

Visual Tracking with Online Multiple Instance Learning

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Kelsie Zhao

Content

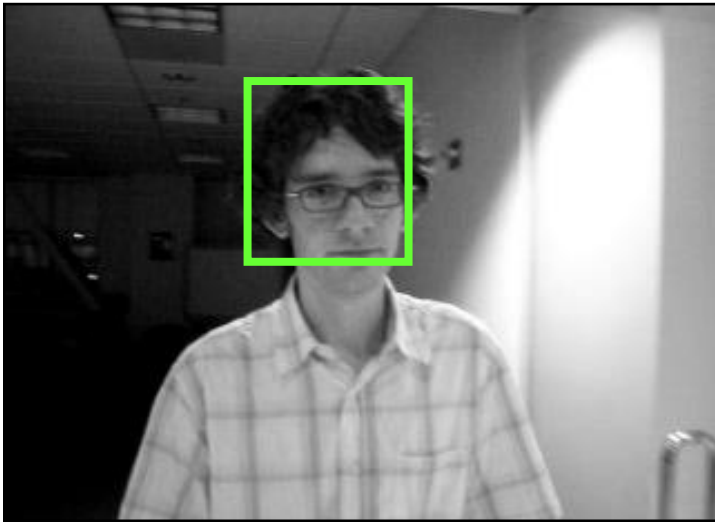
- Goal
- Background: Tracking by Detection
- Previous Work
- New Tracking Solution
 - MILTrack
 - Online MILBoost
- Experiments & Results

Goal

Track one arbitrary object in video, given its location in first frame

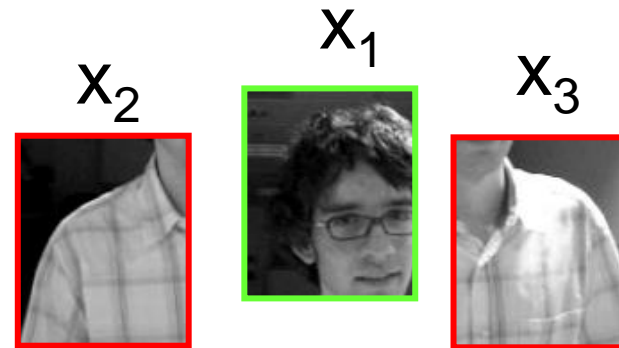
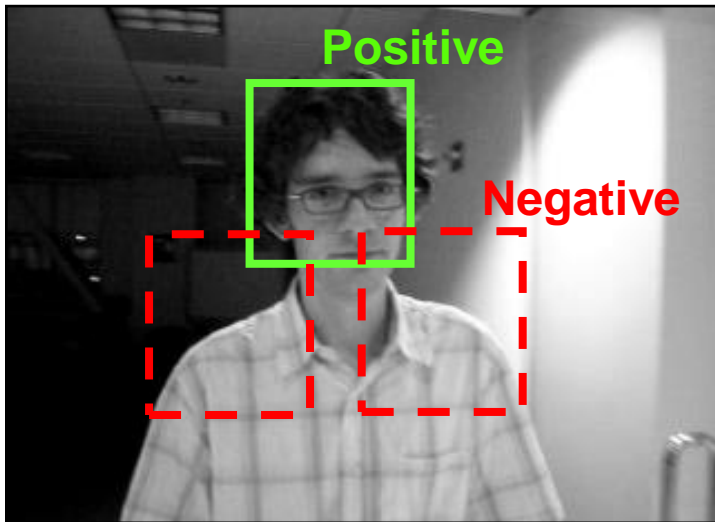
Background: Tracking by detection

- Frame 1 is labeled, tracker location known



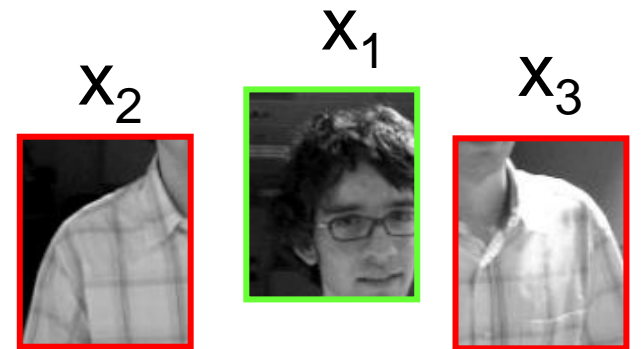
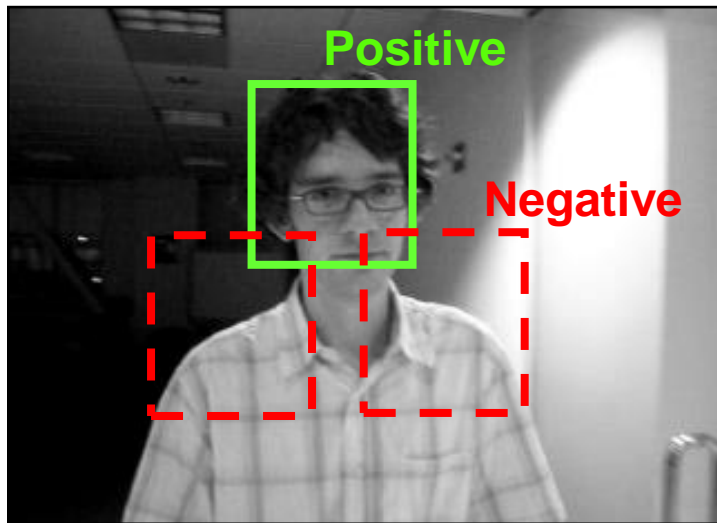
Background: Tracking by detection

