# Evidential combination of pedestrian detectors

**Philippe XU[1]**

**Franck Davoine[1,2]  Thierry Denoeux[1]**

philippe.xu@hds.utc.fr  www.hds.utc.fr/~xuphilip

[1]CNRS, Heudiasyc
Université de Technologie de Compiègne
France

[2]CNRS, LIAMA
Beijing, P. R. China

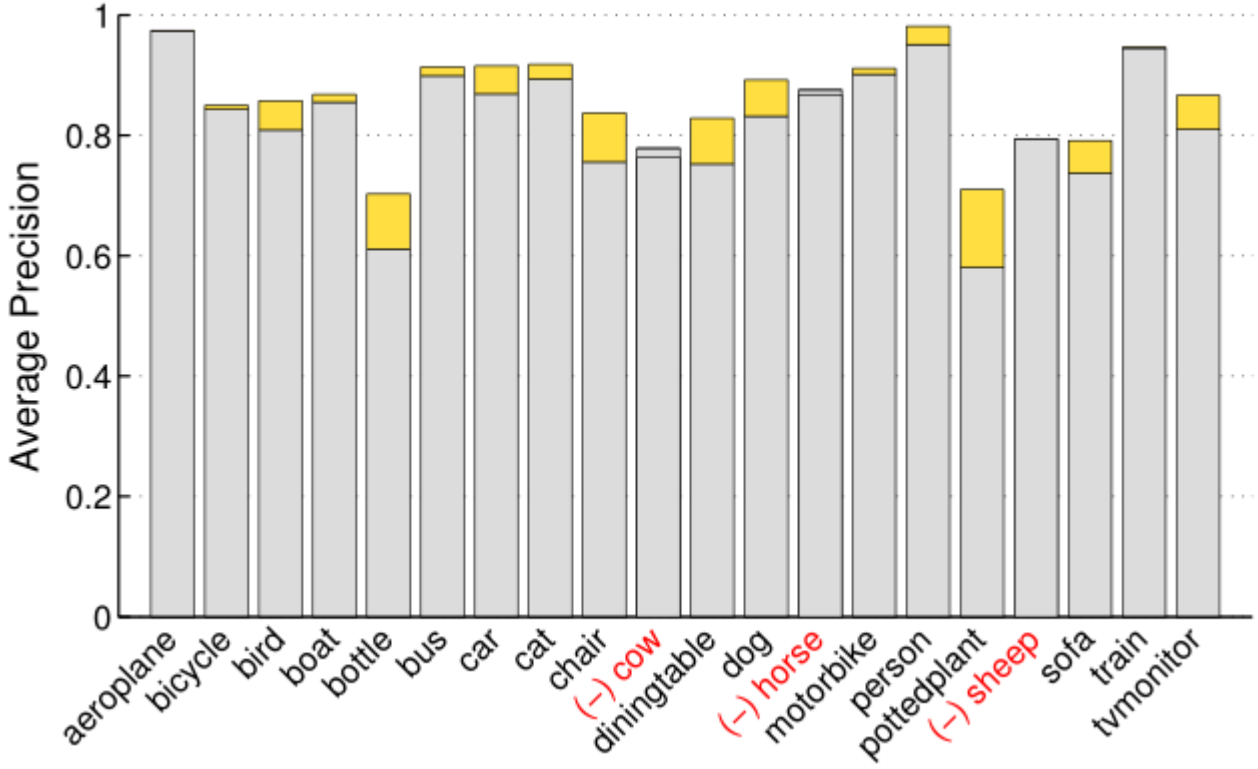
Labex MS2T
ANR-11-IDEX-0004-02

ANR-NFSC PRETIV
ANR-11-IS03-0001

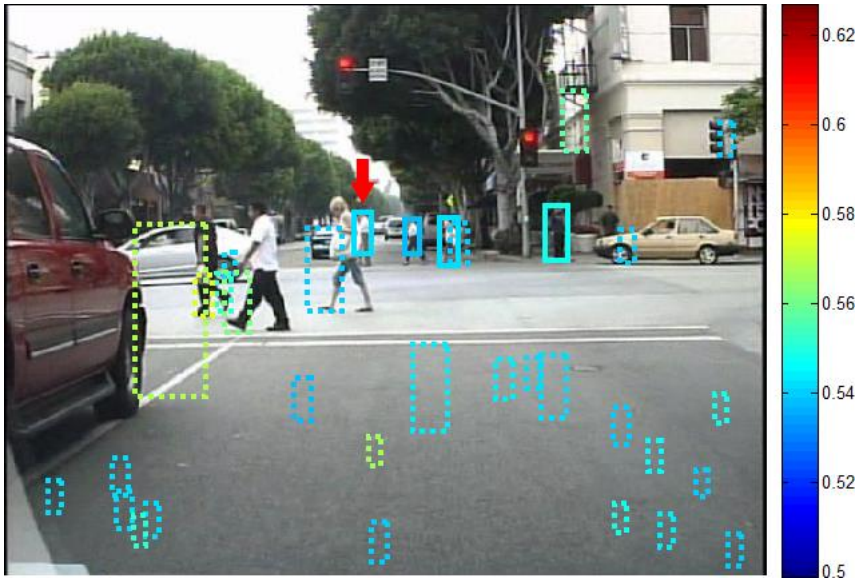
# VOC 2012 super-classifier

**Classification challenge: 6 methods submitted**

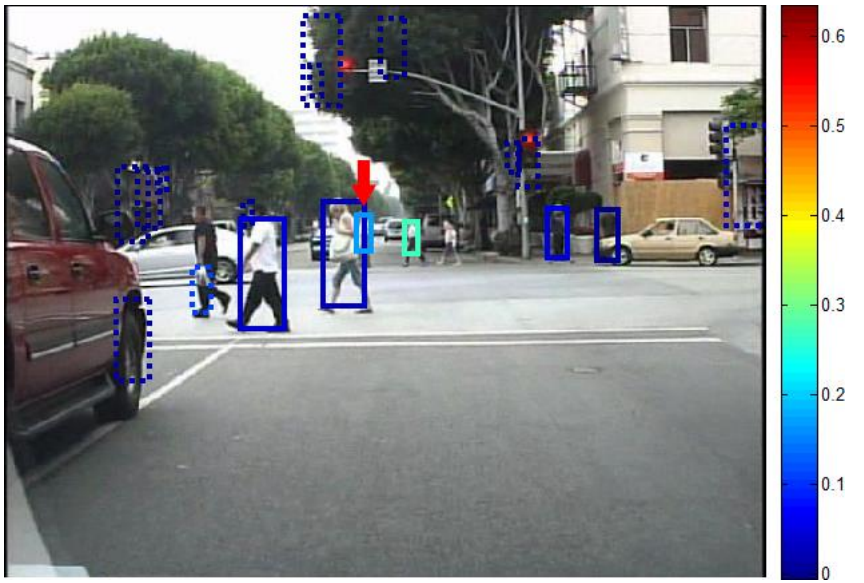
**Super-classifier: SVM using the output scores**



