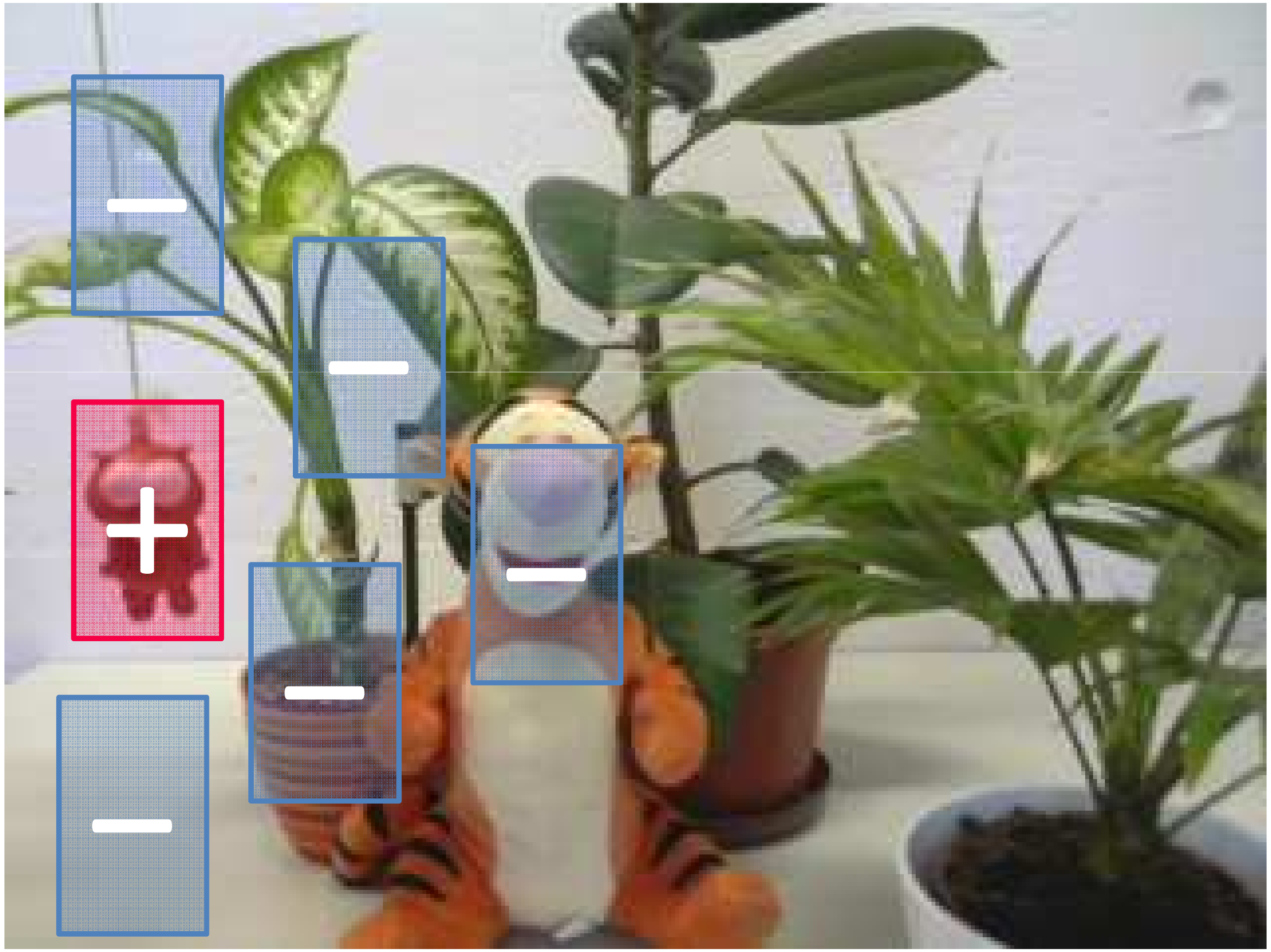
On-line Multi-view Forests for Tracking

C. Leistner, M. Godec, A. Saffari, and H. Bischof

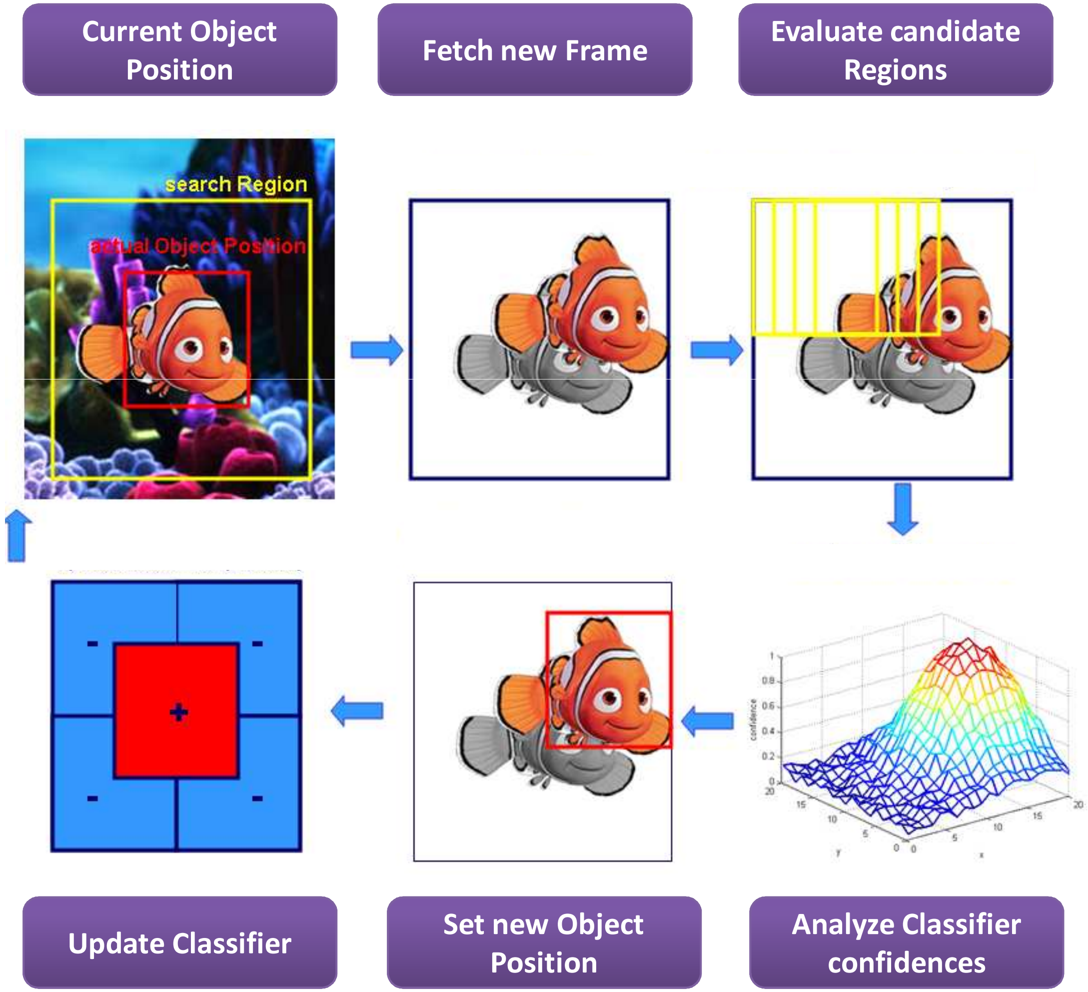
Institute for Computer Graphics and Vision
Graz University of Technology