- Crop one positive and some negative patches near tracker



Background: Tracking by detection

- Use patches to train the classifier



$\{(x_1, 1), (x_2, 0), (x_3, 0)\}$



Classifier

Background: Tracking by detection

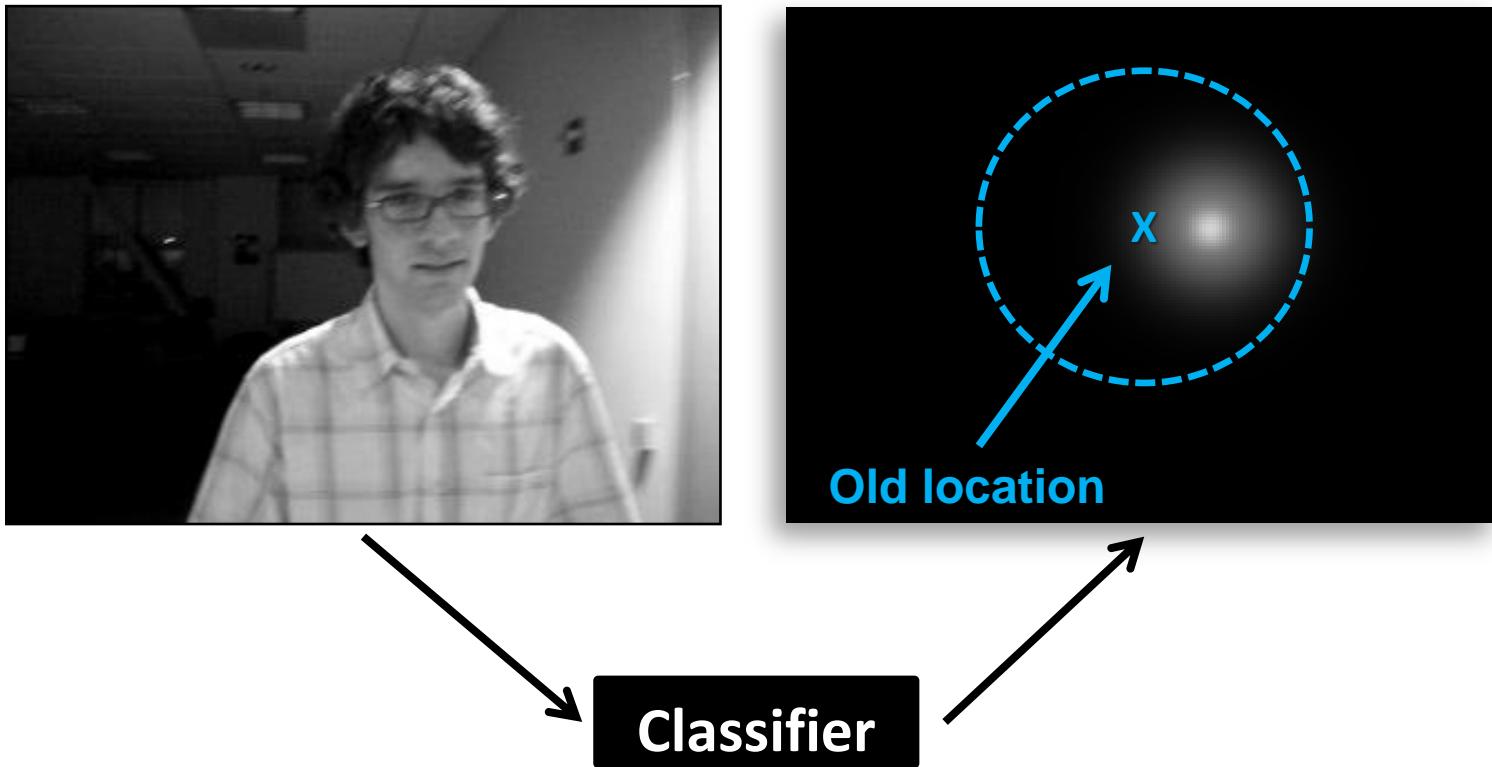
- Frame 2 comes



Classifier

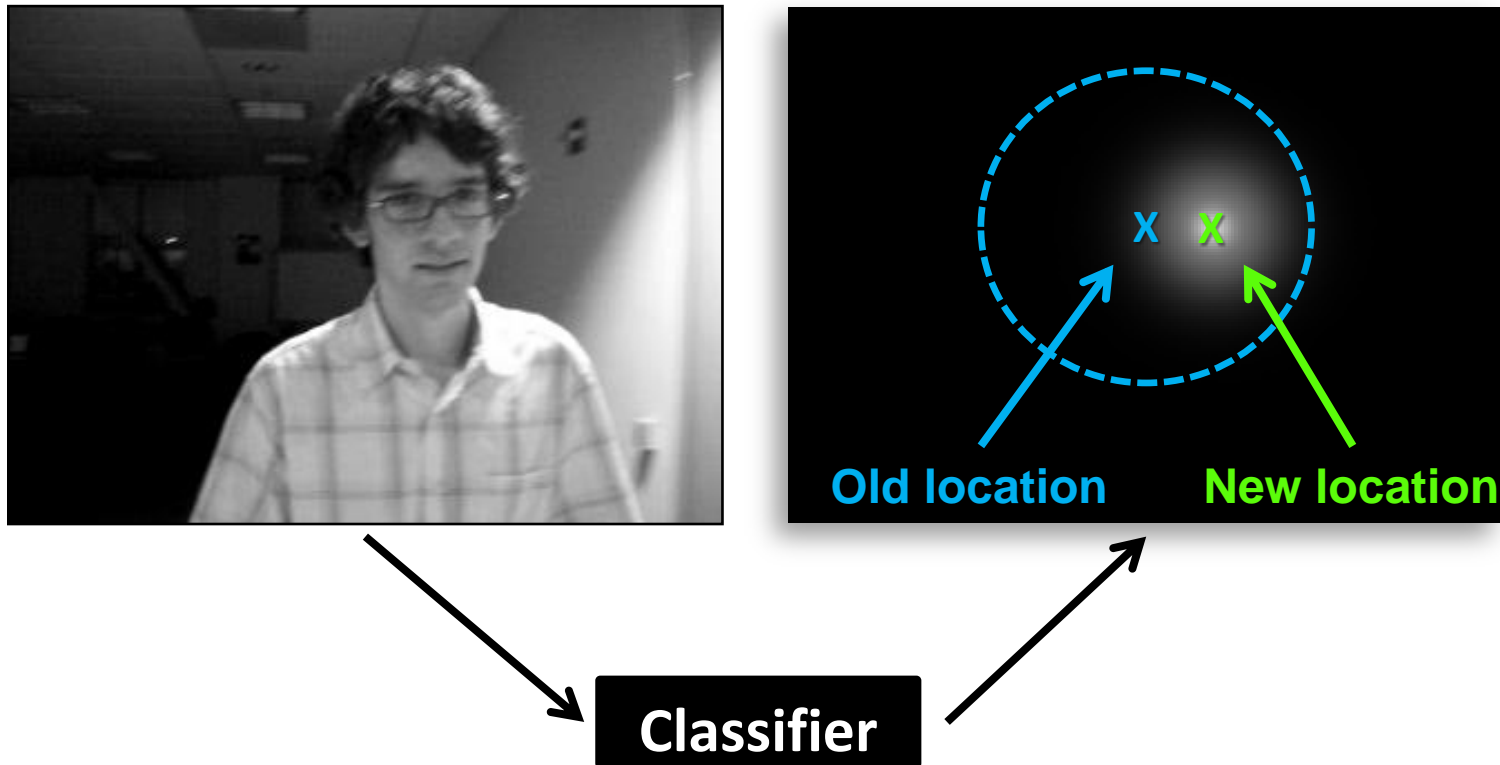
Background: Tracking by detection

- Calculate classifier response within a range of the old tracker location



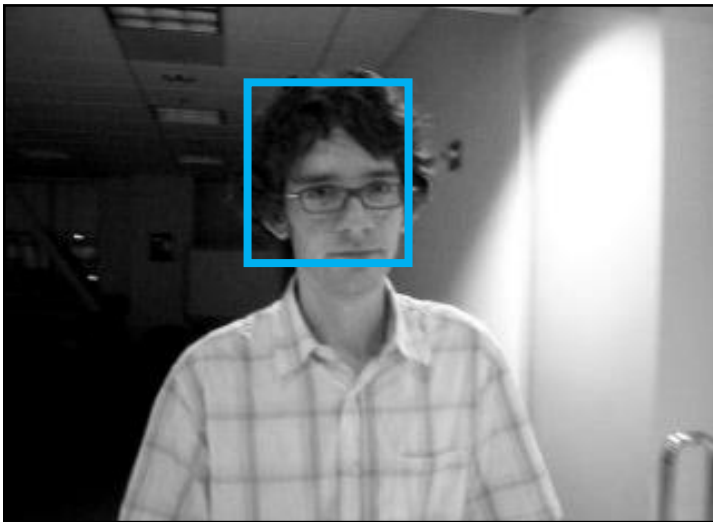
Background: Tracking by detection

- Find the maximum response location

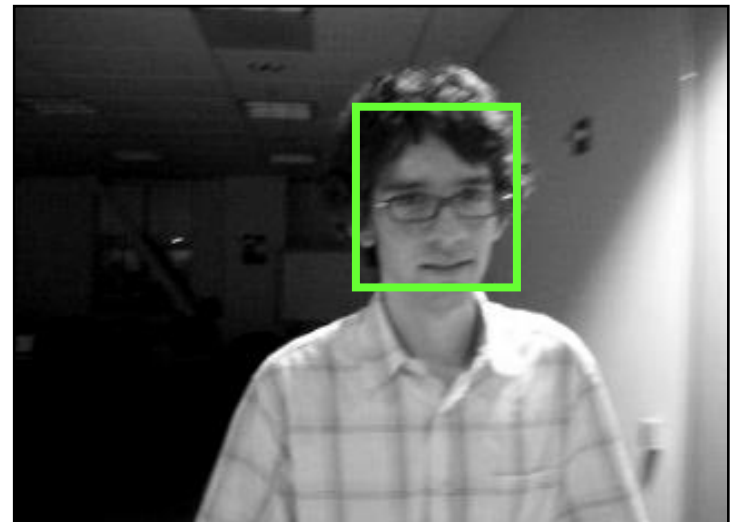


Background: Tracking by detection

- Move tracker



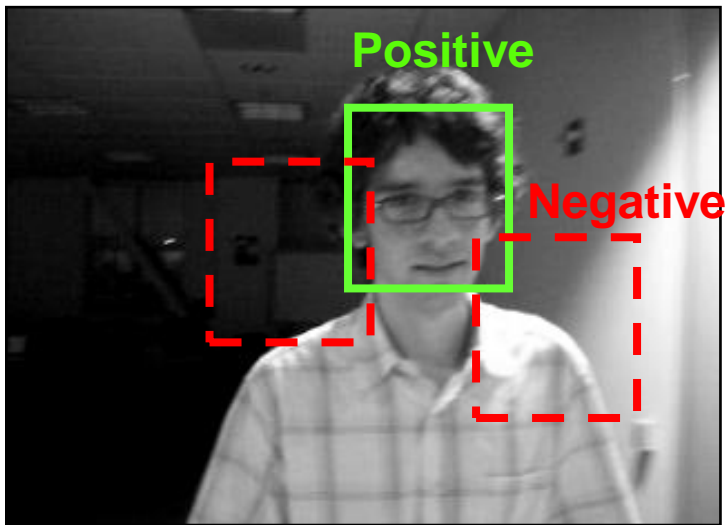
Frame 1



Frame 2

Background: Tracking by detection

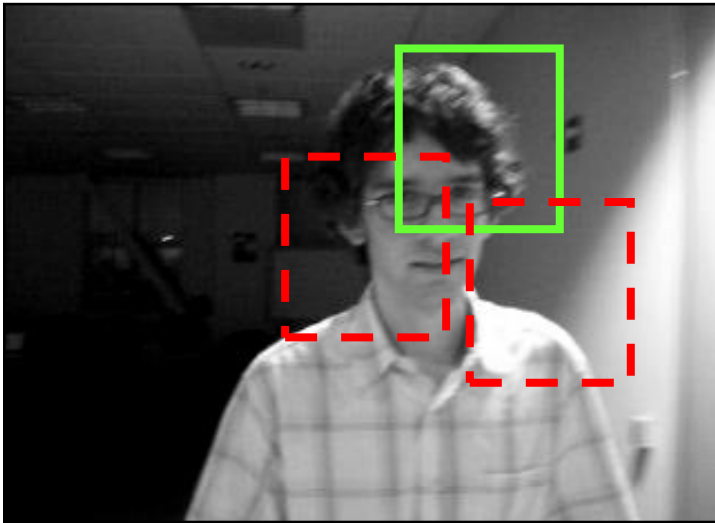
- Repeat



Frame 2

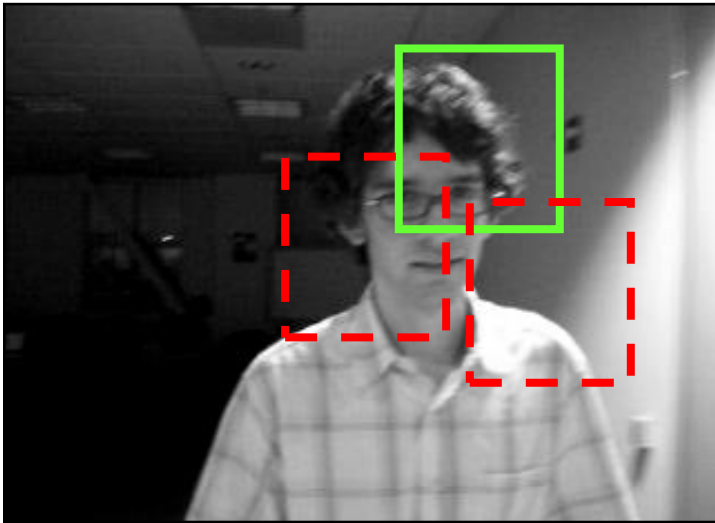
Background: Tracking by detection

- Problem: If tracker location is not precise, might select bad training examples



Background: Tracking by detection

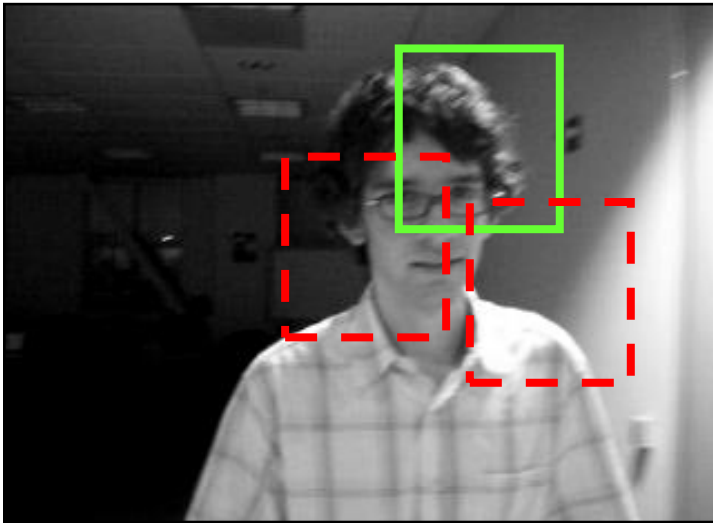
- Problem: If tracker location is not precise, might select bad training examples
- Model start to degrade!



Background: Tracking by detection

- Problem: If tracker location is not precise, might select bad training examples

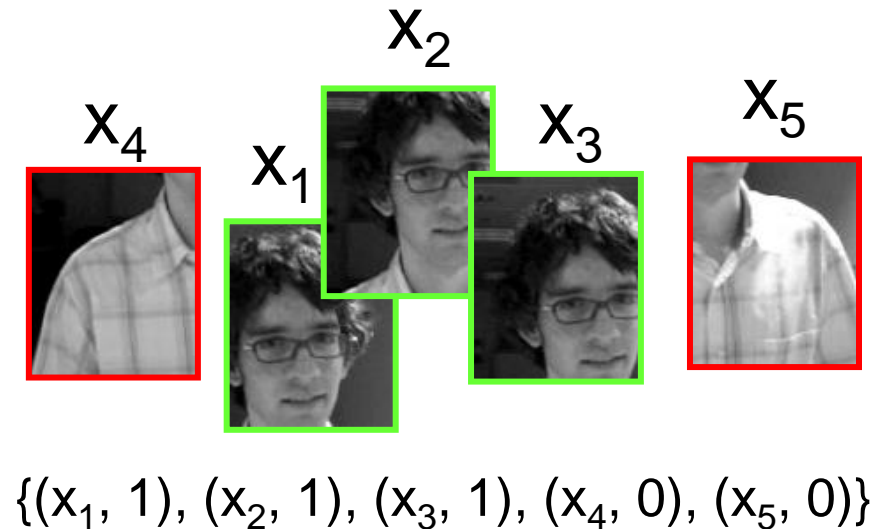
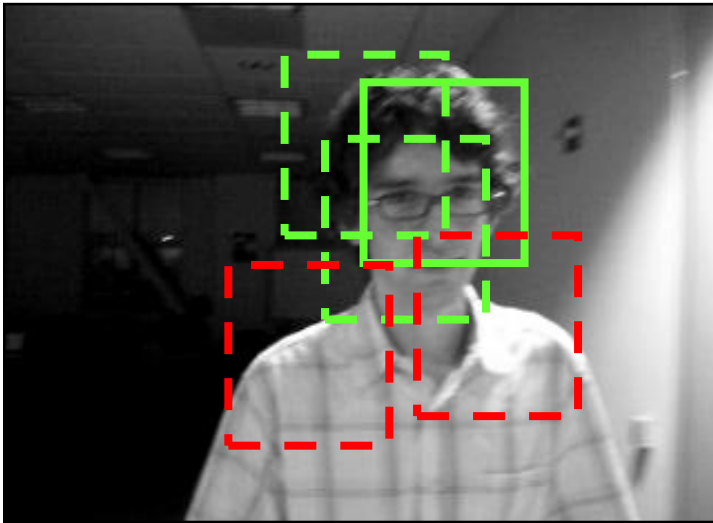
Model start to degrade!