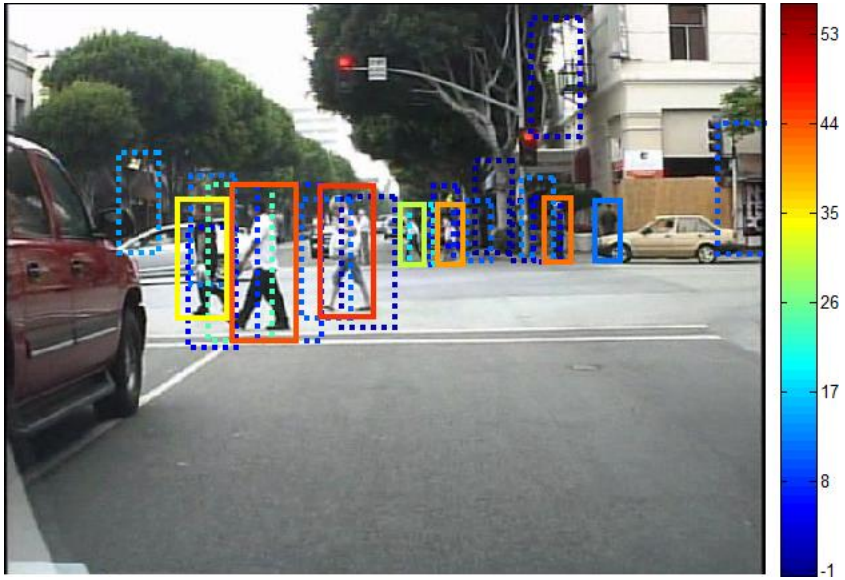
| # | Algorithm | Features | Classifier | Training |
|---|---|---|---|---|
| 1 | VJ | Haar | AdaBoost | INRIA |
| 2 | HOG | HOG | Linear SVM | INRIA |
| 3 | HikSVM | HOG | HIK SVM | INRIA |
| 4 | LatSVM | HOG | Latent SVM | PASCAL/INRIA |
| 5 | MultiResC | HOG | Latent SVM | Caltech |
| 6 | PoseInv | HOG | AdaBoost | INRIA |
| 7 | DBN | HOG | DeepNet | INRIA/Caltech |
| 8 | MOCO | HOG+LBP | Latent SVM | Caltech |
| 9 | pAUCBoost | HOG+COV | pAUCBoost | INRIA |
| 10 | ACF | Channels | AdaBoost | INRIA/Caltech |
| 11 | MultiFtr+Motion | Multiple | Linear SVM | TUD-Motion |
| 12 | PLS | Multiple | PLS+QDA | INRIA |
| 13 | Shapelet | Gradients | AdaBoost | INRIA |
| 14 | ConvNet | Pixels | DeepNet | INRIA |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |




**VJ**
**[Viola05]**




**HOG**
**[Dalal05]**




**ACF+SDt**
**[Park13]**

# Outlines

1. **Combination of pedestrian detectors**
   a) Clustering of bounding boxes
   b) Score calibration
   c) Probabilistic combination of bounding boxes
2. **Theory of belief functions**
   a) Information representation
   b) Evidential combination rules
   c) Clustering detectors
3. **Experimental results**

# Outlines

1. **Combination of pedestrian detectors**
   a) **Clustering of bounding boxes**
   b) Score calibration
   c) Probabilistic combination of bounding boxes
2. Theory of belief functions
   a) Information representation
   b) Evidential combination rules
   c) Clustering detectors
3. Experimental results

# Clustering of bounding boxes

**Non-maximal suppression (NMS)**

**Greedy: NMS with decreasing score**

**$\Rightarrow$ Hierarchical clustering**

**Overlap area:**

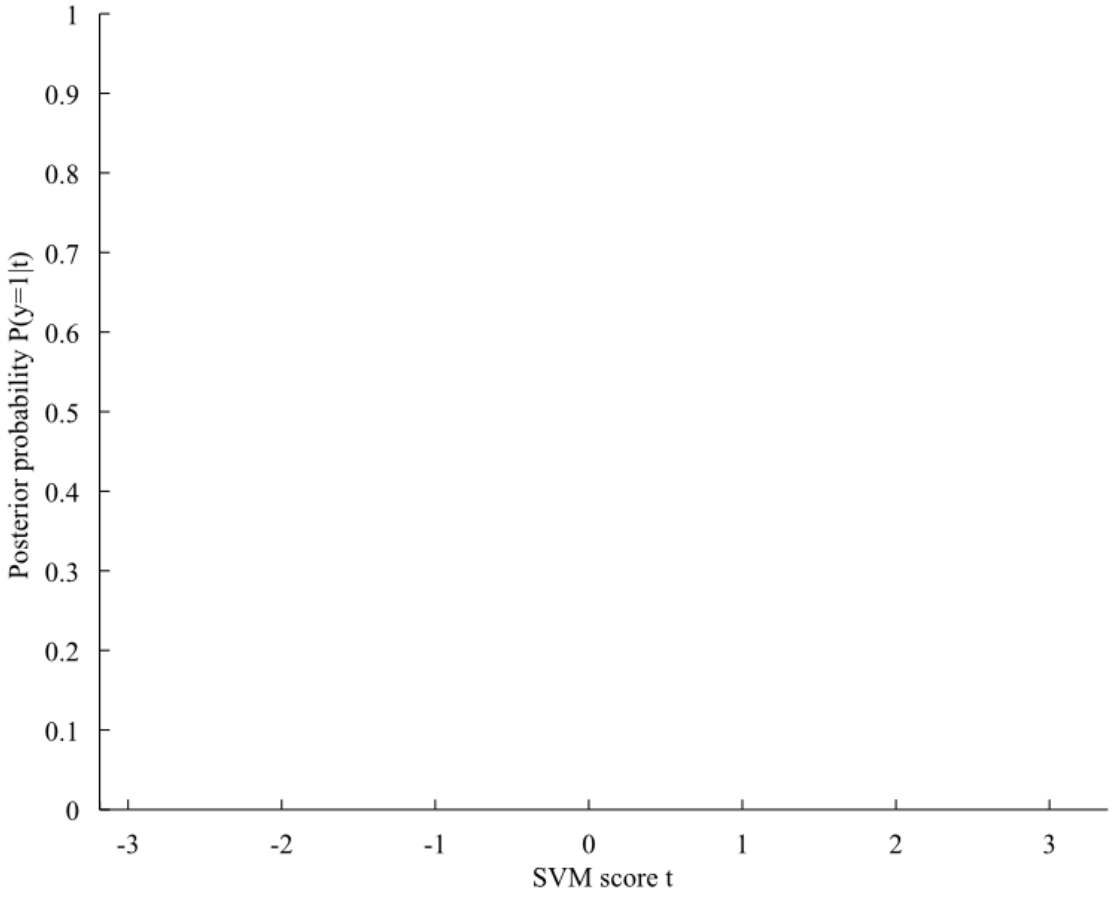
$$a_{\text{union}} = \frac{\text{area}(BB_i \cap BB_j)}{\text{area}(BB_i \cup BB_j)}$$