Goal: Tracking-by-Detection

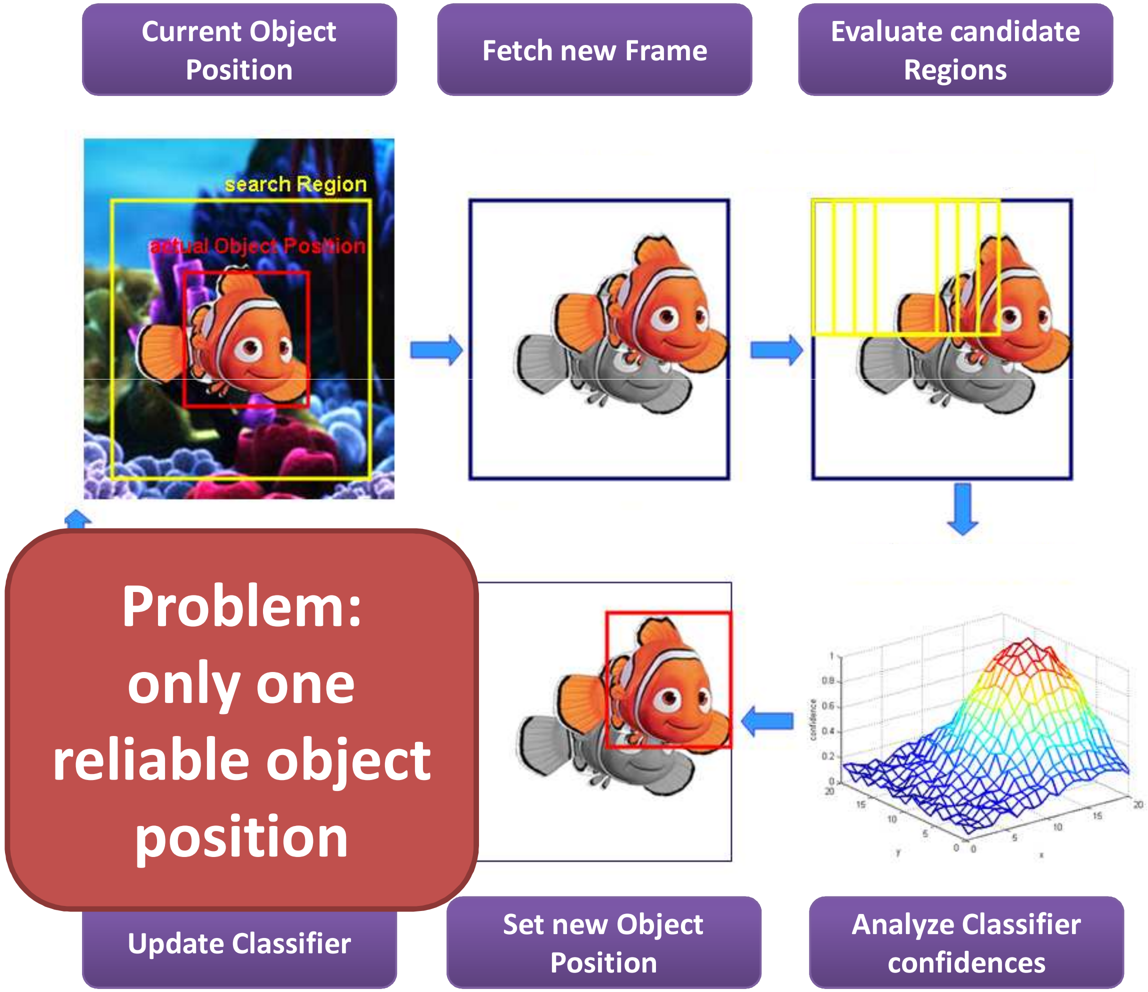
Goal: Tracking-by-Detection



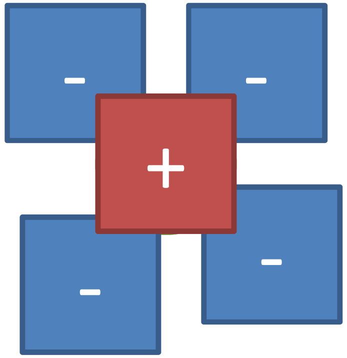
Tracking Loop



Tracking Loop



How to update the classifier

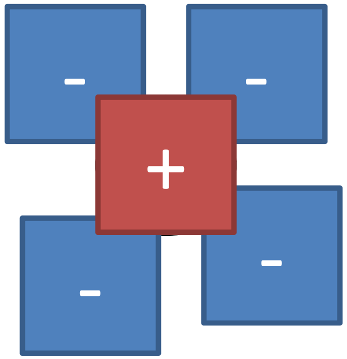


Direct Self-Training

Best detection is used to update the classifier

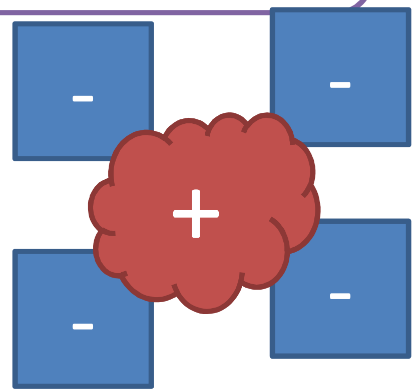
Grabner and Bischof: On-line boosting and vision. CVPR (2006)

How to update the classifier



Direct Self-Training

Best detection is used to update the classifier

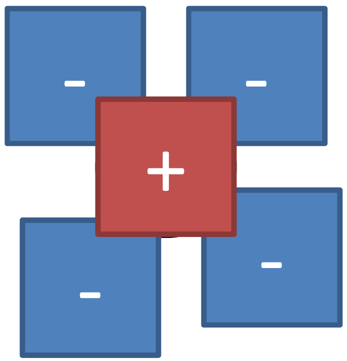


Multiple Instance Learning

Shift sample selection problem to the learner

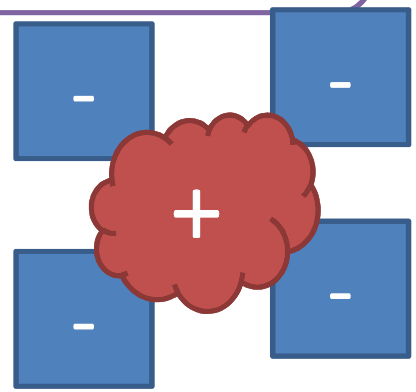
Babenko et. al.: Visual tracking with online multiple instance learning. CVPR (2009)

How to update the classifier



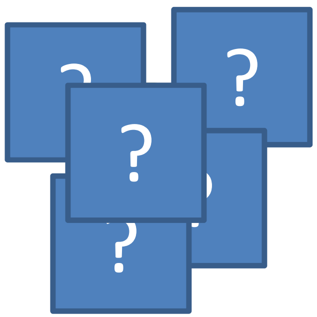
Direct Self-Training