- How to select good training examples?

Previous Work

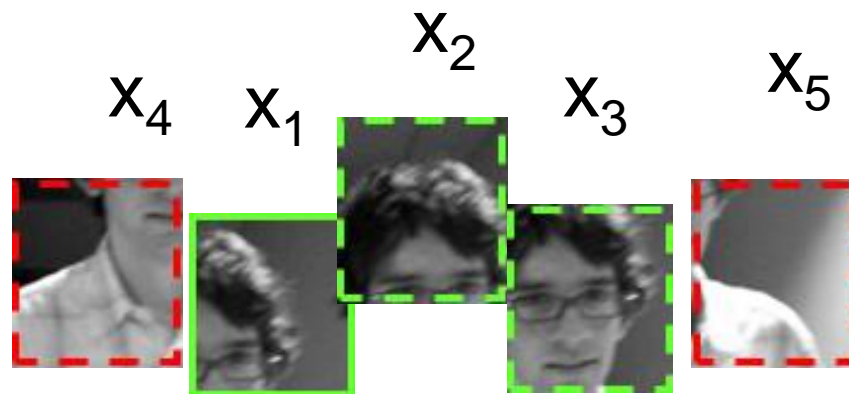
- Solution 1: multiple positive examples around tracker location



Classifier

Previous Work

- Solution 1
Might confuse classifier!



$\{(x_1, 1), (x_2, 1), (x_3, 1), (x_4, 0), (x_5, 0)\}$



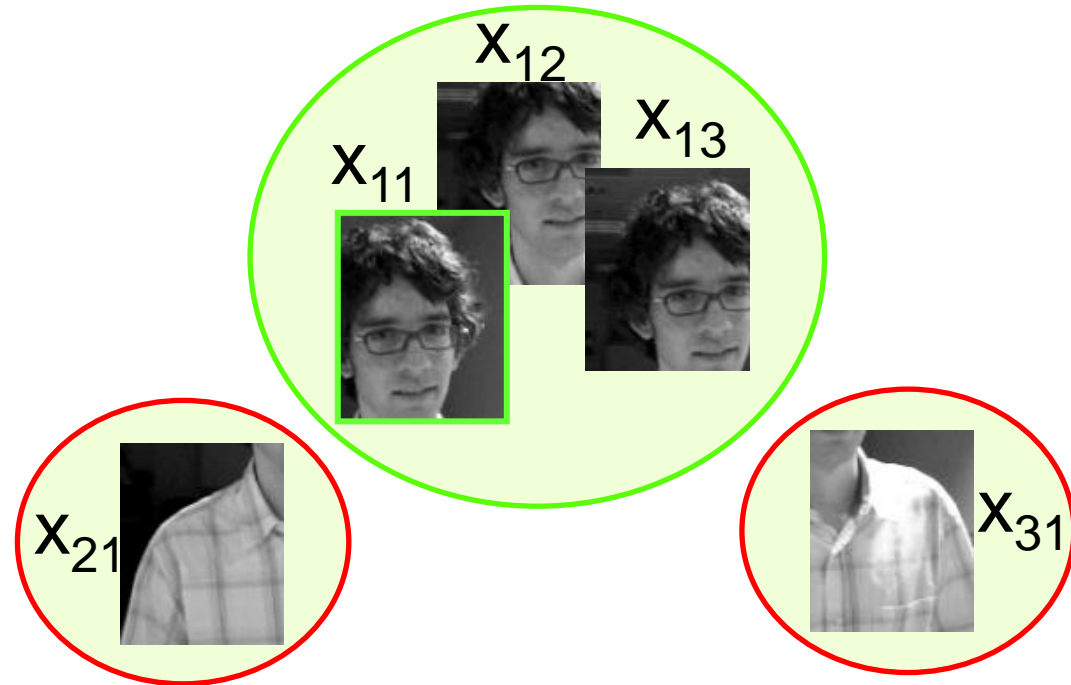
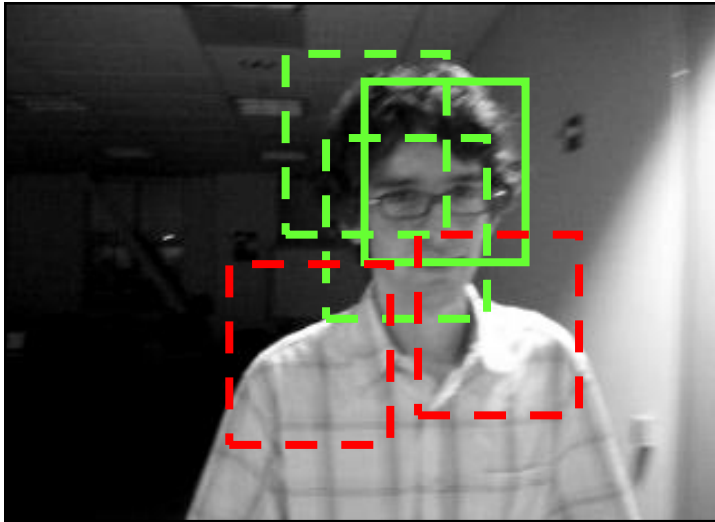
Classifier

Previous Work

- Solution 2: Multiple Instance Learning (MIL)

[Keeler '90, Dietterich et al. '97]

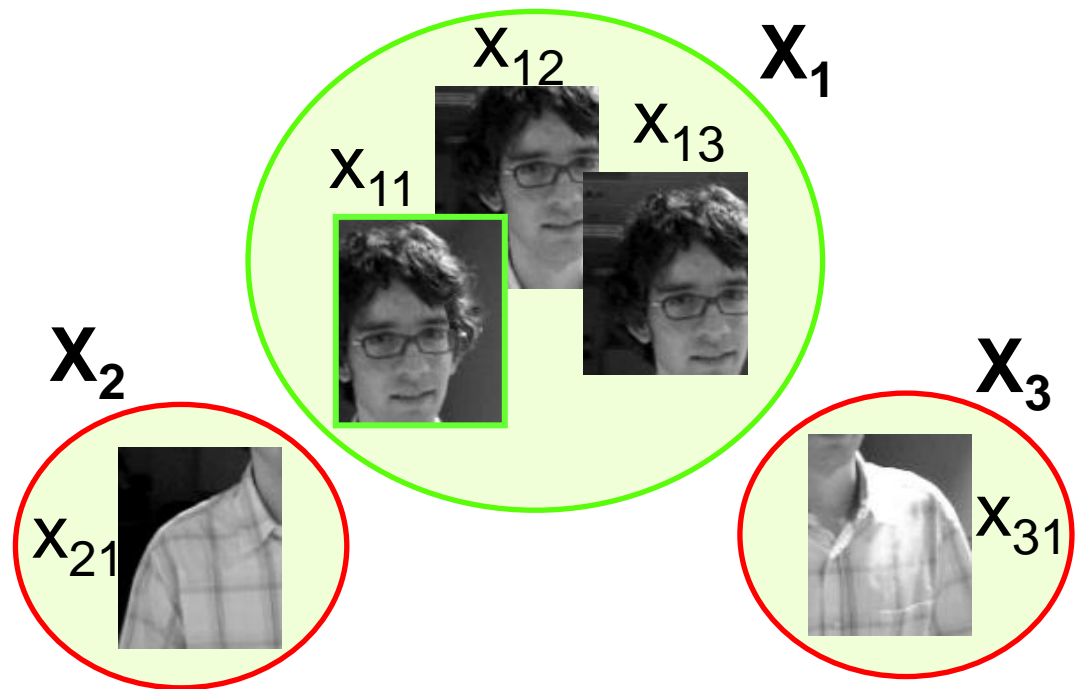
Previous Work: Multiple Instance Learning



- Multiple examples in one bag

[Keeler '90, Dietterich et al. '97]

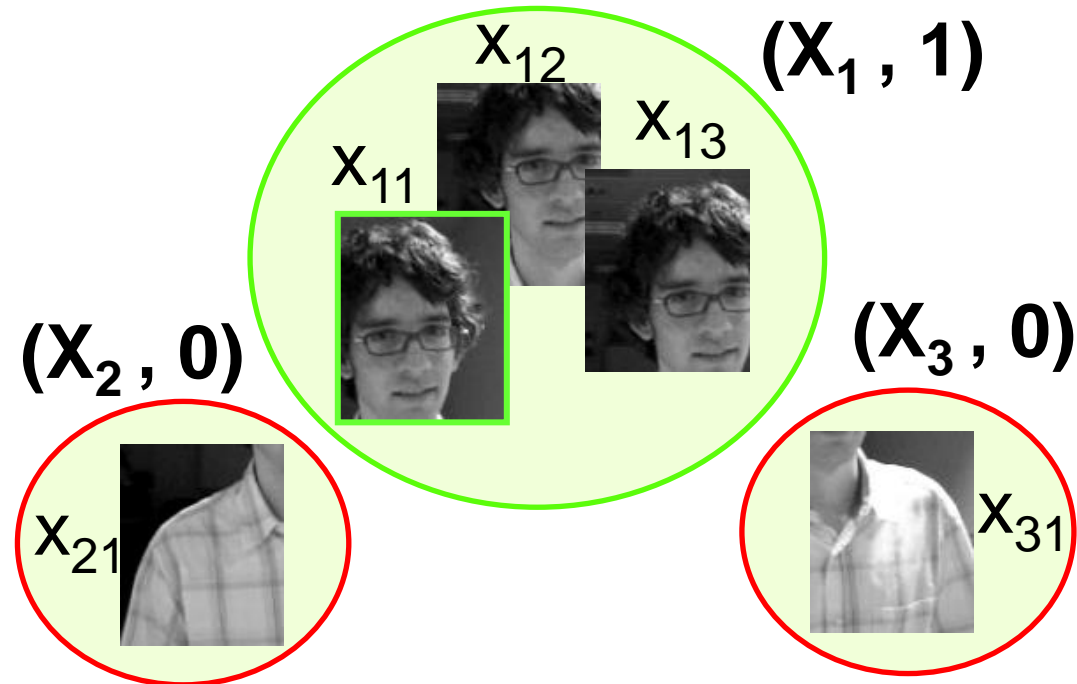
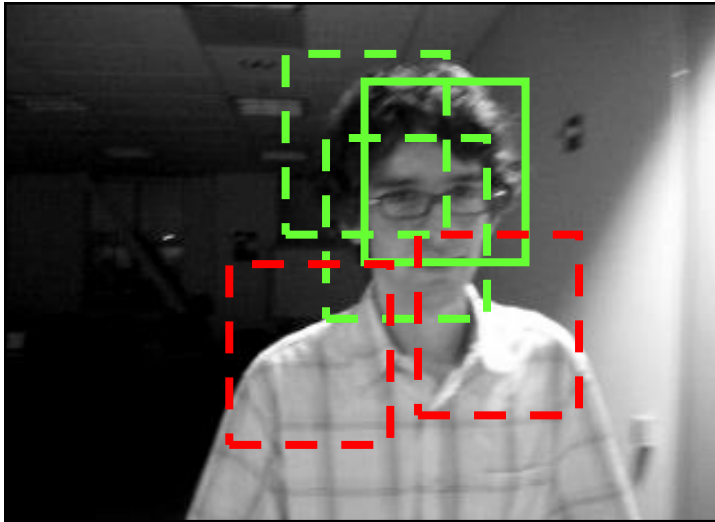
Previous Work: Multiple Instance Learning



