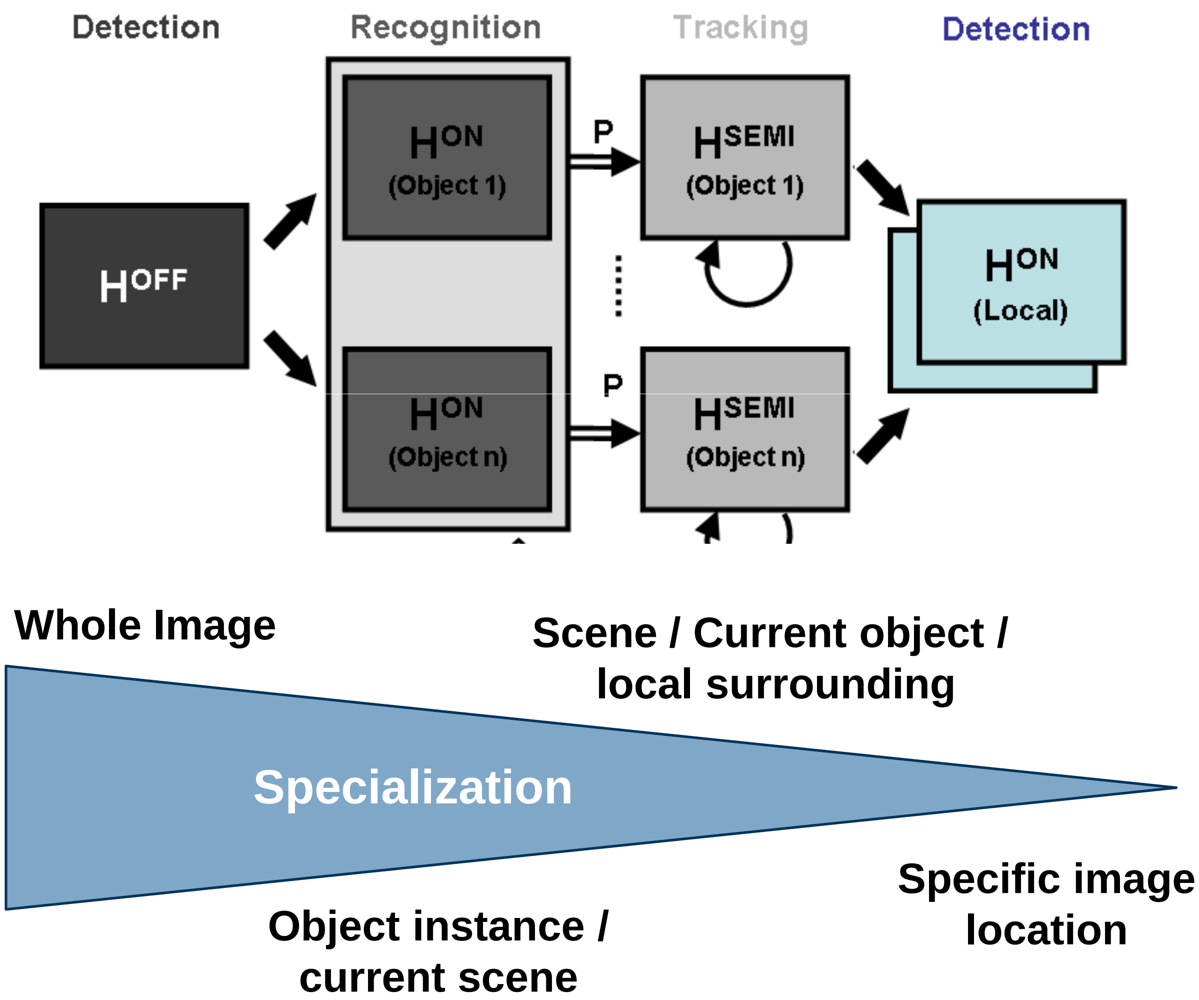


Identifier 1

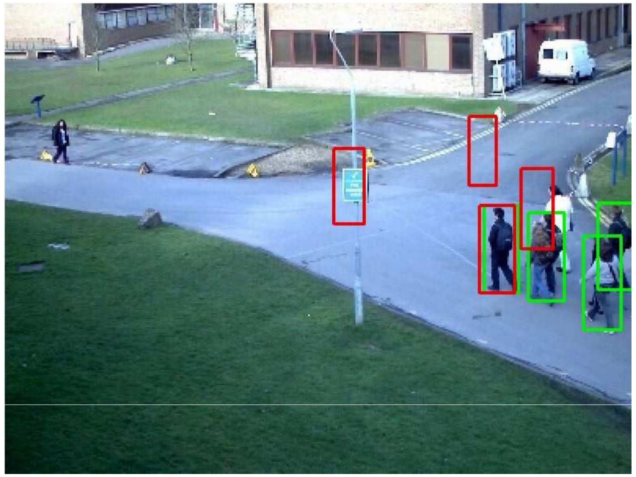
Identifier 2


id0

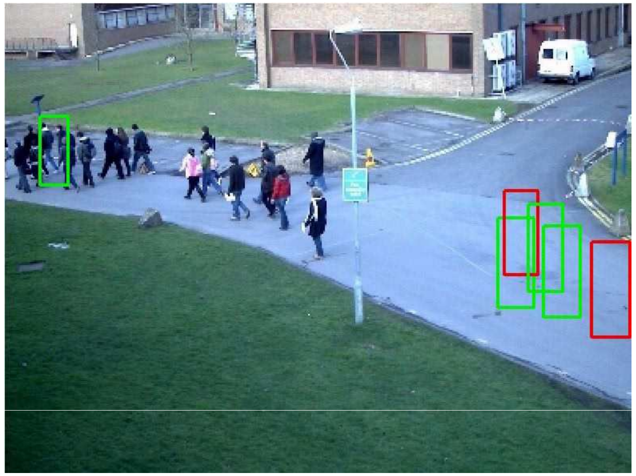
Extension 2: Information Aggregation



Pedestrian Detection (PETS)



Generic Detector & Context

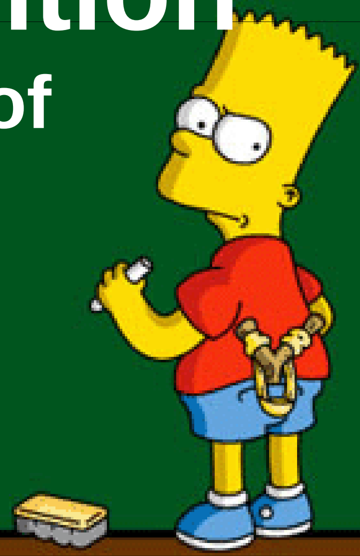


Proposed Approach

LESSON LEARNED 6

Vision ≠ Detection + Tracking + Recognition

(benefitting from a lot of – unlabeled – data)



Conclusion

Tracking is simple

Self-learning → drifting

Semi-Supervised learning

Prior ☠

Vision > Machine Learning

Vision ≠ Det. + Trac. + Rec.

Acknowledgments

Luc van Gool

Severin Stalder

EU-project SCOVIS under grant agreement no 216465.

Institute for Computer Graphics and Vision
Graz, University of Technology, Austria