Best detection is used to update the classifier



Multiple Instance Learning

Shift sample selection problem to the learner

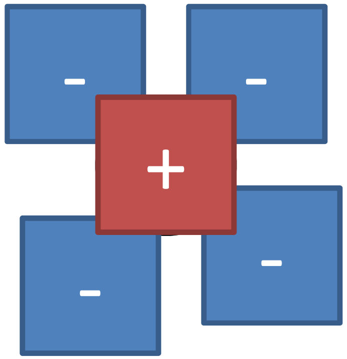


Semi-supervised Learning

Consider runtime-updates as unlabeled

Grabner et. al.: On-line semi-supervised boosting for robust tracking. ECCV (2008)

How to update the classifier

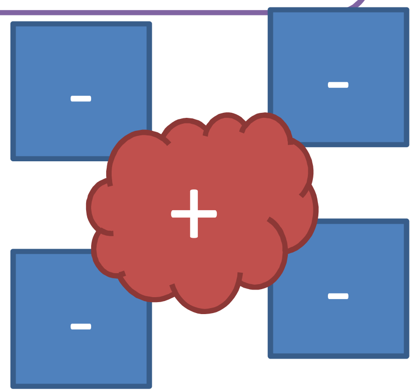


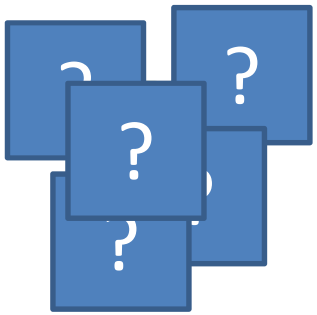
Direct Self-Training

Best detection is used to update the classifier

Multiple Instance Learning

Shift sample selection problem to the learner





Semi-supervised Learning

Consider runtime-updates as unlabeled

Semi-supervised Learning

- …by utilizing different views
  - different features
  - camera views
  - …

➢Co-Training

Blum et. al.: Combining labeled and unlabeled data with co-training. COLT (1998)