- Multiple examples in one bag

[Keeler '90, Dietterich et al. '97]

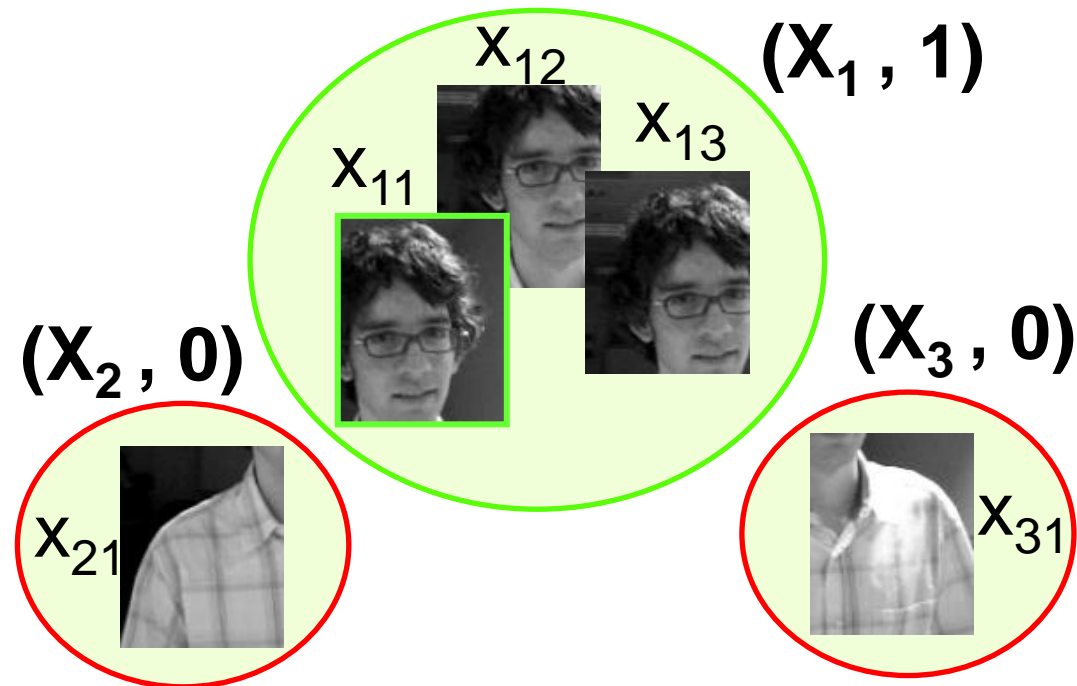
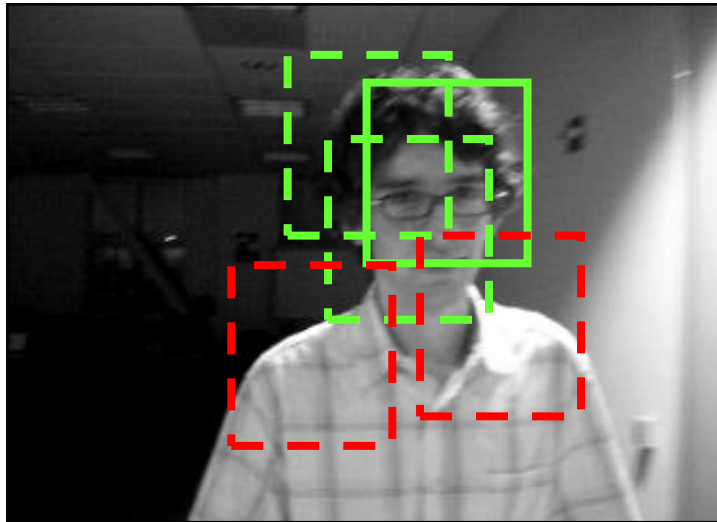
Previous Work: Multiple Instance Learning



- Multiple examples in one bag
- One bag one label

[Keeler '90, Dietterich et al. '97]

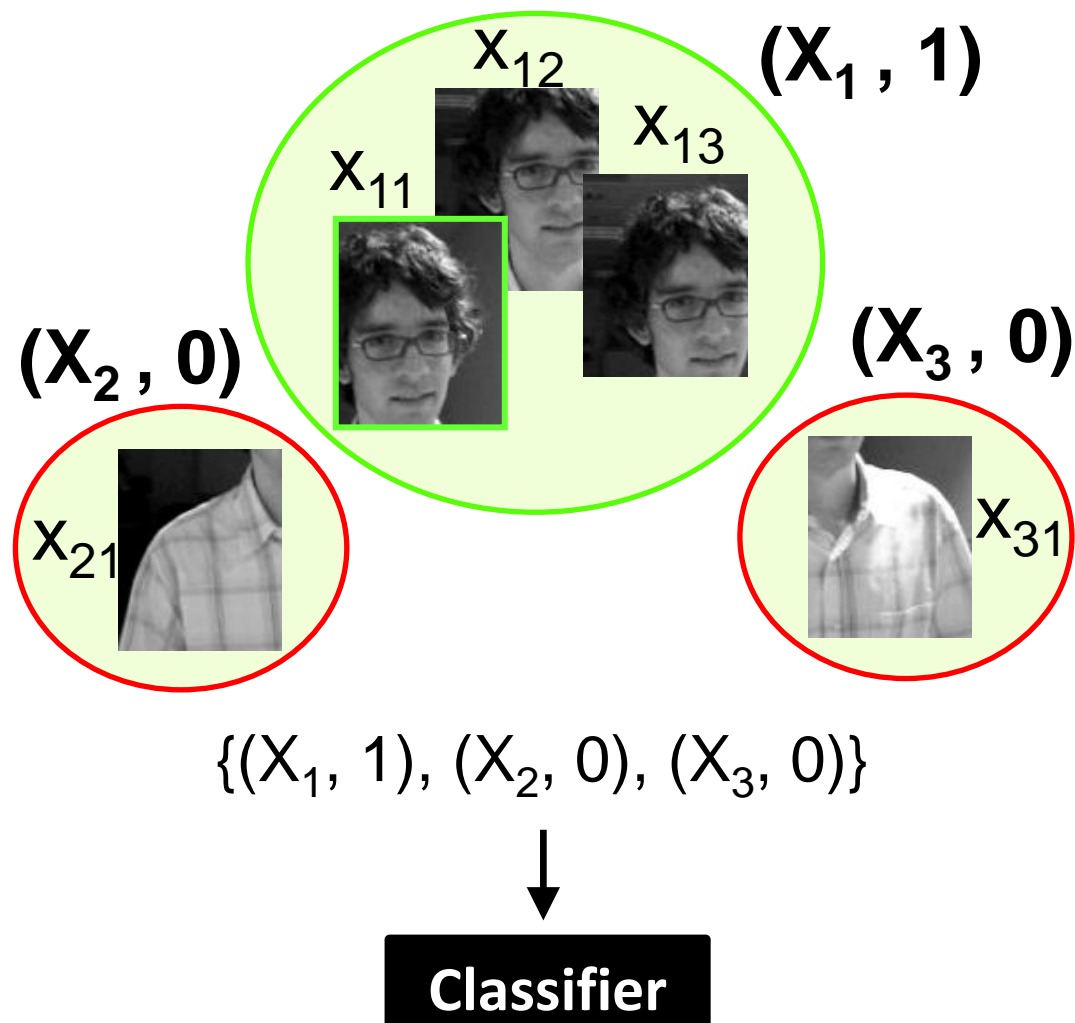
Previous Work: Multiple Instance Learning



- Multiple examples in one bag
- One bag one label
- Bag **Positive** if at least one example is Positive

[Keeler '90, Dietterich et al. '97]

Previous Work: Multiple Instance Learning



[Keeler '90, Dietterich et al. '97]

Previous Work: Multiple Instance Learning

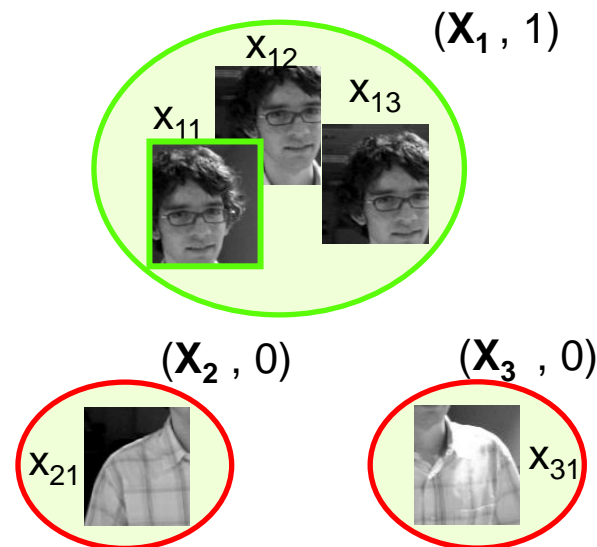
MIL training input:

$$\{(X_1, y_1) \dots (X_n, y_n)\},$$

where,

$$X_i = \{x_{i1} \dots x_{im}\},$$

$$y_i = \max_j y_{ij}$$



[Keeler '90, Dietterich et al. '97]

Previous Work: Multiple Instance Learning

MIL training input:

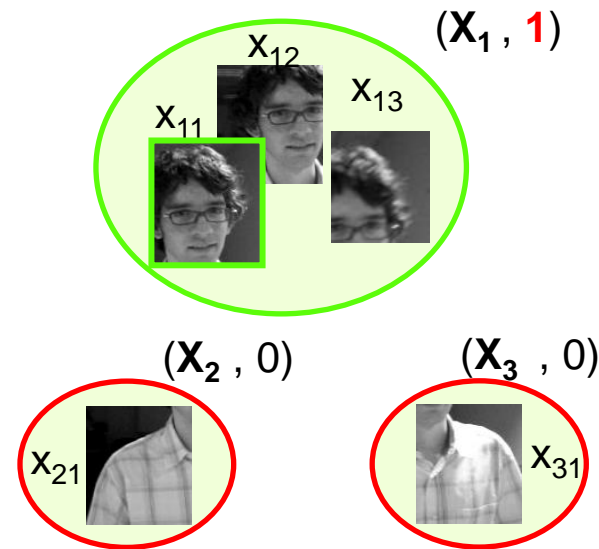
$$\{(X_1, y_1) \dots (X_n, y_n)\},$$

where,

$$X_i = \{x_{i1} \dots x_{im}\},$$

$$y_i = \max_j y_{ij}$$

Bag label is 1
if at least one instance is 1



[Keeler '90, Dietterich et al. '97]

Now we have training examples!