**Threshold $t \approx 1/2$**

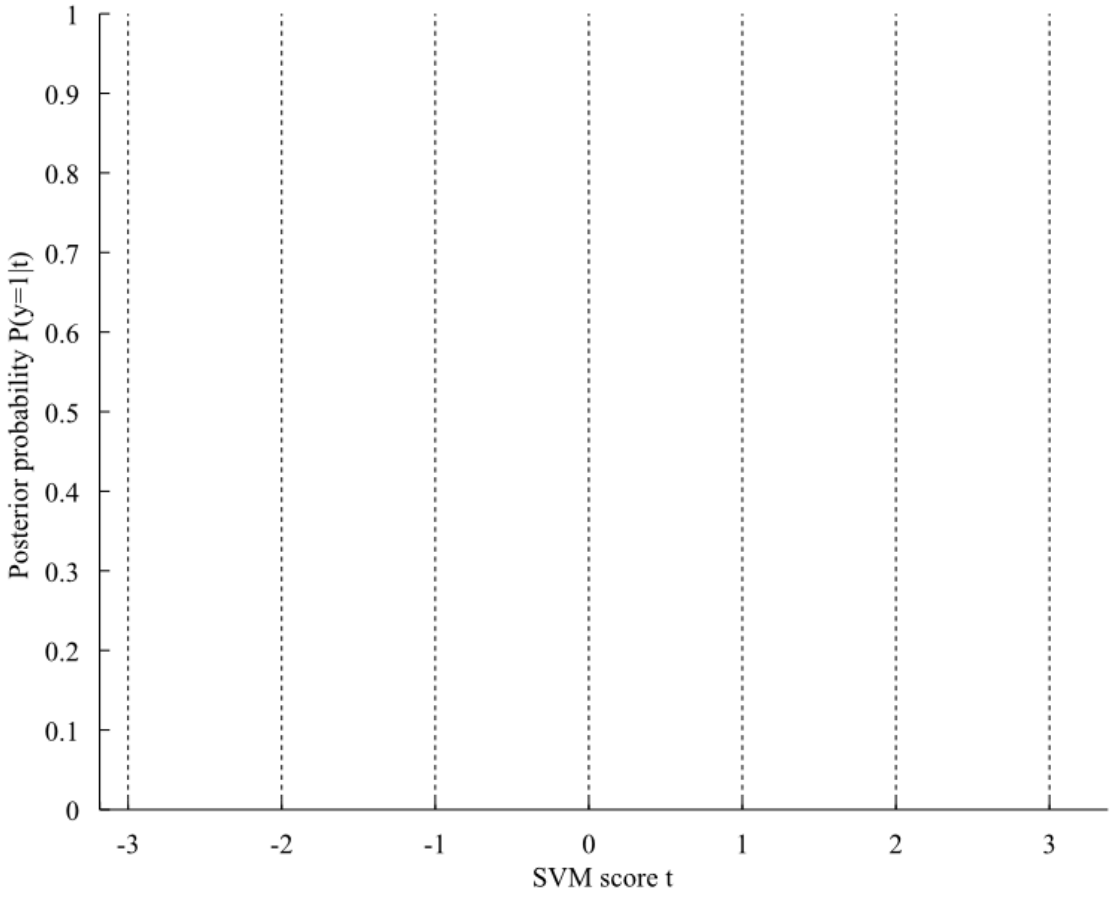
# Outlines

1. **Combination of pedestrian detectors**
   a) **Clustering of bounding boxes**
   b) **Score calibration**
   c) Probabilistic combination of bounding boxes
2. Theory of belief functions
   a) Information representation
   b) Evidential combination rules
   c) Clustering detectors
3. Experimental results