Within this paper…

- Integrate more than 2 views
  - Multi-view Training
- Direct Integration Ensemble Learner
  - i.e. Random Forest
- Apply to Tracking-by-Detection
  - On-line learning

Outline

- Motivation
- Introduction
  - Random Forests
  - Co-Training
- Multi-View Ensemble Learning
- Evaluation
- Conclusion

Random Forests

- Ensemble of Randomized Decision Trees
  - Bagging of many Trees

- Binary Tree-structure
  - Try to split classes within training data by simple recursive binary tests
  - Select splitting criterion for a specific node based on sample subset which ends up at this node

Breiman: Random forests. Machine Learning (2001)

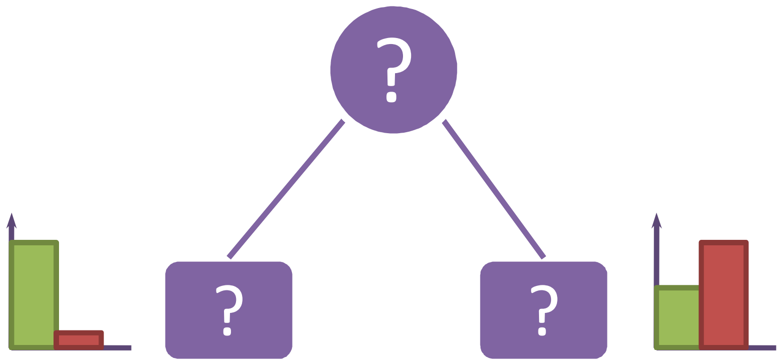
Let’s go on-line!

- On-line Bagging
  - Oza 2001, PhD-Thesis
  - Set according to Poisson distribution

- On-line recursive splitting problem
  - Saffari 2009
  - Tree growing procedure

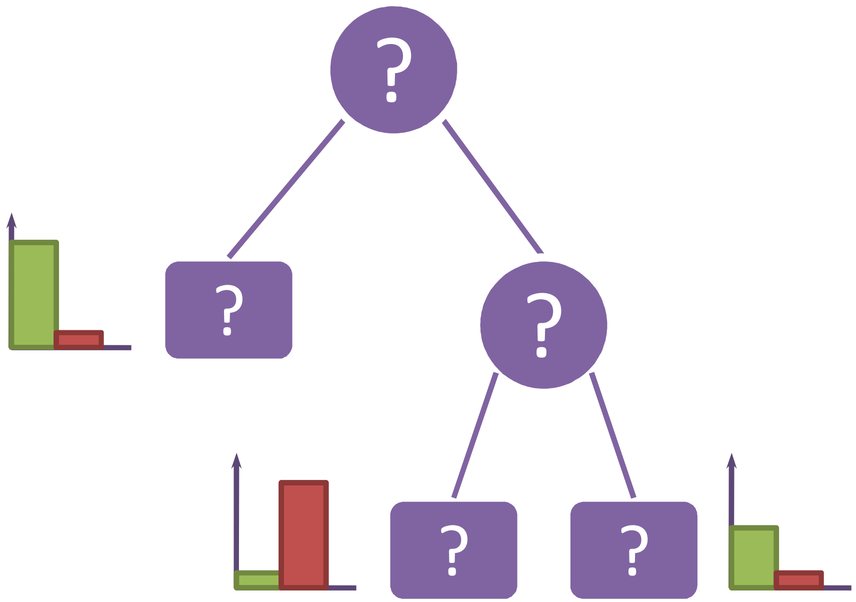
Oza: Online Ensemble Learning. PhD Thesis (2001)
Saffari et. al.: On-line random forests. OLCV (2009)

On-line Recursive Tree Splitting



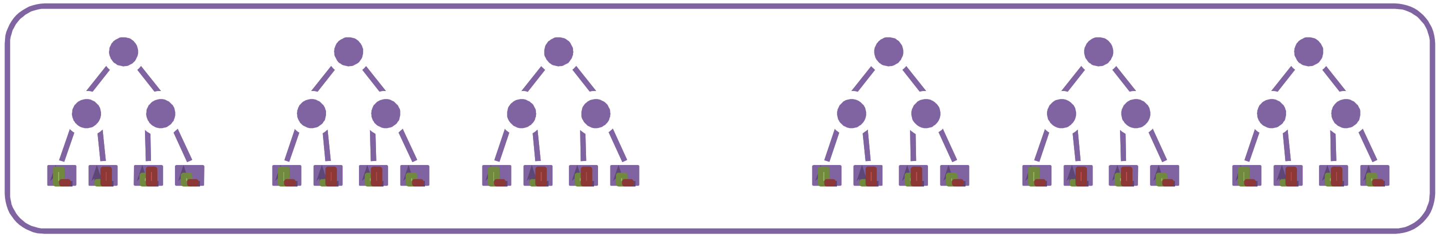
- Tree-growing scheme
- Fast in training and evaluation
- Converges to off-line version (empirically)