How to train the classifier?

Previous Work: MILBoost

- MIL + boosting

Train a boosting classifier that maximizes log likelihood of bags

$$\log L = \sum_i \log(p(y_i | \mathbf{X}_i))$$

where,

$$p(y_i | \mathbf{X}_i) = 1 - \prod_j (1 - p(y_i | x_{ij}))$$

Previous Work: MILBoost

- MIL + boosting

Train a boosting classifier that maximizes log likelihood of bags

$$\log L = \sum_i \log(p(y_i | \mathbf{X}_i))$$

where,

$$p(y_i | \mathbf{X}_i) = 1 - \prod_j (1 - p(y_i | x_{ij}))$$

\uparrow \uparrow
 ~ 1 1

[Viola et al. '05]

Previous Work: MILBoost

- Problem: need all training examples



[Viola et al. '05]

Previous Work: MILBoost

But in tracking, only current frame available

[Viola et al. '05]

Previous Work: MILBoost

But in tracking, only current frame available

Need an **online** training algorithm for MIL

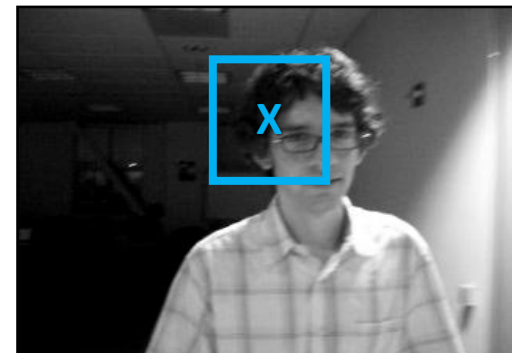
[Viola et al. '05]

Main Contribution of this paper

- Online-MILBoost:
Online training for MIL-based classifier
- MILTrack
New tracking solution using Online-MILBoost

MILTrack workflow

New frame comes in:



1. Crop out a set of image patches

$$X^s = \{x \mid x \text{ is } < s^1 \text{ pixels from tracker location}\}$$

1: $s = 35$ in authors' experiment

MILTrack workflow

New frame comes in:



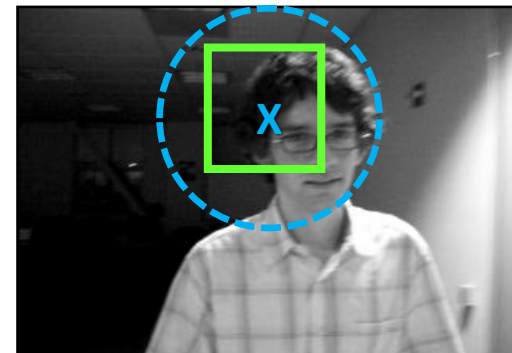
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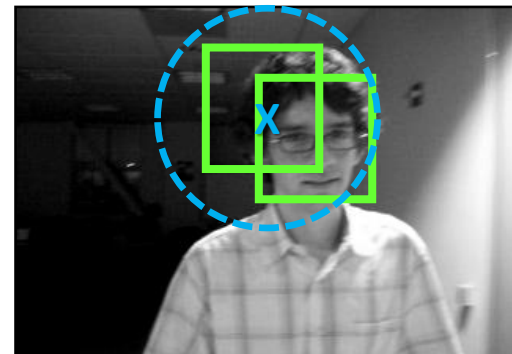
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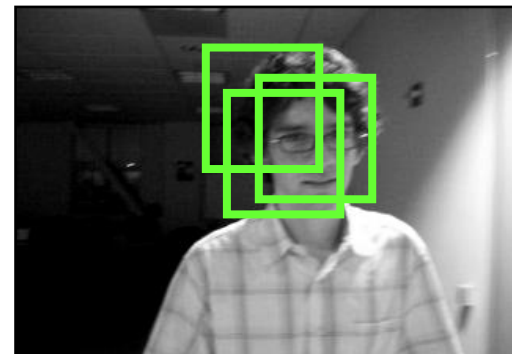
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New frame comes in:

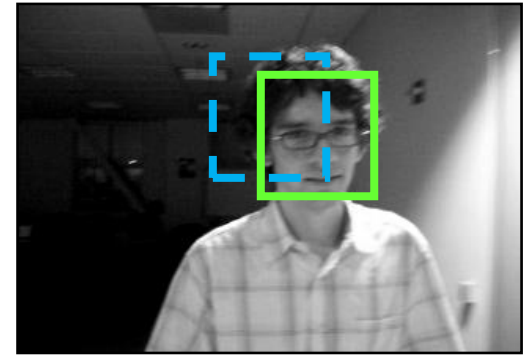


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MILTrack workflow



New frame comes in:

1. Crop out a set of image patches

$$X^s = \{x \mid x \text{ is } s \text{ pixels from tracker location}\}$$

2. Use MIL classifier to find new tracker location

$$l_{new} = l(\operatorname{argmax}_{x \in X^s} p(y = 1|x))$$

MILTrack workflow



New frame comes in:

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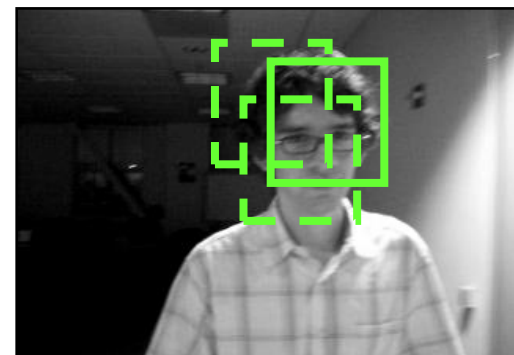
3. 1) Crop positive examples

$$X^r = \{x \mid x \text{ is } r \text{ pixels from tracker location}\}$$

1: $r = 5$ in authors' experiment

MILTrack workflow

New frame comes in:



1. Crop out a set of image patches

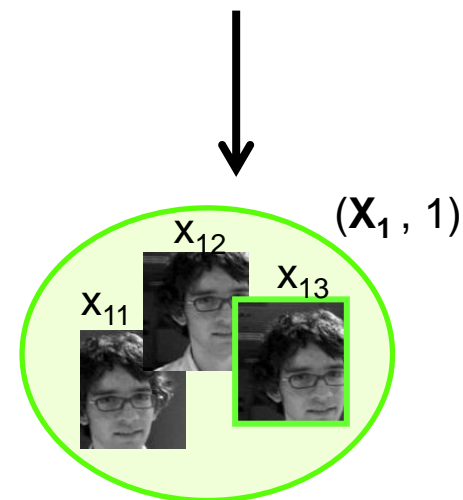
$$X^s = \{x \mid x \text{ is } s \text{ pixels from tracker location}\}$$

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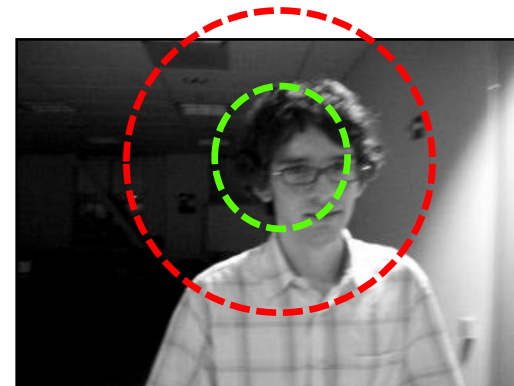
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MILTrack workflow



New frame comes in:

1. Crop out a set of image patches

$$X^s = \{x \mid x \text{ is } s \text{ pixels from tracker location}\}$$

2. Use MIL classifier to find new tracker location

$$l_{new} = l(\operatorname{argmax}_{x \in X^s} p(y = 1|x))$$

3. 1) Crop positive examples

$$X^r = \{x \mid x \text{ is } r \text{ pixels from tracker location}\}$$

3. 2) Crop Negative examples

$$X^{r,\beta} = \{x \mid x \text{ is } r \text{ to } \beta^1 \text{ pixels away from tracker location}\}$$

1: $\beta = 50$ in authors' experiment

MILTrack workflow

New frame comes in:



1. Crop out a set of image patches

$$X^s = \{x \mid x \text{ is } < s \text{ pixels from tracker location}\}$$

2. Use MIL classifier to find new tracker location

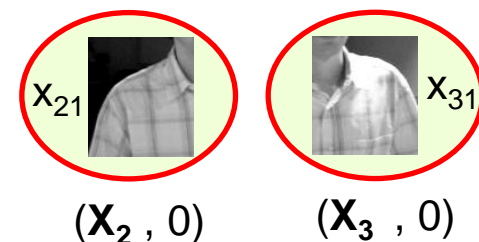
$$l_{new} = l(\operatorname{argmax}_{x \in X^s} p(y = 1|x))$$

3. 1) Crop positive examples

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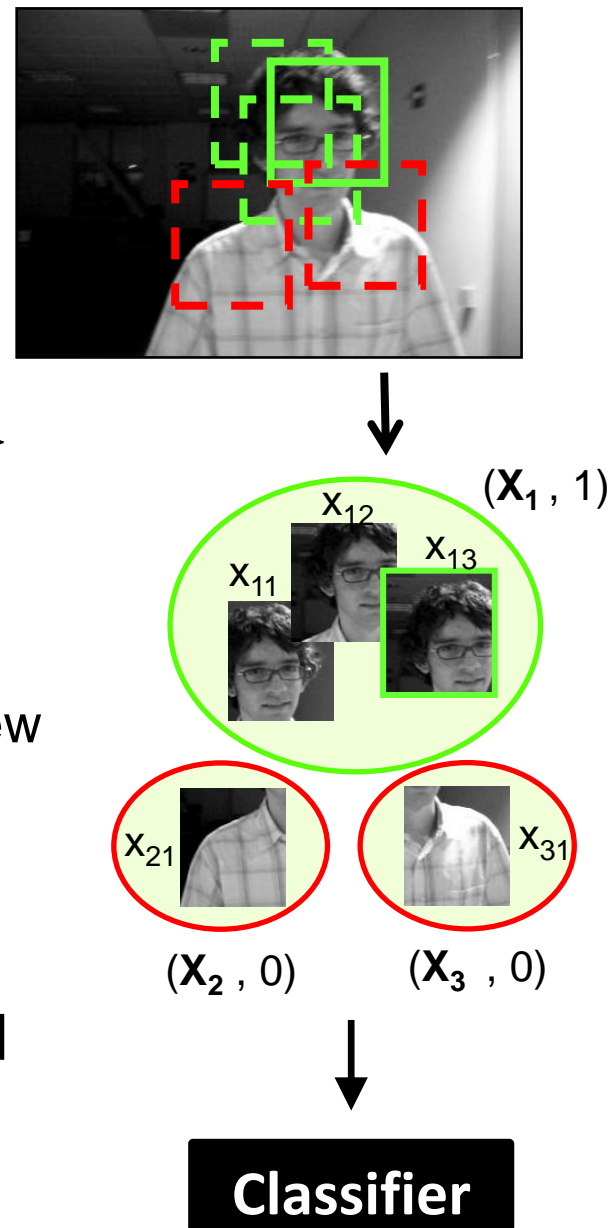


1: $\beta = 50$ in authors' experiment

MILTrack workflow

New frame comes in:

1. Crop out a set of image patches
 $X^s = \{x \mid x \text{ is } s \text{ pixels from tracker location}\}$
2. Use MIL classifier to find new tracker location
$$l_{new} = l(\operatorname{argmax}_{x \in X^s} p(y = 1|x))$$
3. Crop positive and negative examples near new object location
4. Online MILBoost:
Update MIL classifier with positive and negative example bags



Online-MILBoost:

Image patch x



f_1
f_2
f_3
\dots

Babenko et al., 09

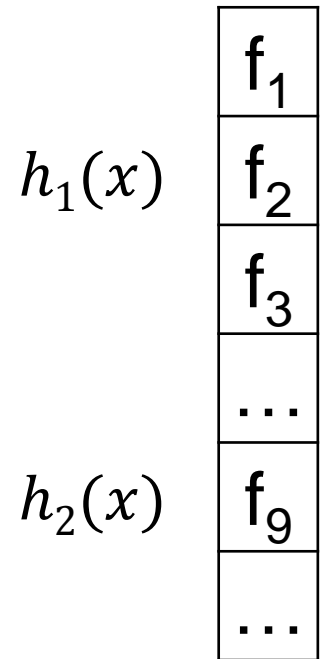
Stanford University

Online-MILBoost:

Image patch x



- h_k : a weak classifier using one feature



Online-MILBoost:

Image patch x



- h_k : a weak classifier using one feature

$$h_k(x) = \log \left[\frac{p(y = 1 | f_k(x))}{p(y = 0 | f_k(x))} \right]$$

$$h_k(x) \begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ \dots \\ f_t \\ \dots \end{bmatrix}$$

Online-MILBoost:

Image patch x



- h_k : a weak classifier using one feature

$$h_k(x) = \log \left[\frac{p(y = 1 | f_k(x))}{p(y = 0 | f_k(x))} \right]$$

with,

$$\begin{aligned} p(f_k(x) | y = 1) &\sim \mathcal{N}(\mu_1, \sigma_1) \\ p(f_k(x) | y = 0) &\sim \mathcal{N}(\mu_0, \sigma_0) \\ p(y = 1) &= p(y = 0) \end{aligned}$$

$$h_k(x) \begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ \dots \\ f_t \\ \dots \end{bmatrix}$$

Online-MILBoost:

Image patch x



- $H(x)$: the MIL classifier made from weak classifiers

$$H(x) = \sum_{k=1}^K h_k(x)$$

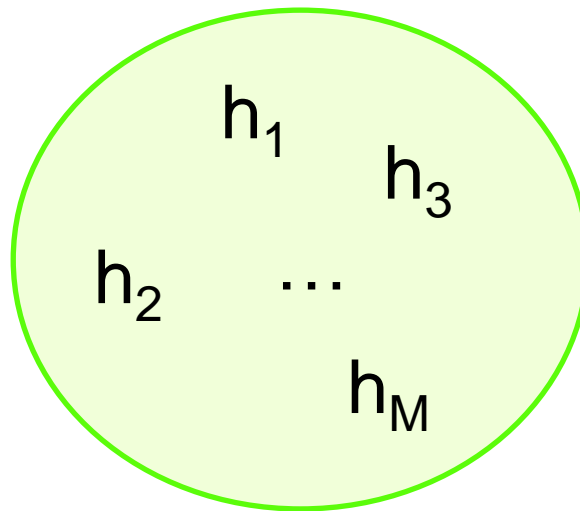
	f_1
$h_1(x)$	f_2
	f_3
...	...
$h_k(x)$	f_t
...	...

$K = 50$ in authors' experiment

Babenko et al., 09

Online-MILBoost:

- Always keep a pool of $M \gg K$ weak classifier candidates

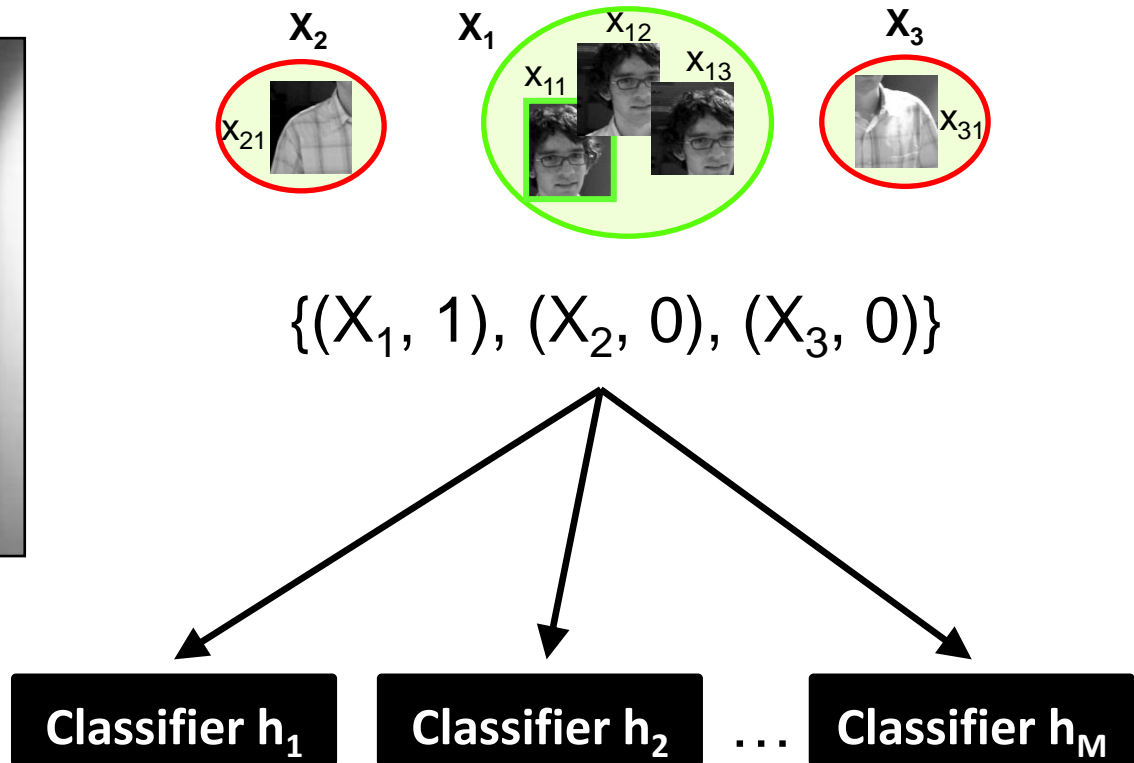
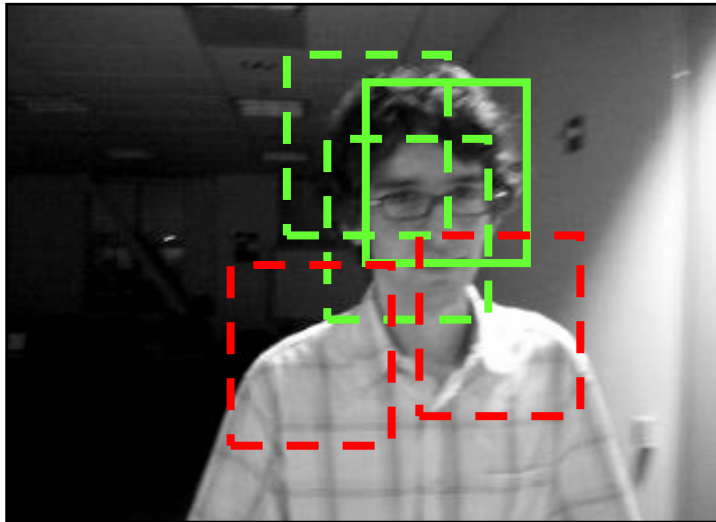


$M = 250$ & $K = 50$ in authors' experiment

Babenko et al., 09

Online-MILBoost:

- Update all M weak classifiers with positive and negative bags



Babenko et al., 09

Online-MILBoost:

- Pick best K weak classifiers to form $\mathbf{H}(\mathbf{x})$, where

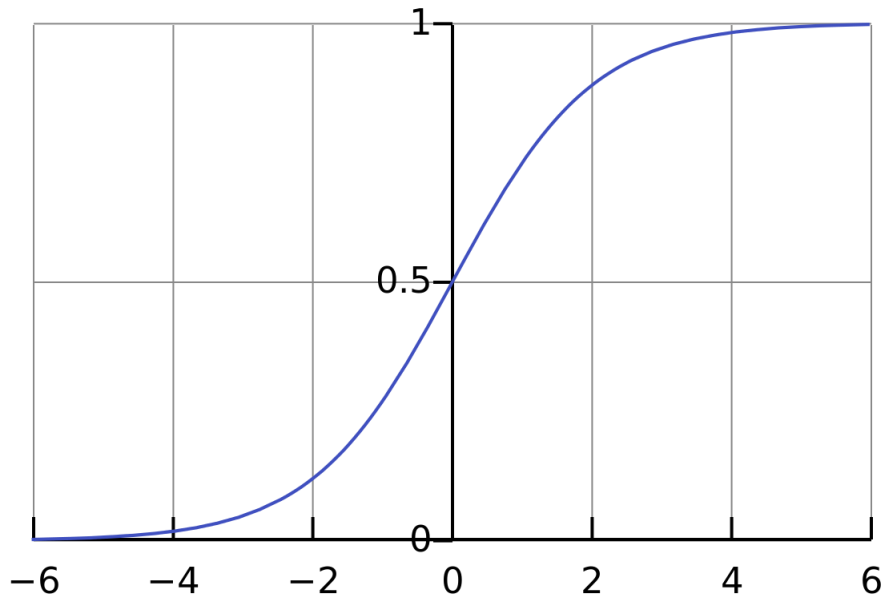
$$h_k = \operatorname{argmax}_{h \in \{h_1 \dots h_M\}} \log L(H_{k-1} + h)$$

$$\mathbf{H}(\mathbf{x}) = \sum_{k=1}^K h_k(\mathbf{x})$$

where H_{k-1} is the classifier made up of the first $k-1$ weak classifiers

Online-MILBoost:

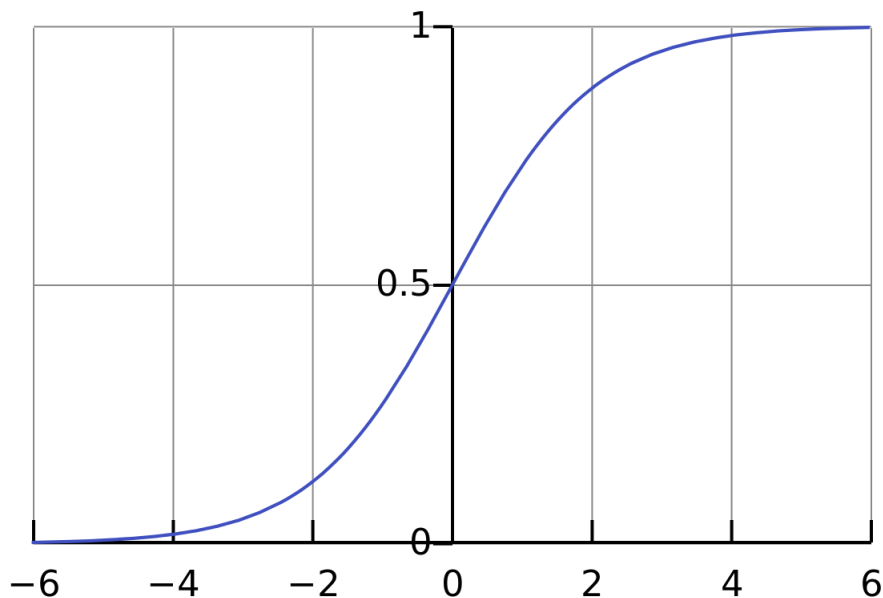
- Prediction : $p(y = 1|x) = \sigma(\mathbf{H}(\mathbf{x}))$