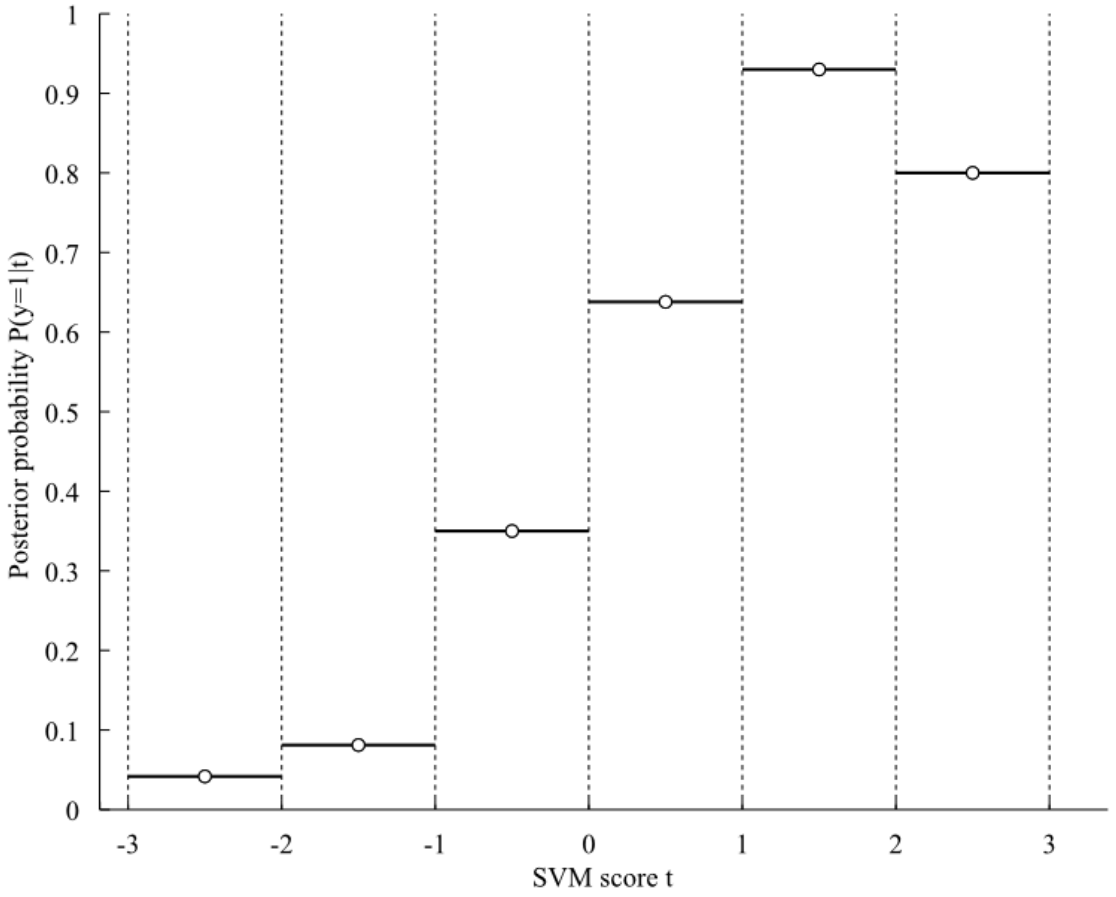
# Calibration of SVM scores



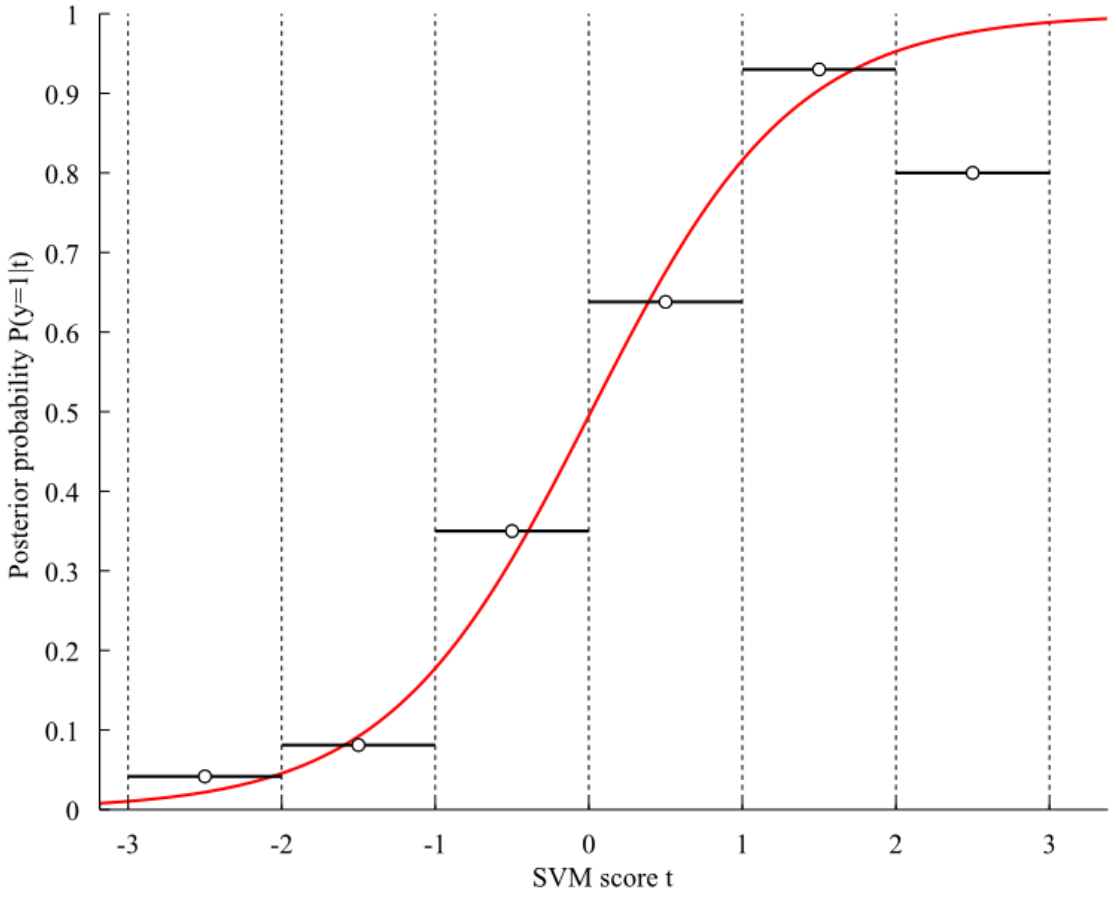
# Calibration of SVM scores



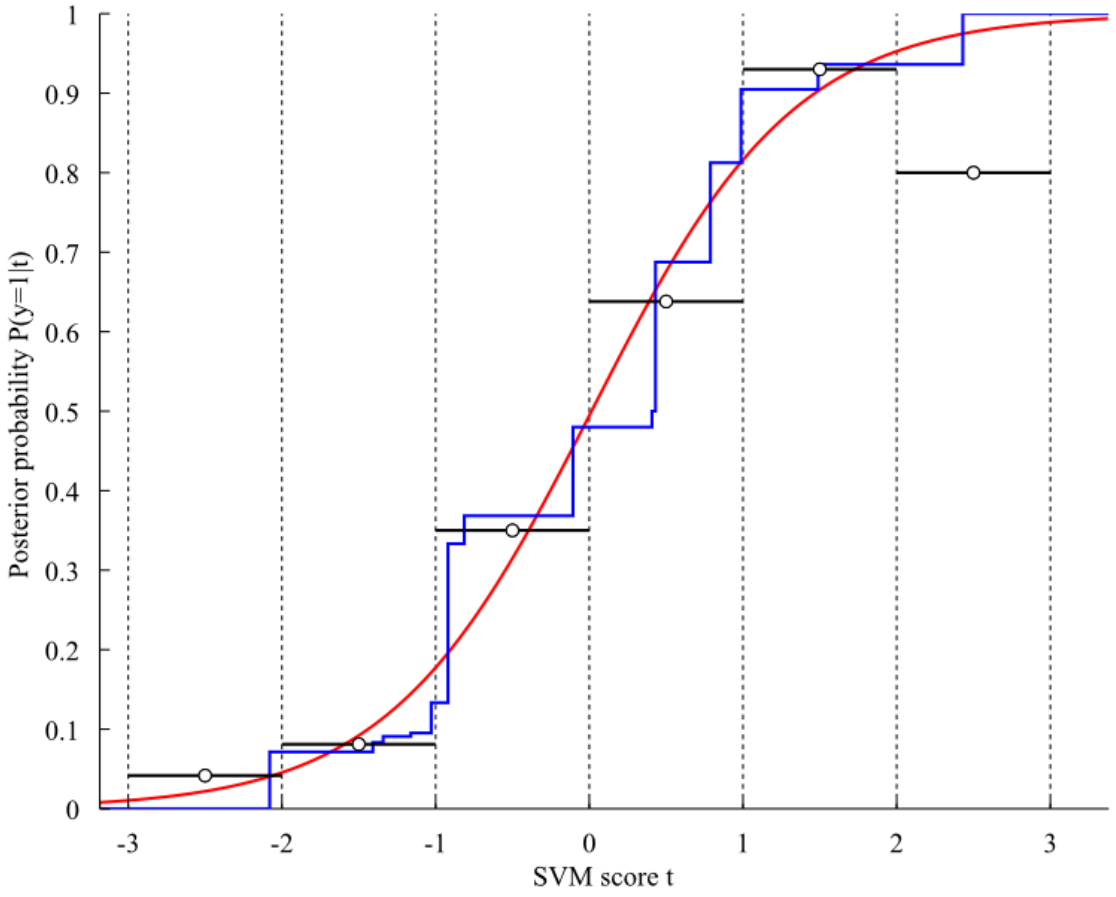
# Calibration of SVM scores



# Calibration of SVM scores



# Calibration of SVM scores



# Outlines

1. **Combination of pedestrian detectors**
   a) **Clustering of bounding boxes**
   b) **Score calibration**
   c) **Probabilistic combination of bounding boxes**
2. **Theory of belief functions**
   a) **Information representation**
   b) **Evidential combination rules**
   c) **Clustering detectors**
3. **Experimental results**

# Bayesian combination

**Scores from detectors:** $s_{(1)}, s_{(2)}, \dots, s_{(k)}$

**Conditional independence:**

$$p\left(s_{(1)}, \dots, s_{(k)} \middle| y = 1\right) = \prod_{i=1}^{k} p(s_{(i)} | y = 1)$$

**Bayes' rule:**

$$P\left(y = 1 \middle| s_{(1)}, \dots, s_{(k)}\right) = \frac{p\left(s_{(1)}, \dots, s_{(k)} \middle| y = 1\right) P(y = 1)}{p(s_{(1)}, \dots, s_{(k)})}$$

$$= \frac{P(y = 1)}{p(s_{(1)}, \dots, s_{(k)})} \prod_{i=1}^{k} p(s_{(i)} | y = 1)$$

$$= \frac{p(s_{(1)}) \cdots p(s_{(k)})}{p(s_{(1)}, \dots, s_{(k)})} P(y = 1)^{1-k} \prod_{i=1}^{k} P(y = 1 | s_{(i)})$$