Centere of Machine Preception
Czech Technical University

Horst Bischof

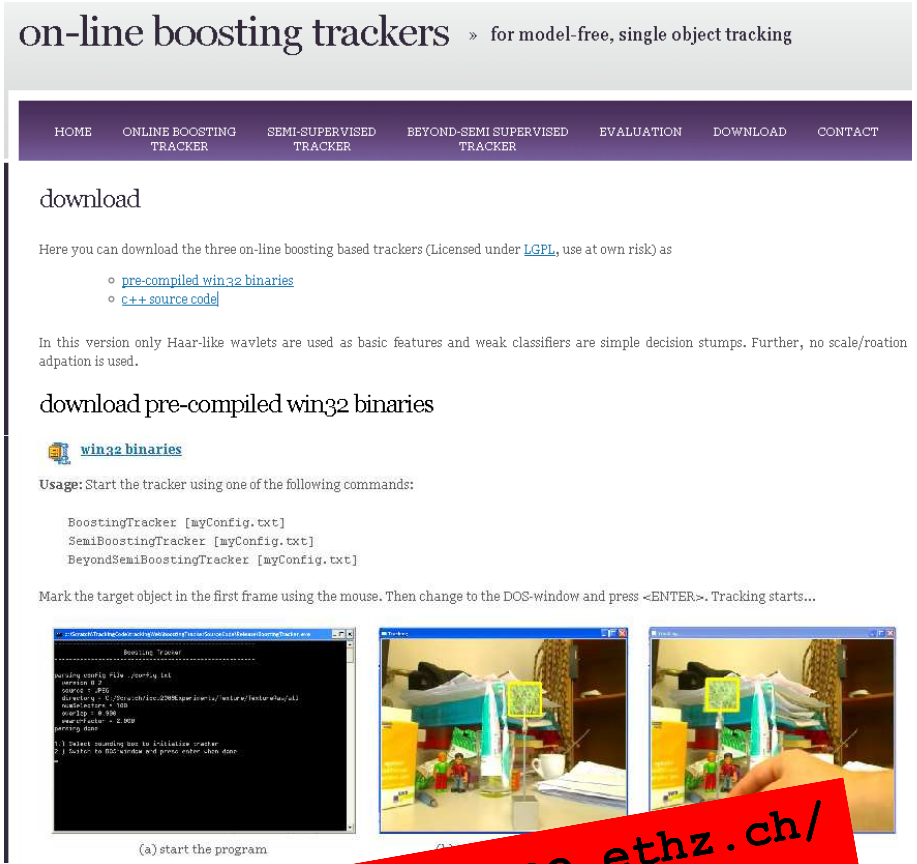
Michael Grabner

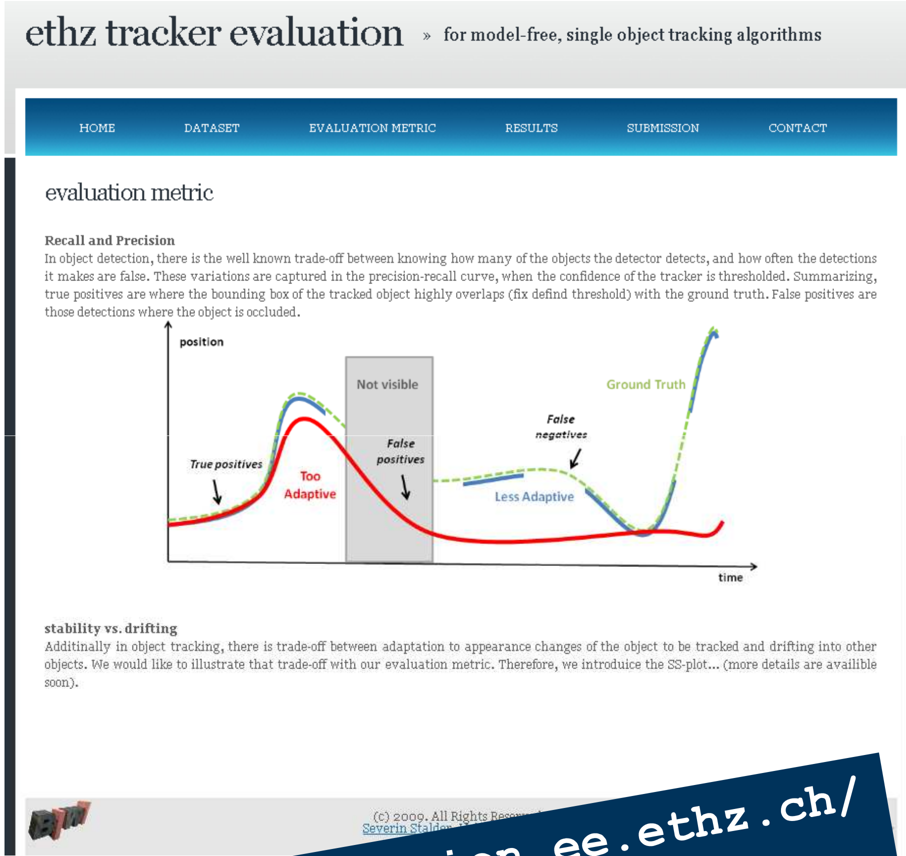
Christian Leistner