$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

Online-MILBoost:

- Prediction : $p(y = 1|x) = \sigma(\mathbf{H}(x))$



$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

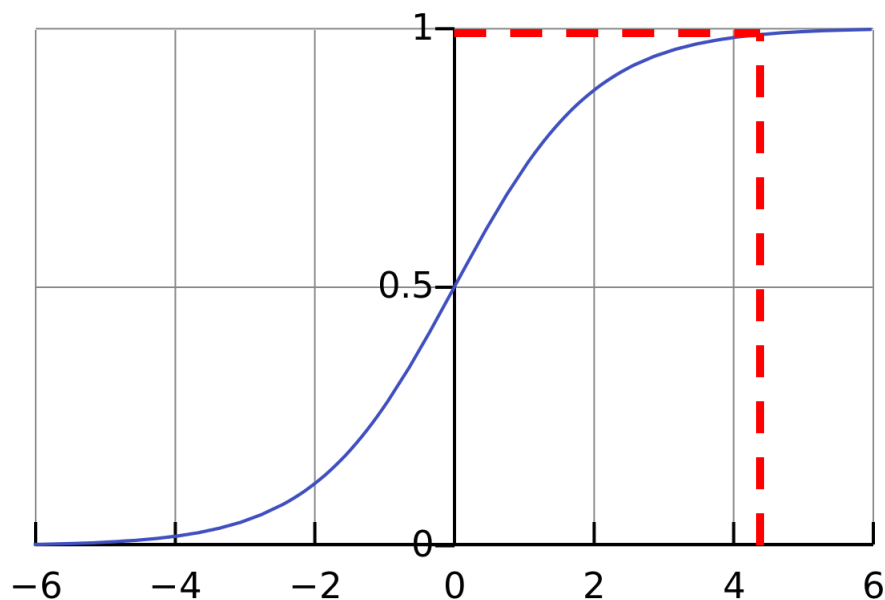


$h_1(x)$	\mathbf{f}_1
$h_2(x)$	\mathbf{f}_2
$h_3(x)$	\mathbf{f}_3

$$h_1(x) = 2, \quad h_2(x) = 1.8, \quad h_3(x) = 0.6$$

Online-MILBoost:

- Prediction : $p(y = 1|x) = \sigma(\mathbf{H}(x))$



$$\sigma(t) = \frac{1}{1 + e^{-t}}$$



$h_1(x)$	\mathbf{f}_1
$h_2(x)$	\mathbf{f}_2
$h_3(x)$	\mathbf{f}_3

$$h_1(x) = 2, \quad h_2(x) = 1.8, \quad h_3(x) = 0.6$$

$$\mathbf{H}(x) = \sum_{k=1}^K h_k(x) = 4.4$$

$$p(y = 1|x) = \sigma(\mathbf{H}(x)) = 0.99$$

MILTrack workflow

New frame comes in:

1. Crop out a set of image patches

$$X^s = \{x \mid x \text{ is } s \text{ pixels from tracker location}\}$$

2. **Use MIL classifier to find new tracker location**

$$l_{new} = l(\operatorname{argmax}_{x \in X^s} p(y = 1|x))$$

3. Crop positive and negative examples near new object location

4. **Online MILBoost:**

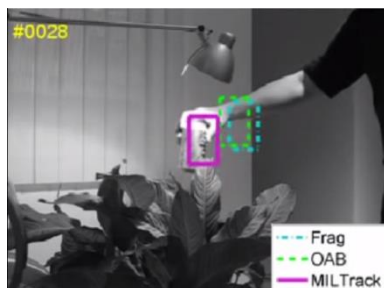
Update MIL classifier with positive and negative example bags

Experiments

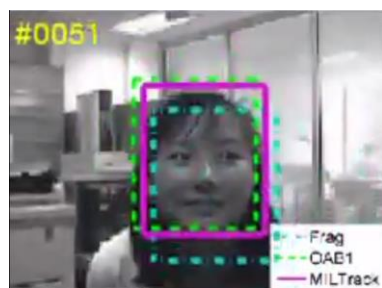
Datasets: 8 publicly available videos,

- Grayscale, 320 x 240 pixels
- Ground truth labeled every 5 frames by hand

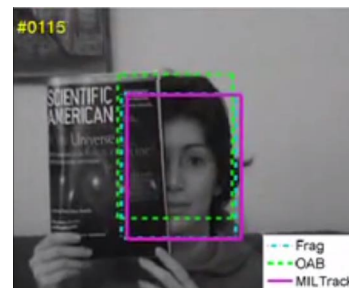
Coke can



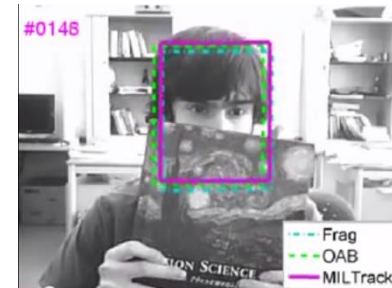
Girl



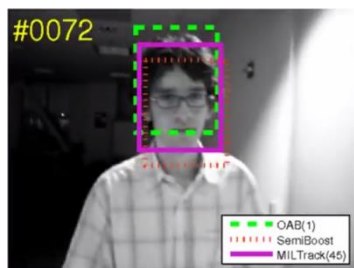
Occluded face



Occluded face 2



David



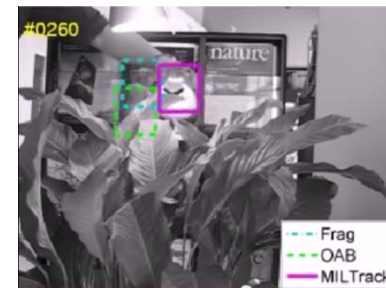
Sylvester



Tiger 1



Tiger 2



Babenko et al., 2009

Stanford University

Experiments

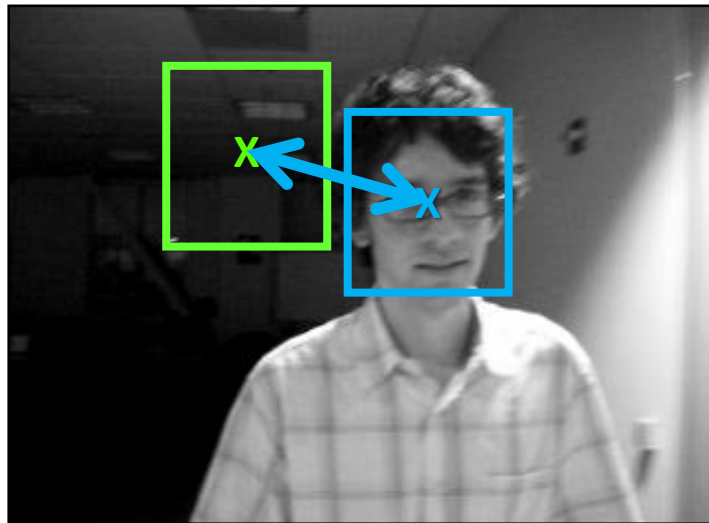
Compared with:

- **OAB1**
Online AdaBoost w/ 1 positive example per frame
- **OAB5**
Online AdaBoost w/ 45 positive examples per frame
- **SemiBoost**
Label in 1st frame only.
- **FragTrack**
Static appearance model

Experiments

Evaluation criterion:

Tracker position error (pixels) w.r.t. Ground truth

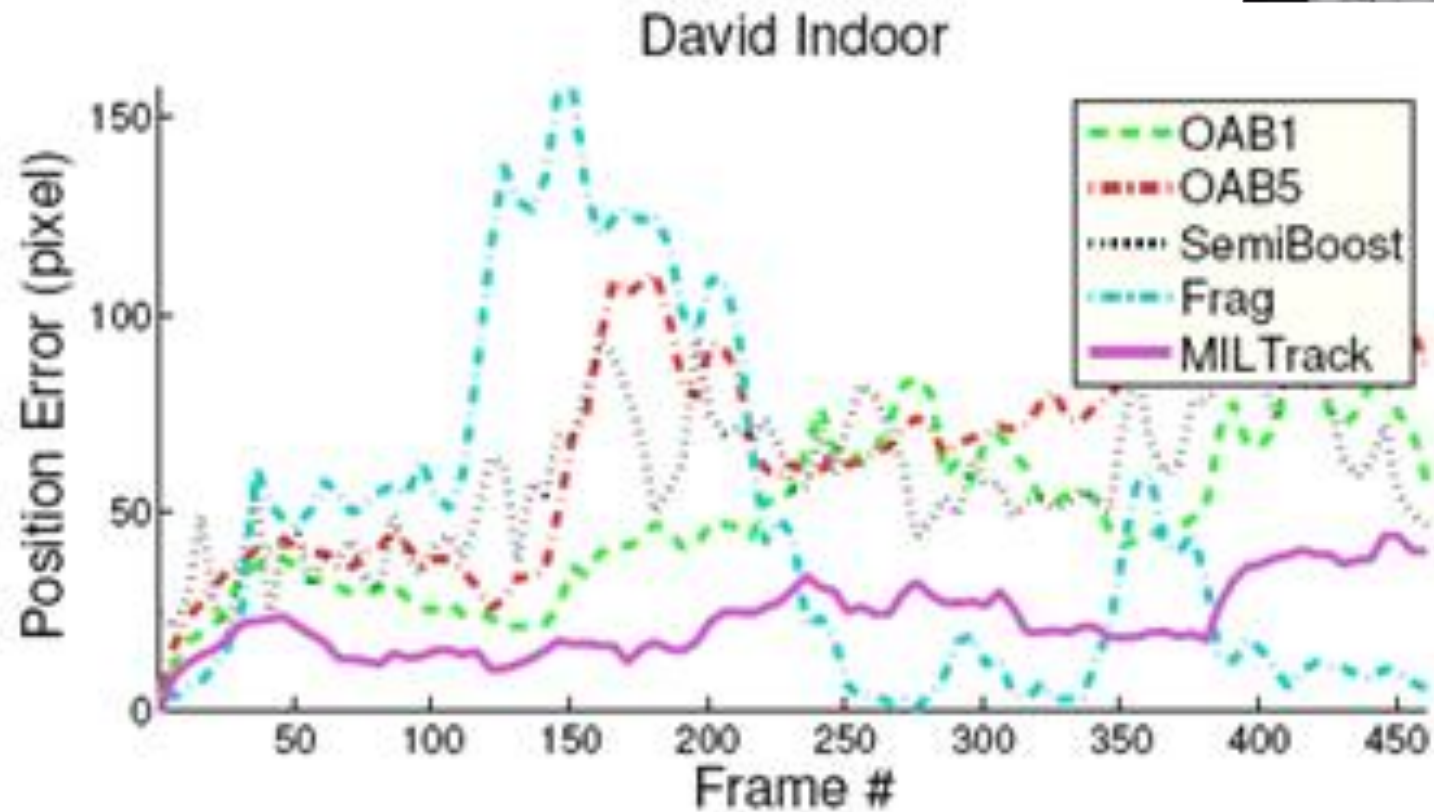
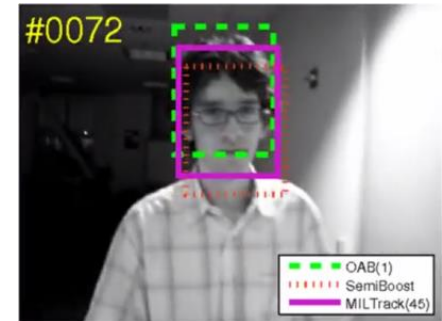