On-line Recursive Tree Splitting

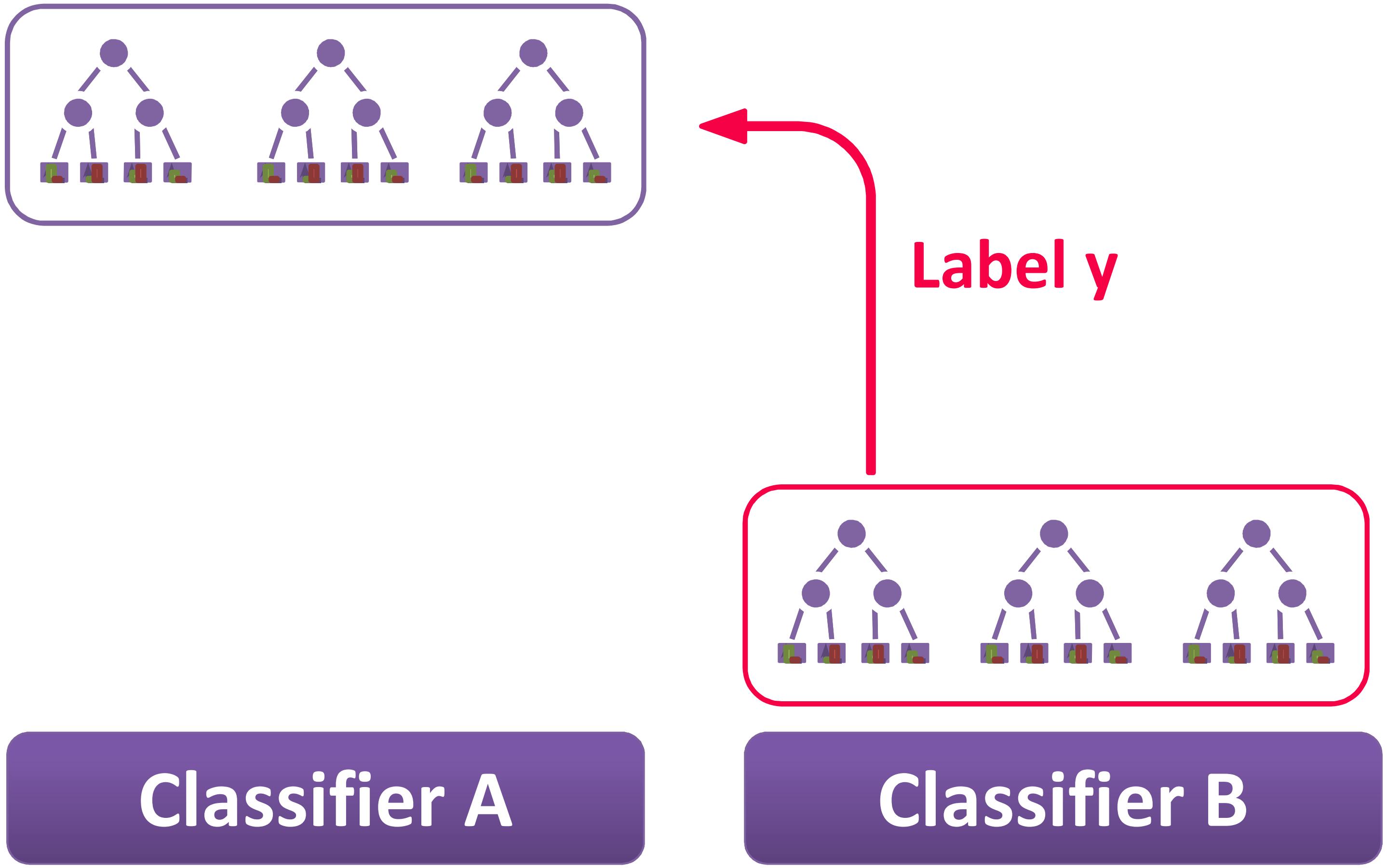


- Tree-growing scheme
- Fast in training and evaluation
- Converges to off-line version