# Bayesian combination

**Scores from detectors:** $s_{(1)}, s_{(2)}, \dots, s_{(k)}$

**Conditional independence:**

$$p(s_{(1)}, \dots, s_{(k)} | y = 1) = \prod_{i=1}^{k} p(s_{(i)} | y = 1)$$

**Bayes' r**

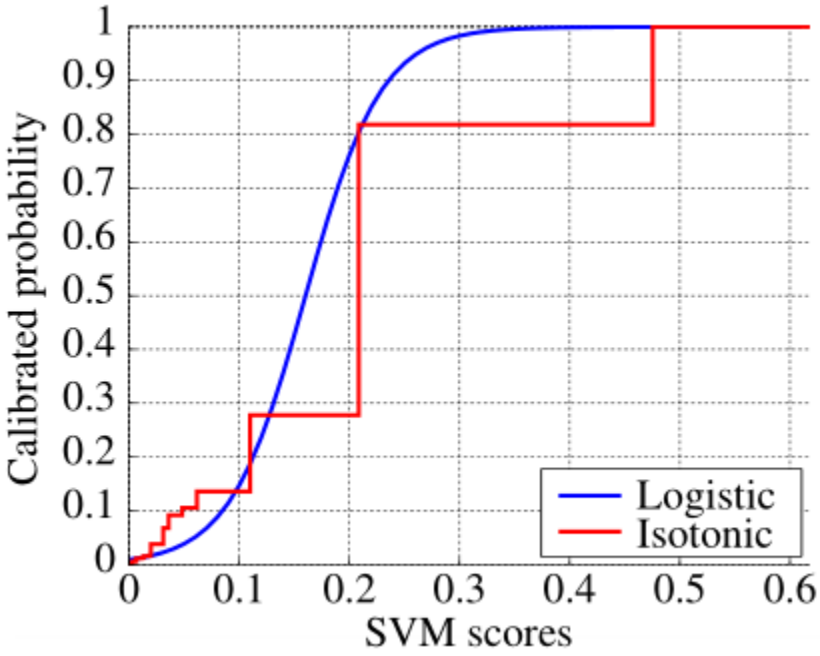
**Bayesian product combination rule:**

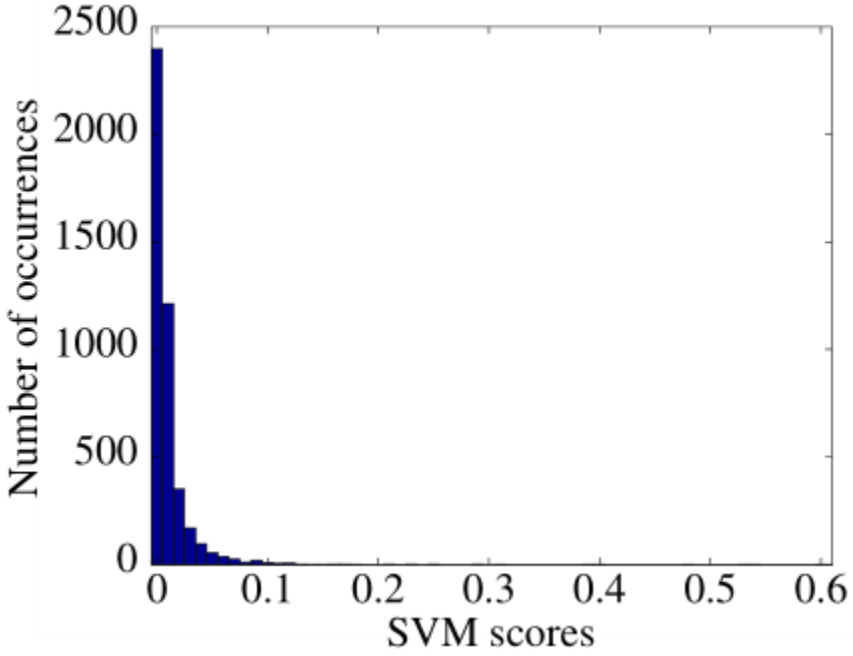
$$P(y = 1 | s_{(1)}, \dots, s_{(k)}) \propto \prod_{i=1}^{k} P(y = 1 | s_{(i)})$$

$$= \frac{}{p(s_{(1)}, \dots, s_{(k)})} \prod_{i=1}^{k} p(s_{(i)} | y = 1)$$

$$= \frac{p(s_{(1)}) \cdots p(s_{(k)})}{p(s_{(1)}, \dots, s_{(k)})} P(y = 1)^{1-k} \prod_{i=1}^{k} P(y = 1 | s_{(i)})$$

# Calibration of the HOG detector




**There are almost *infinitely* more negative samples than positive samples.**

# Probabilistic combination rules

| Combination rule | Support |
|---|---|
| Product | $\prod_{i=1}^{k} \boldsymbol{P(y=1\|s_{(i)})}$ |
| Minimum | $\min_{i=1,\ldots,k} \boldsymbol{P(y=1\|s_{(i)})}$ |
| Sum | $\sum_{i=1}^{k} \boldsymbol{P(y=1\|s_{(i)})}$ |
| Maximum | $\max_{i=1,\ldots,k} \boldsymbol{P(y=1\|s_{(i)})}$ |

# Outlines

1. **Combination of pedestrian detectors**
   a) **Clustering of bounding boxes**
   b) **Score calibration**
   c) **Probabilistic combination of bounding boxes**
2. **Theory of belief functions**
   a) **Information representation**
   b) **Evidential combination rules**
   c) **Clustering detectors**
3. **Experimental results**

# Information representation

**Mass function over $\Omega = \{\omega_1, \dots, \omega_n\}$, $m: 2^{\Omega} \rightarrow [0,1]$:**

$$\sum_{A \subseteq \Omega} m(A) = 1, \qquad m(\emptyset) = 0$$

**Binary problem $\Omega = \{-1, 1\}$:**

$$m(\{-1\}) \qquad m(\{1\}) \qquad m(\{-1,1\})$$

**Output of calibration $f(s) = P(y = 1|s) : \{1\}^{1-f(s)}$**

$$m(\{1\}) = f(s), \qquad m(\{-1,1\}) = 1 - f(s)$$

**Discounting:** $${}^{\delta}m(A) = \begin{cases} (1-\delta)m(A) & \text{if } A \subset \Omega \\ (1-\delta)m(\Omega) + \delta & \text{otherwise} \end{cases}$$

# Outlines

1. **Combination of pedestrian detectors**
   a) **Clustering of bounding boxes**
   b) **Score calibration**
   c) **Probabilistic combination of bounding boxes**
2. **Theory of belief functions**
   a) **Information representation**
   b) **Evidential combination rules**
   c) **Clustering detectors**
3. **Experimental results**

# Evidential combination rules (1/2)

**Demspter's rule of combination:**

$$(m_1 \oplus m_2)(A) = \frac{1}{1-K} \sum_{B \cap C} m_1(B) m_2(C)$$

**For two simple mass functions:**

$$\{1\}^{\alpha_1} \oplus \{1\}^{\alpha_2} = \{1\}^{\alpha_1 \alpha_2}$$

**Cautious rule of combination:**

$$\{1\}^{\alpha_1} \textcircled{\wedge} \{1\}^{\alpha_2} = \{1\}^{\alpha_1 \wedge \alpha_2}$$

# Evidential combination rules (2/2)

**Franck's family of triangular norms:**

$$\alpha_1 \top_p \alpha_2 = \begin{cases} \alpha_1 \wedge \alpha_2 & \text{if } p = 0 \\ \alpha_1 \alpha_2 & \text{if } p = 1 \\ \log_p \left( 1 + \dfrac{(p^{\alpha_1} - 1)(p^{\alpha_2} - 1)}{p - 1} \right) & \text{otherwise} \end{cases}$$

**For all $p \in [0, 1]$: $\alpha_1 \alpha_2 \leq \alpha_1 \top_p \alpha_2 \leq \alpha_1 \wedge \alpha_2$**

**Cautious rule:**

$$\{1\}^{\alpha_1} \textcircled{\top}_p \{1\}^{\alpha_2} = \{1\}^{\alpha_1 \top_p \alpha_2}$$

# Outlines

1. **Combination of pedestrian detectors**
   a) **Clustering of bounding boxes**
   b) **Score calibration**
   c) **Probabilistic combination of bounding boxes**
2. **Theory of belief functions**
   a) **Information representation**
   b) **Evidential combination rules**
   c) **Clustering detectors**
3. **Experimental results**

# Clustering detectors

**Distance between two mass functions $d(m_1, m_2)$:**

$$\sqrt{\frac{1}{2}\sum_{A,B\subseteq\Omega\setminus\{\emptyset\}}\frac{|A\cap B|}{|A\cup B|}(m_1(A)-m_2(A))(m_1(B)-m_2(B))}$$

**Distance between two simple mass functions:**

$$0 \leq d(\{1\}^{\alpha_1},\{1\}^{\alpha_2}) = \frac{|\alpha_1-\alpha_2|}{\sqrt{2}} \leq \frac{1}{\sqrt{2}}$$