Jiri Matas

Jan Sochamn

Code/Demos & Tracker Evaluation



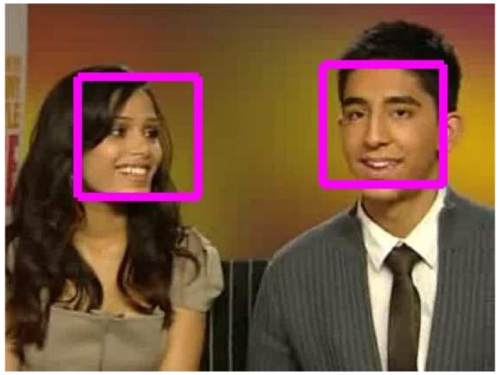


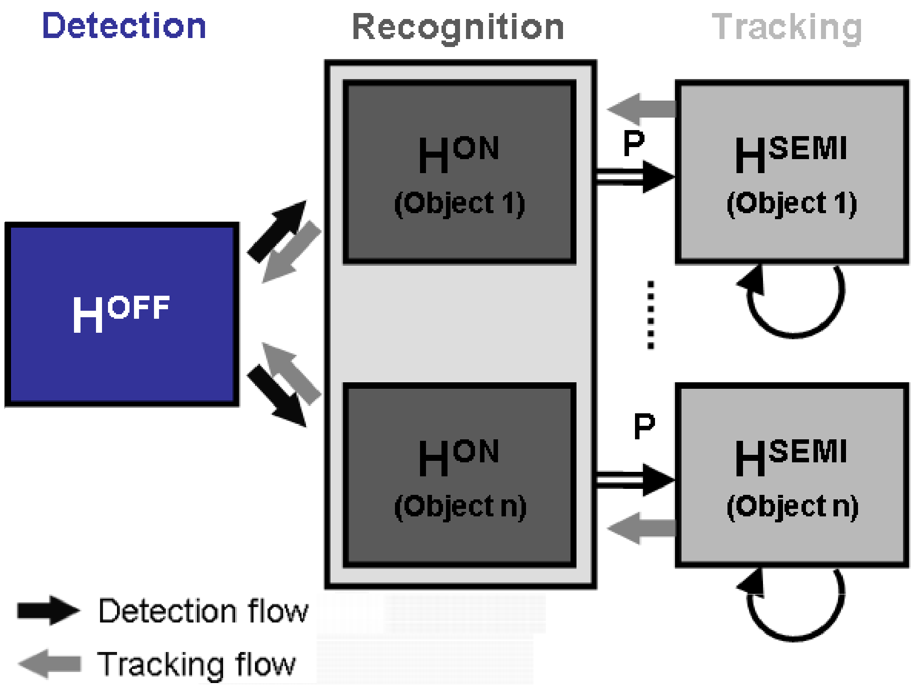
http://vision.ee.ethz.ch/boostingTrackers