Co-Training



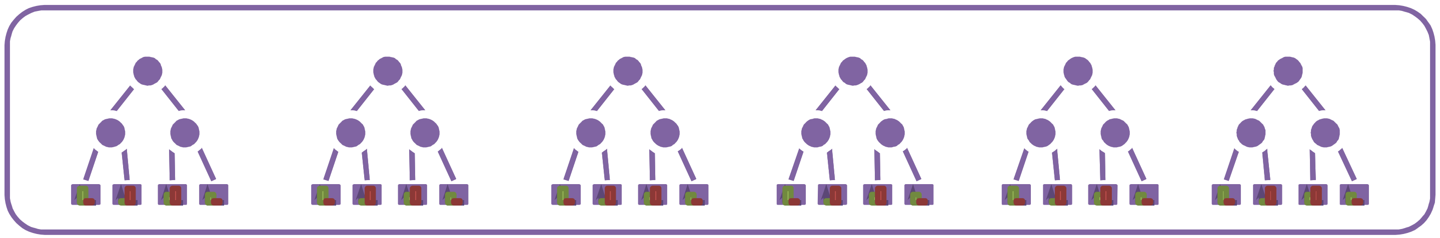
Co-Training



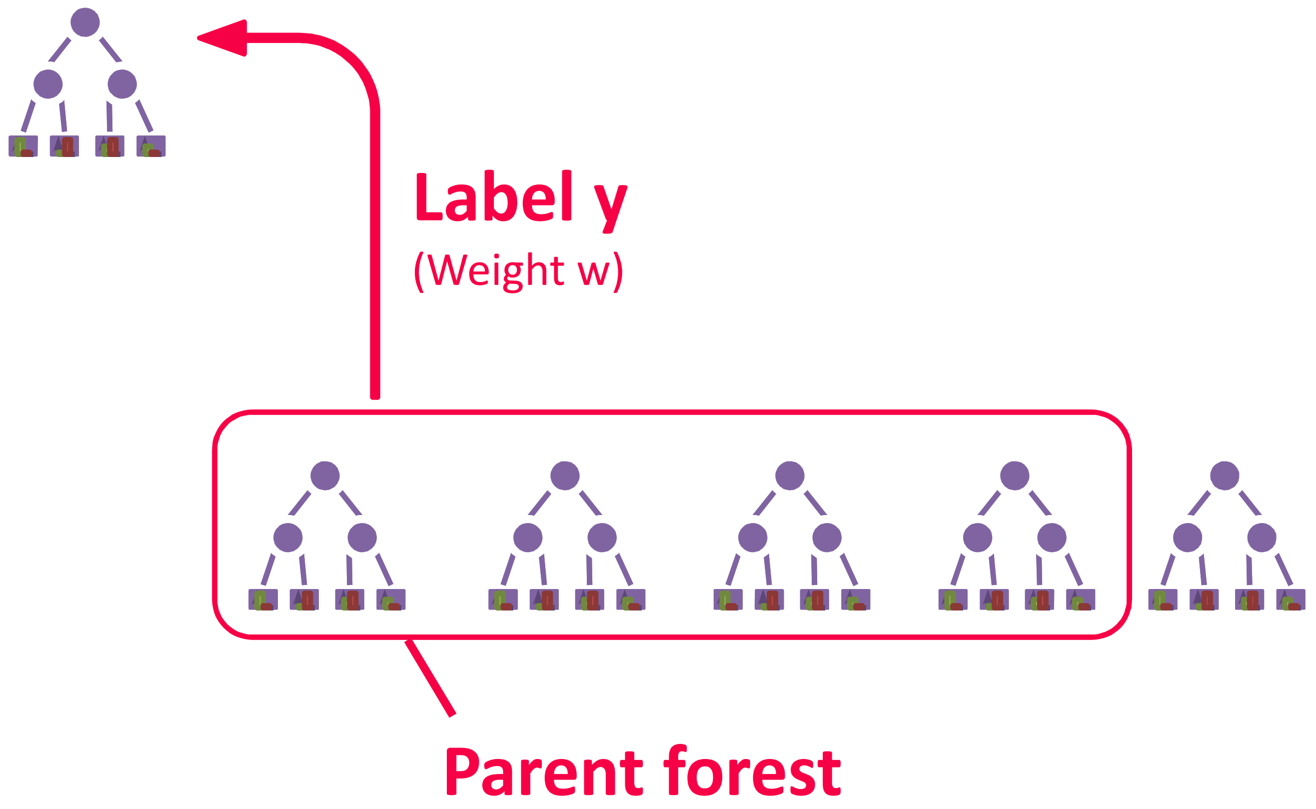
Outline

- Motivation
- Introduction
- Multi-View Ensemble Learning
  - Multi-view Forests
  - Sample labeling and weighting
- Evaluation
- Conclusion