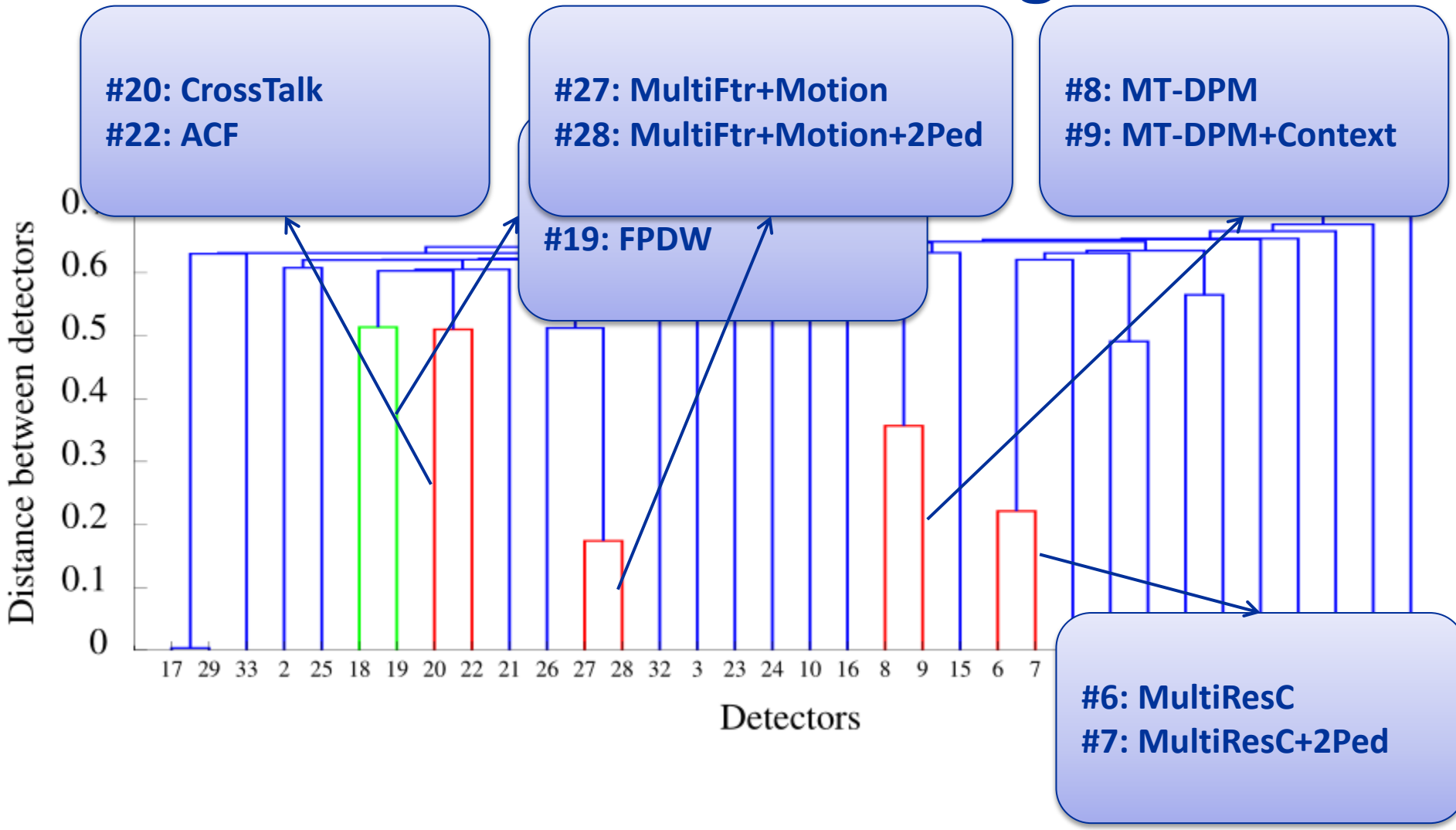
$$\frac{1}{\sqrt{2}} \leq d\left(\{1\}^{\alpha_1},\{0\}^{0}\right) = \sqrt{\frac{1+(1-\alpha_1)^2}{2}} \leq 1$$

**Detectors:** $D\left(C_{(k)}, C_{(l)}\right) = \frac{1}{n}\sum_{i=1}^{n} d(m_{(k),i}, m_{(l),i})$

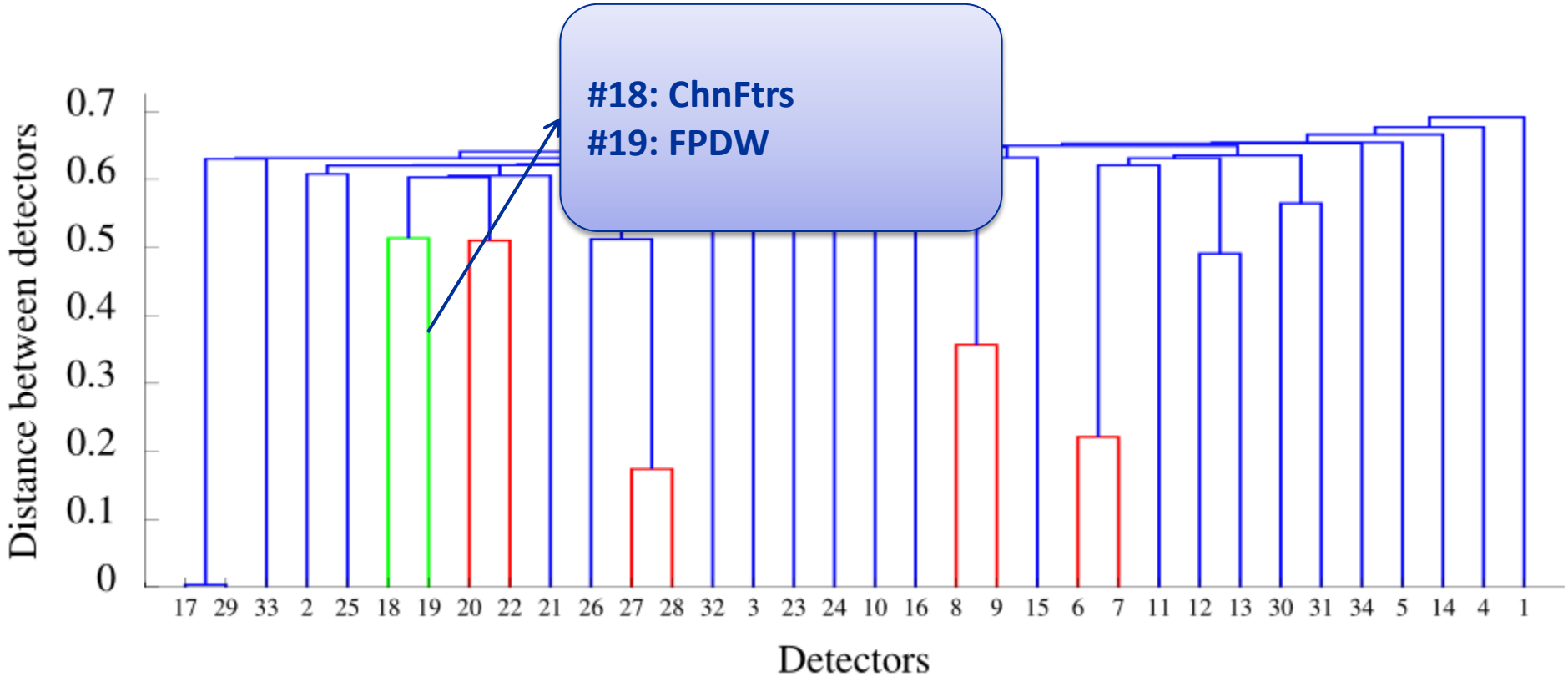
# Outlines

1. **Combination of pedestrian detectors**
   a) Clustering of bounding boxes
   b) Score calibration
   c) Probabilistic combination of bounding boxes
2. **Theory of belief functions**
   a) Information representation
   b) Evidential combination rules
   c) Clustering detectors
3. **Experimental results**