Results

Video David

Results

Position error versus Frame #, Video David



Babenko et al., 2009

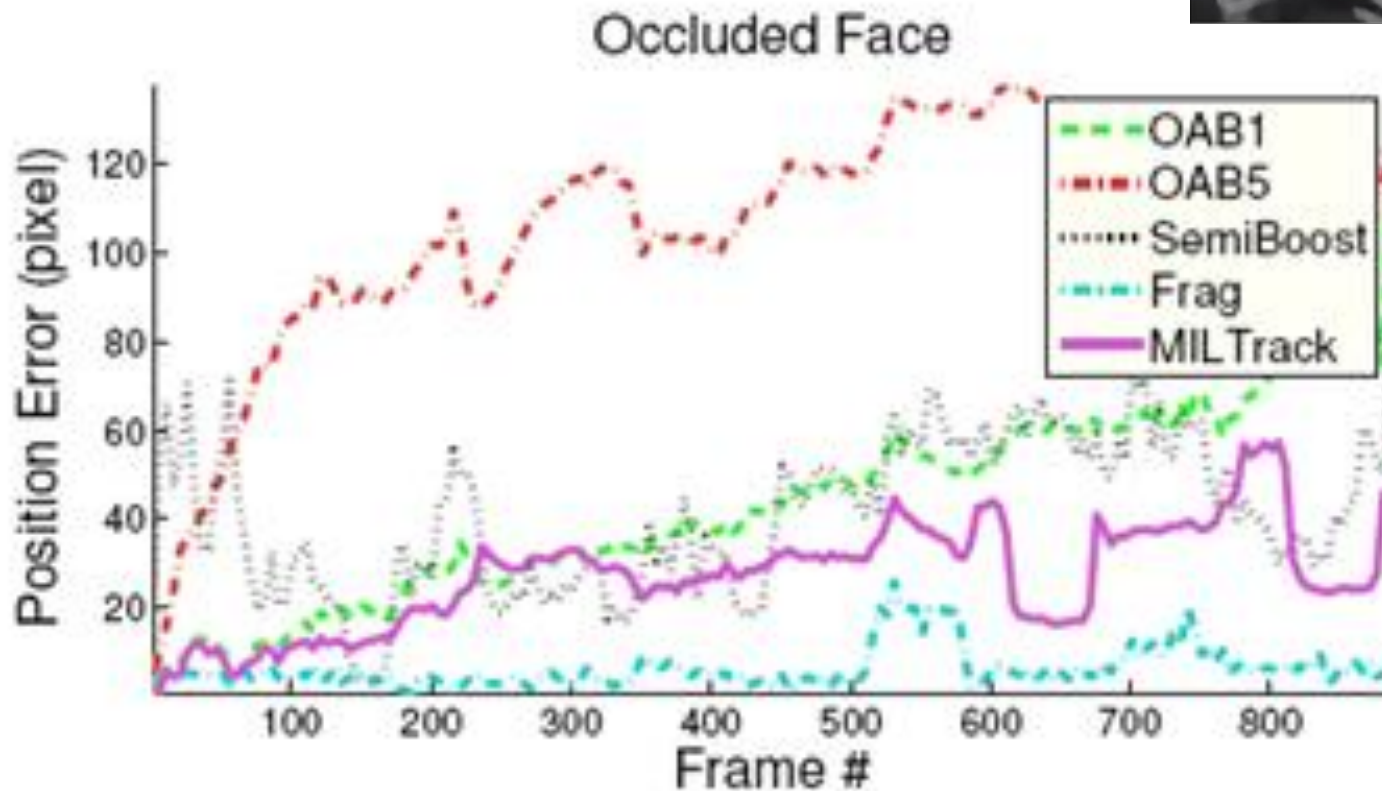
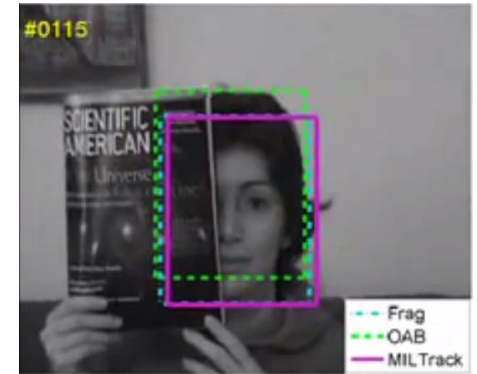
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Results

Video Occluded Face

Results

Position error versus Frame #,
Video Occluded Face



Babenko et al., 2009

Stanford University

Results

Average Center location errors (pixels)

— Best
— Second Best

Video Clip	OAB1	OAB5	SemiBoost	Frag	MILTrack
David Indoor	49	72	59	46	23
Sylvester	25	79	22	11	11
Occluded Face	44	105	41	6	27
Occluded Face 2	21	93	43	45	20
Girl	48	68	52	27	32
Tiger 1	35	58	46	40	15
Tiger 2	34	33	53	38	17
Coke Can	25	57	85	63	21

Conclusion

- Online MILBoost:
Online algorithm to update MIL-based classifier
- Performance of “MILTrack” is stable

Discussion

- Why it can handle occlusion?
- Possible improvements
 - Motion Model
 - Features
 - Part based representation

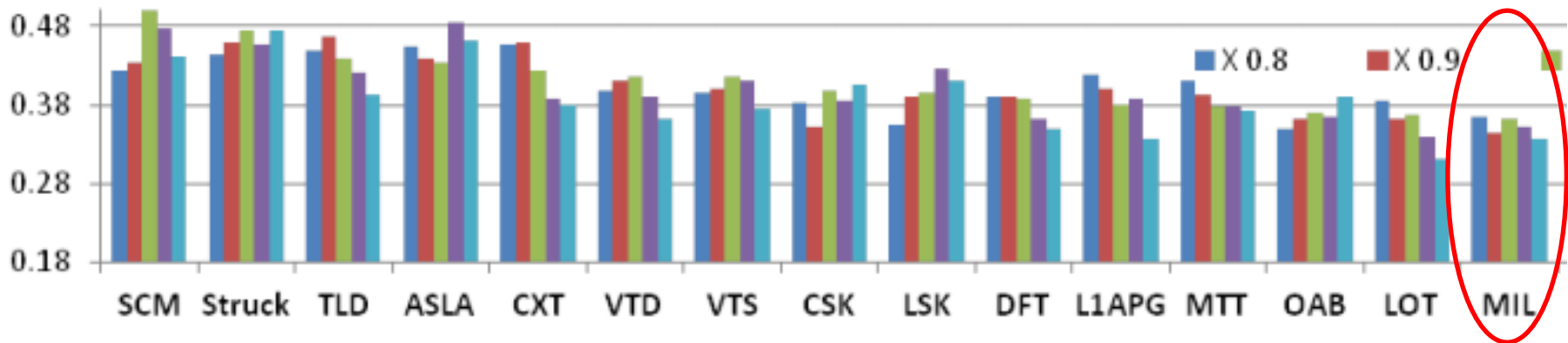
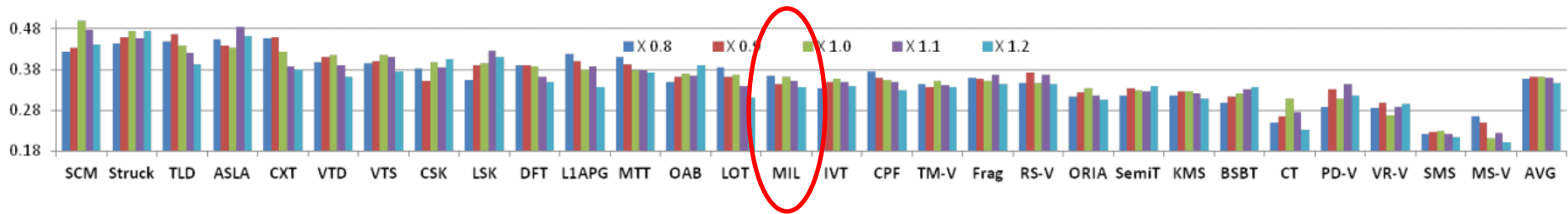
Note...



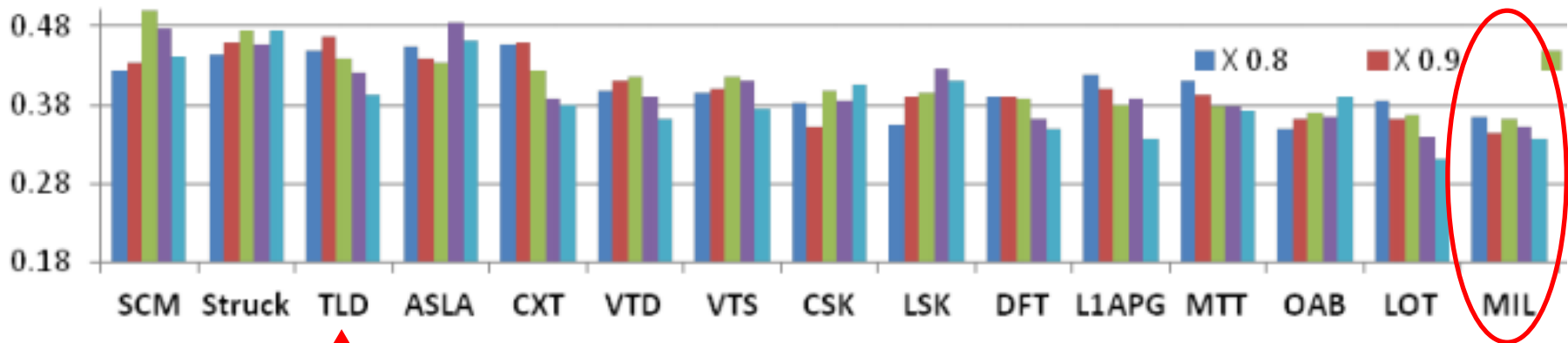
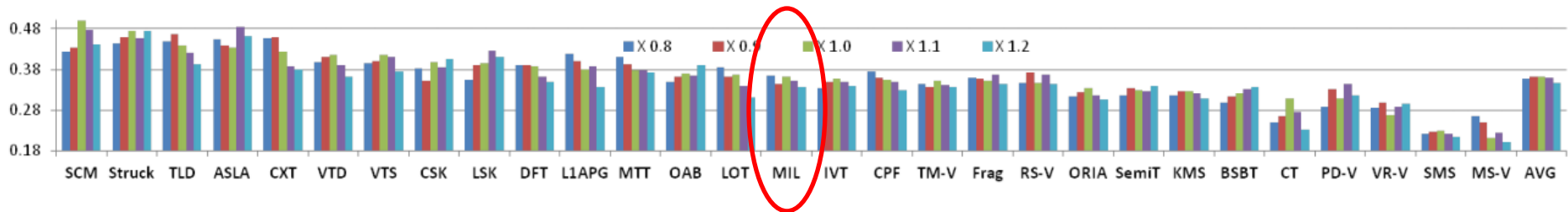
Wu et al., 2013

Stanford University

Note...



Note...



Project 2 use this!

Wu et al., 2013

Stanford University

Thank You!
Q&A