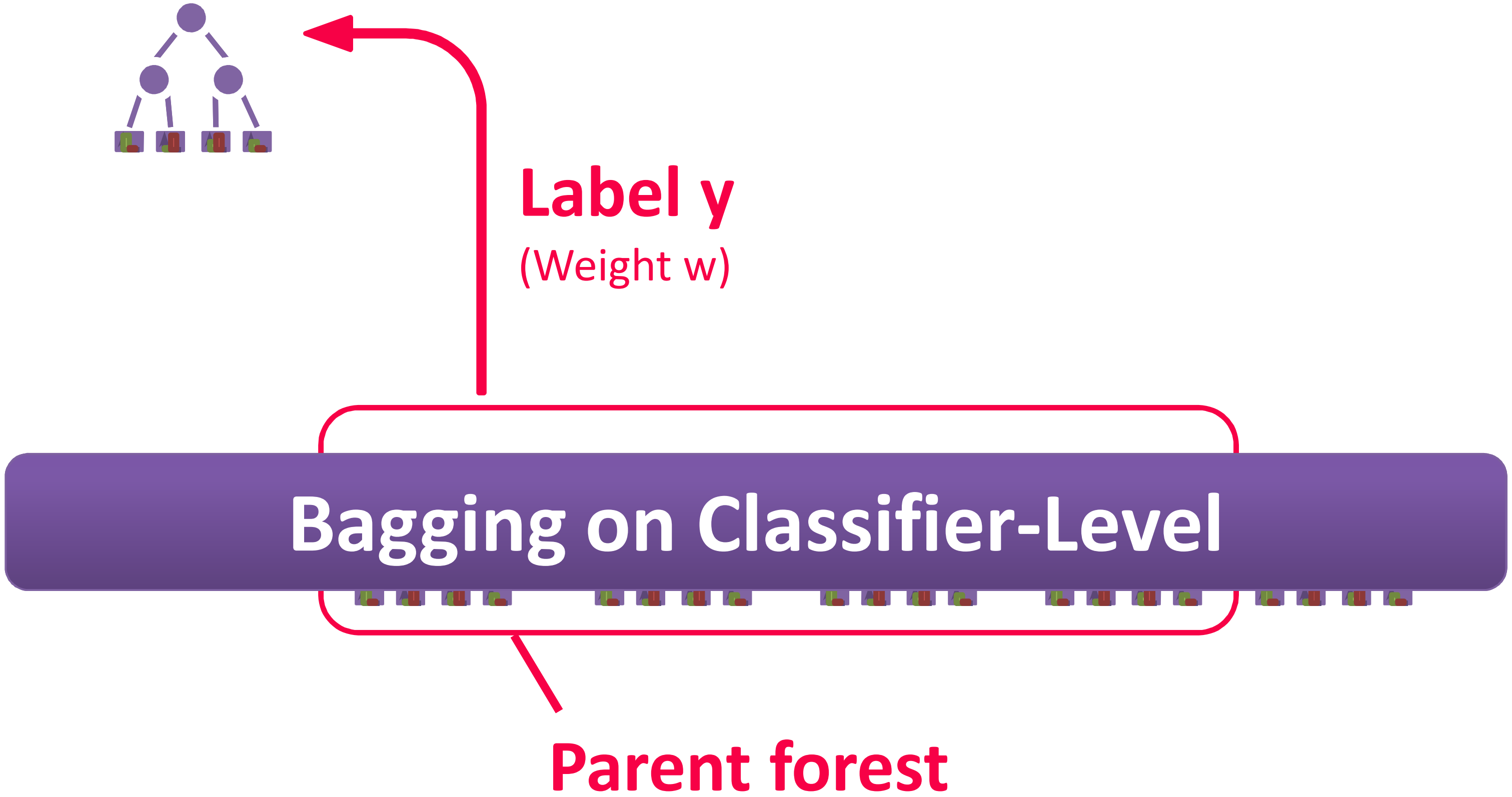
Our Approach: Multi-View Training



Our Approach: Multi-View Training



Our Approach: Multi-View Training



Multi-View Training

- Each tree represents a separate view
  - Real multi-view setup

- *Emulated* multi-view setup
  - Diverse training set (bagging)
  - Diverse feature set (randomized feature pool)
  - Diverse *parent forest*

Labeling and Weighting

- Combination of parent results
  - Majority voting
  - Averaging
  - Agreement

- Handling of unlabeled sample
  - Select or discard unlabeled sample
  - Select label for unlabeled sample
  - Select weight for unlabeled sample

Outline

- Motivation
- Introduction
- Multi-View Ensemble Lea
- Evaluation
- Conclusion

Tracking-by-Detection

- Challenges
  - Only one reliable object position
  - Unreliable tracking result for on-line updates

- Related Approaches
  - SemiBoost (Grabner et. al., ECCV 2008)
  - MILBoost (Babenko, et. al., CVPR 2009)
  - CoBoost (Liu et. al., ICCV 2009)
  - Random Forests (Lepetit et. al., CVPR 2006)
  - On-line Random Forests (Saffari et. al., OLCV 2009)

Results

Sequence	MVForest	CoBoost	On-line RF	Off-line RF	MILBoost	SemiBoost
Sylvester	<u>0.54</u>	0.53	0.53	0.50	**0.60**	0.46
David	**0.71**	0.52	<u>0.69</u>	0.32	0.57	0.31
Face Occlusion 2	<u>0.78</u>	**0.79**	0.72	**0.79**	0.65	0.63
Tiger1	**0.51**	0.41	0.38	0.34	<u>0.49</u>	0.17
Tiger2	<u>0.45</u>	0.13	0.43	0.32	**0.53**	0.08
Coke	0.28	**0.41**	<u>0.35</u>	0.15	0.33	0.08
Face Occlusion 1	**0.79**	<u>0.78</u>	0.71	0.77	0.60	0.71
Girl	**0.77**	0.69	0.70	<u>0.74</u>	0.53	0.69

Average overlap measure (higher is better)
Sequences from Babenko (http://vision.ucsd.edu/~bbabenko/project_miltrack.shtml)

Results

Sequence	MVForest	e RF	MILBoost	SemiBoost
Sylvester	0.54	0	**0.60**	0.46
David	**0.71**	2	0.57	0.31
Face Occlusion 2	0.78	9	0.65	0.63
Tiger1	**0.51**	4	0.49	0.17
Tiger2	0.45	2	**0.53**	0.08
Coke	0.28		0.33	0.08
Face Occlusion 1	**0.79**		0.60	0.71
Girl				.69

Such tables are boring!

Average overlap measure (higher is better)
Sequences from Babenko (http://vision.ucsd.edu/~bbabenko/project_miltrack.shtml)

Results

Sequence	MVForest	CoBoost	On-line RF	Off-line RF	MILBoost	SemiBoost
Sylvester	0.54	0.53	0.53	0.50	**0.60**	0.46
David	**0.71**	0.52	0.69	0.32	0.57	0.31
Face Occlusion 2	0.78	**0.79**	0.72	**0.79**	0.65	0.63
Tiger1	**0.51**	0.41	0.38	0.34	0.49	0.17
Tiger2	0.45	0.13	0.43	0.32	**0.53**	0.08
Coke	0.28	**0.41**	0.35	0.15	0.33	0.08
Face Occ[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.71
Girl	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.69

But why / when does the approach work?