# Detector clustering



# Detector clustering

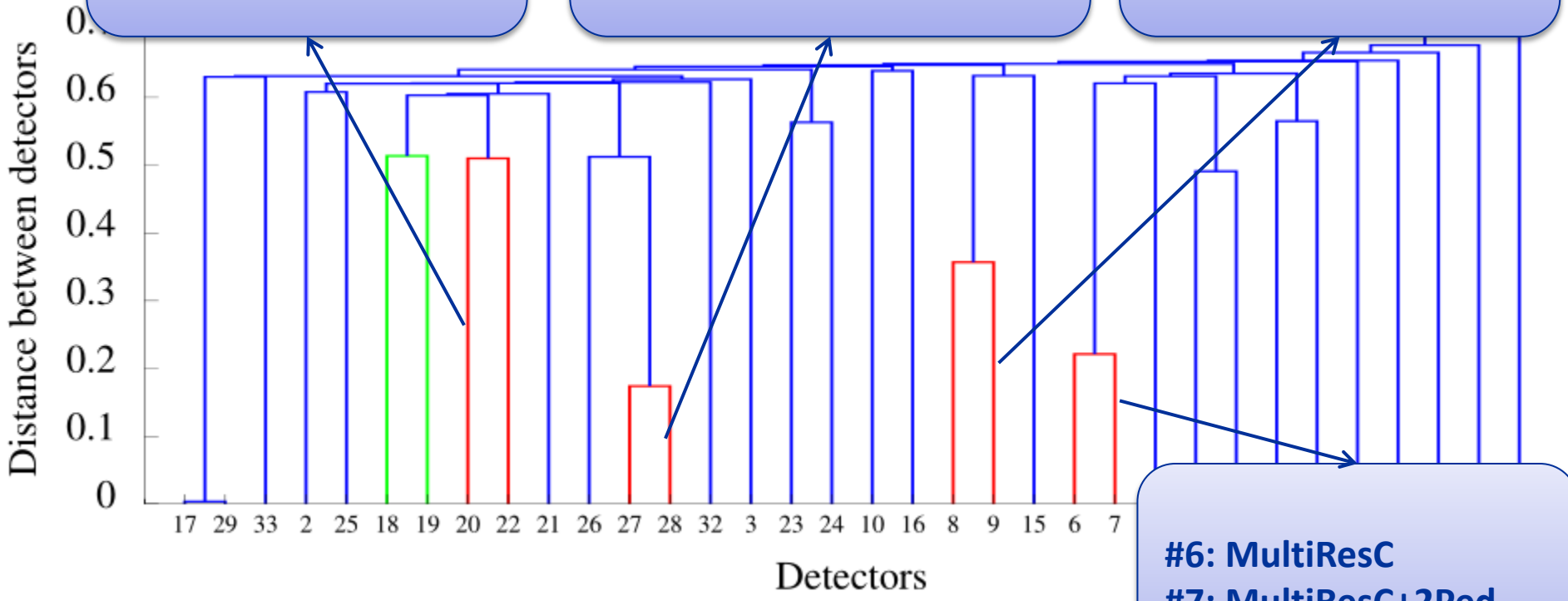


# Detector clustering

**#20: CrossTalk**
**#22: ACF**

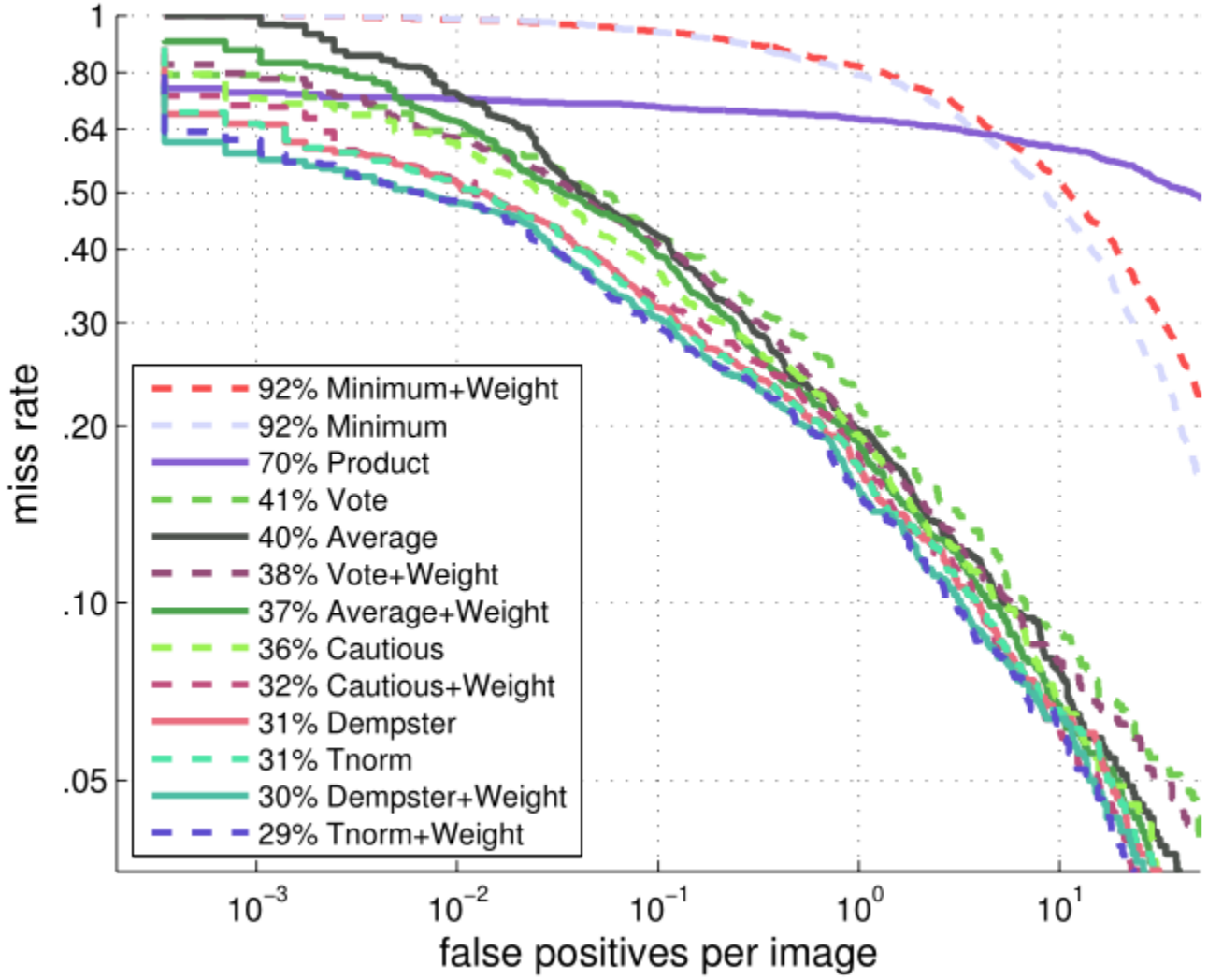
**#27: MultiFtr+Motion**
**#28: MultiFtr+Motion+2Ped**