http://www.vision.ee.ethz.ch/trackerEvaluation

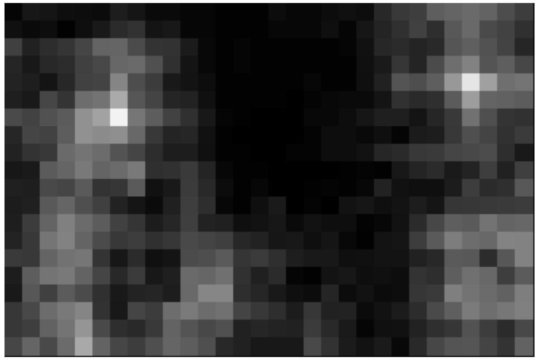
Additional Slides…

Detector





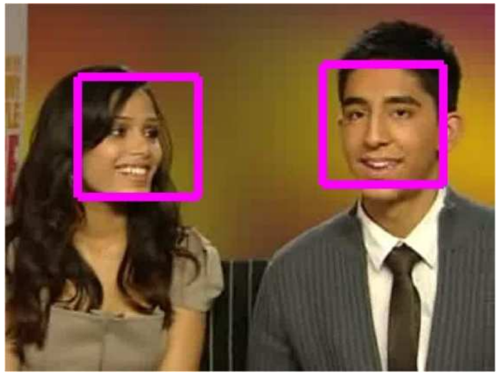
Valid samples

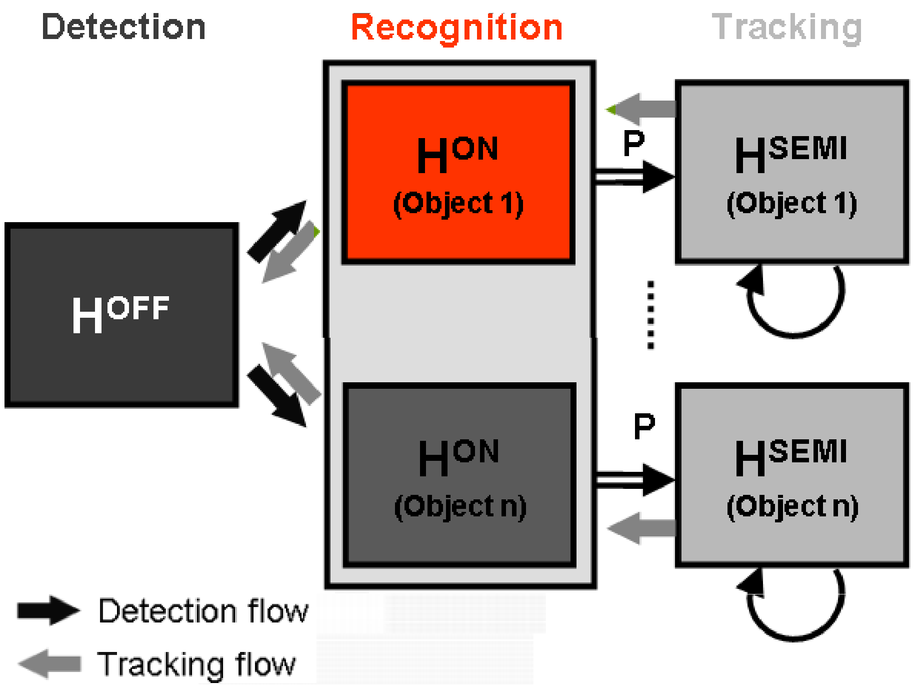


Confidence map

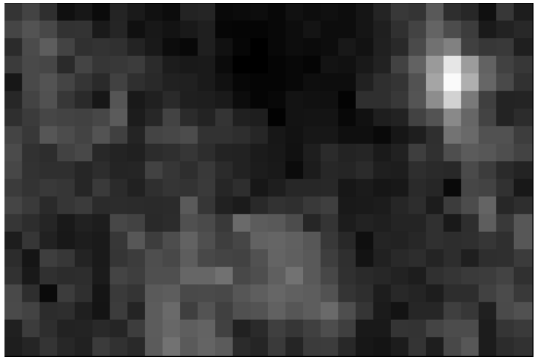
No Updates