Average overlap measure (higher is better)
Sequences from Babenko (http://vision.ucsd.edu/~bbabenko/project_miltrack.shtml)

Results

Sequence	MVForest	CoBoost	On-line RF	Off-line RF	MILBoost	SemiBoost
Sylvester	<u>0.54</u>	0.53	0.53	0.50	**0.60**	0.46
David	**0.71**	0.52	<u>0.69</u>	0.32	0.57	0.31
Face Occlusion 2	<u>0.78</u>	**0.79**	0.72	**0.79**	0.65	0.63
Tiger1	**0.51**	0.41	0.38	0.34	<u>0.49</u>	0.17
Tiger2	<u>0.45</u>	0.13	0.43	0.32	**0.53**	0.08
Coke	0.28	**0.41**	<u>0.35</u>	0.15	0.33	0.08
Face Occlusion 1	**0.79**	<u>0.78</u>	0.71	0.77	0.60	0.71
Girl	**0.77**	0.69	0.70	<u>0.74</u>	0.53	0.69

low adaptivity

Results

Sequence	MVForest	CoBoost	On-line RF	Off-line RF	MILBoost	SemiBoost
Sylvester	<u>0.54</u>	0.53	0.53	0.50	**0.60**	0.46
David	**0.71**	0.52	<u>0.69</u>	0.32	0.57	0.31
Face Occlusion 2	<u>0.78</u>	**0.79**	0.72	**0.79**	0.65	0.63
Tiger1	**0.51**	0.41	0.38	0.34	<u>0.49</u>	0.17
Tiger2	<u>0.45</u>	0.13	0.43	0.32	**0.53**	0.08
Coke	0.28	**0.41**	<u>0.35</u>	0.15	0.33	0.08
Face Occlusion 1	**0.79**	<u>0.78</u>	0.71	0.77	0.60	0.71
Girl	**0.77**	0.69	0.70	<u>0.74</u>	0.53	0.69

medium adaptivity

Results

Sequence	MVForest	CoBoost	On-line RF	Off-line RF	MILBoost	SemiBoost
Sylvester	<u>0.54</u>	0.53	0.53	0.50	**0.60**	0.46
David	**0.71**	0.52	<u>0.69</u>	0.32	0.57	0.31
Face Occlusion 2	<u>0.78</u>	**0.79**	0.72	**0.79**	0.65	0.63
Tiger1	**0.51**	0.41	0.38	0.34	<u>0.49</u>	0.17
Tiger2	<u>0.45</u>	0.13	0.43	0.32	**0.53**	0.08
Coke	0.28	**0.41**	<u>0.35</u>	0.15	0.33	0.08
Face Occlusion 1	**0.79**	<u>0.78</u>	0.71	0.77	0.60	0.71
Girl	**0.77**	0.69	0.70	<u>0.74</u>	0.53	0.69

medium adaptivity

Results

Sequence	MVForest	CoBoost	On-line RF	Off-line RF	MILBoost	SemiBoost
Sylvester	<u>0.54</u>	0.53	0.53	0.50	**0.60**	0.46
David	**0.71**	0.52	<u>0.69</u>	0.32	0.57	0.31
Face Occlusion 2	<u>0.78</u>	**0.79**	0.72	**0.79**	0.65	0.63
Tiger1	**0.51**	0.41	0.38	0.34	<u>0.49</u>	0.17
Tiger2	<u>0.45</u>	0.13	0.43	0.32	**0.53**	0.08
Coke	0.28	**0.41**	<u>0.35</u>	0.15	0.33	0.08
Face Occlusion 1	**0.79**	<u>0.78</u>	0.71	0.77	0.60	0.71
Girl	**0.77**	0.69	0.70	<u>0.74</u>	0.53	0.69

high adaptivity

Results

Sequence	MVForest	CoBoost	On-line RF	Off-line RF	MILBoost	SemiBoost
Sylvester	0.54	0.53	0.53	0.50	**0.60**	0.46
David	**0.71**	0.52	0.69	0.32	0.57	0.31
Face Occlusion 2	0.78	**0.79**	0.72	**0.79**	0.65	0.63
Tiger1	**0.51**	0.41	0.38	0.34	0.49	0.17
Tiger2	0.45	0.13	0.43	0.32	**0.53**	0.08
Coke	0.28	**0.41**	0.35	0.15	0.33	0.08
Face Occlusion 1	**0.79**	0.78	0.71	0.77	0.60	0.71
Girl	**0.77**	0.69	0.70	0.74	0.53	0.69

high adaptivity

Results

Sequence	MVForest	CoBoost	On-line RF	Off-line RF	MILBoost	SemiBoost
Sylvester	<u>0.54</u>	0.53	0.53	0.50	**0.60**	0.46
David	**0.71**	0.52	<u>0.69</u>	0.32	0.57	0.31
Face Occlusion 2	<u>0.78</u>	**0.79**	0.72	**0.79**	0.65	0.63
Tiger1	**0.51**	0.41	0.38	0.34	<u>0.49</u>	0.17
Tiger2	<u>0.45</u>	0.13	0.43	0.32	**0.53**	0.08
Coke	0.28	**0.41**	<u>0.35</u>	0.15	0.33	0.08
Face Occlusion 1	**0.79**	<u>0.78</u>	0.71	<u>0.77</u>	0.60	0.71
Girl	**0.77**	0.69	0.70	<u>0.74</u>	0.53	0.69

Outline

- Motivation
- Introduction
- Multi-View Ensemble Learning
- Evaluation
- Conclusion

Key Benefit of MV-Training

- Sample labeling
  - Make use of unlabeled data (SSL)
  - Weakly supervised learning possible (e.g., MIL)

- Sample weighting
  - According to averaged decision,…
  - Eases sample selection for tracking

Conclusion

- MVForests
  - New on-line multi-view learning algorithm using random forests
- Key Idea
  - Use classifier-bagging to emulate multiple views inside the Random Forests
- Tracking
  - More robust update strategy

Conclusion

- Benefits
  - Generalization of Co-Training
  - Works with single or multiple views
  - Easy to implement, fast, scalable
  - Not limited to Random Forests




Questions?

This work has been supported by the Austrian FFG project **MobiTrick** (825840) and **Outlier** (820923) under the FIT-IT program.

http://lrs.icg.tugraz.at