Detector





Valid samples

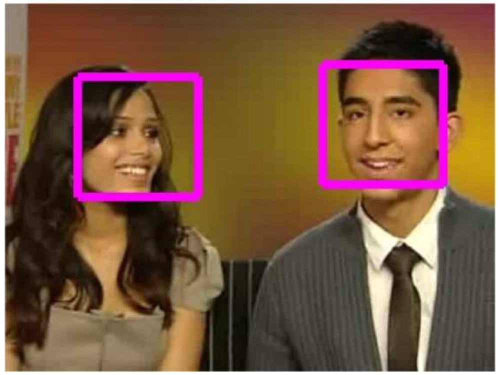


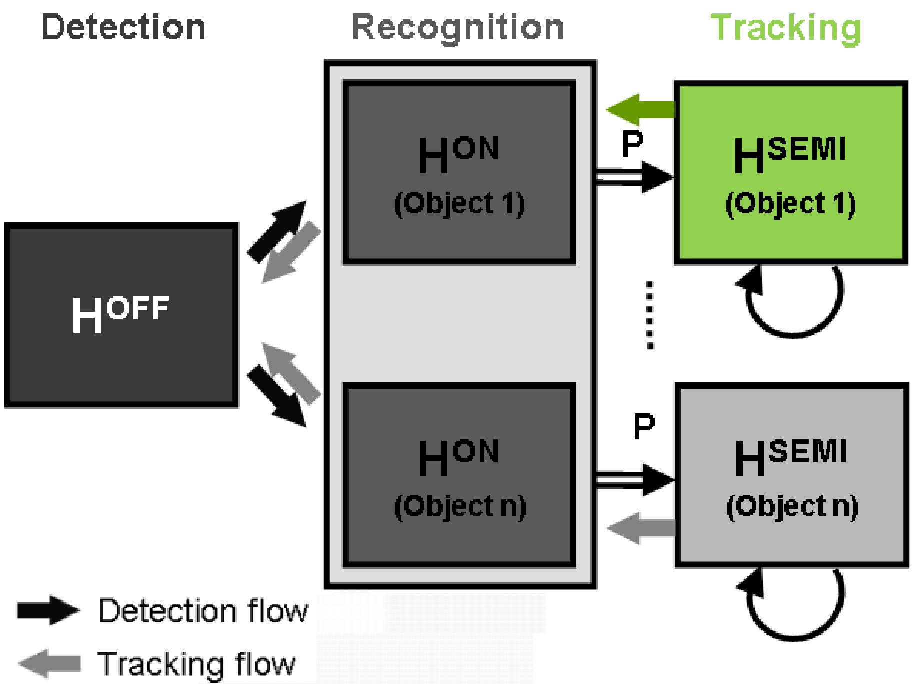
Confidence map

pos. updates

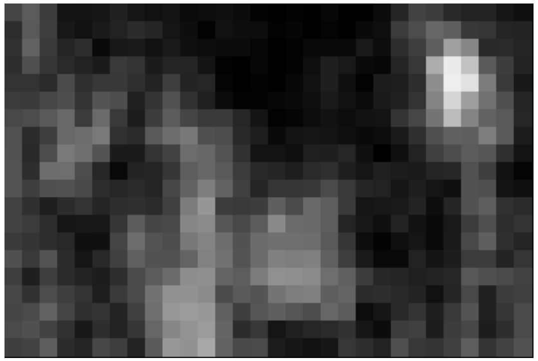
Neg. updates

Detector





Valid samples



Confidence map

Unlabeled updates
(foreground & local background)