**#8: MT-DPM**
**#9: MT-DPM+Context**

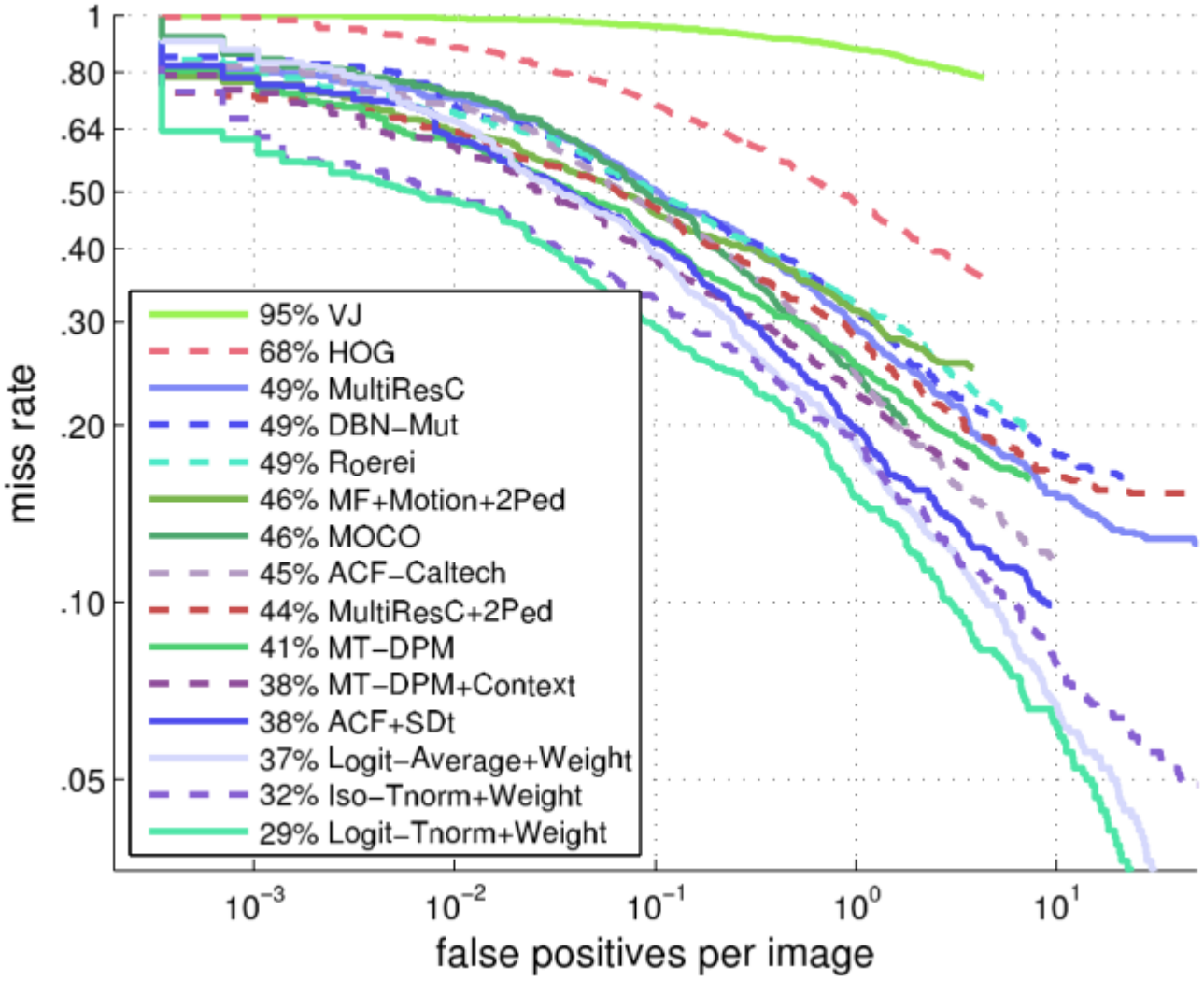



**#6: MultiResC**
**#7: MultiResC+2Ped**

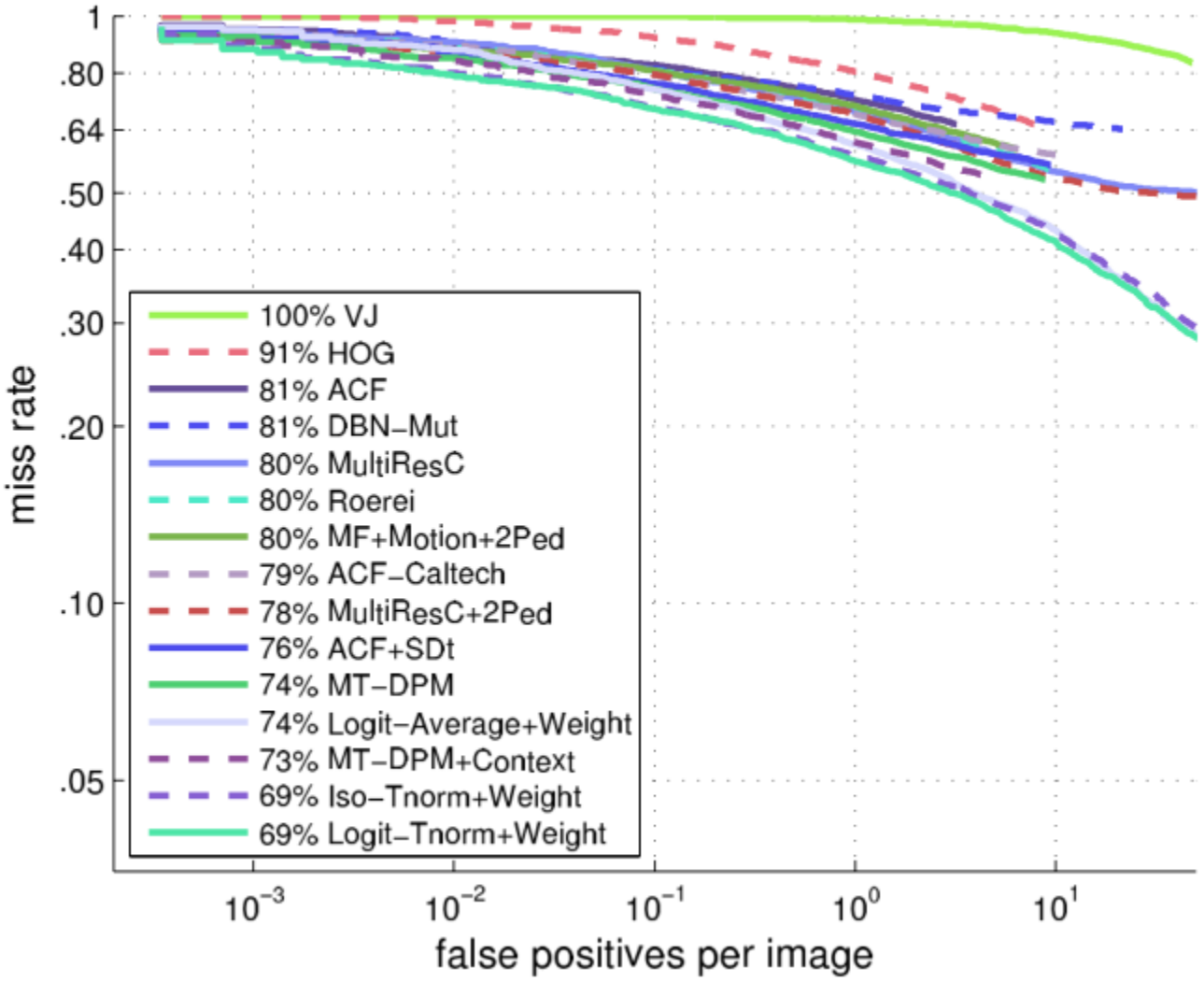
# Comparison of combination rules



# Reasonable case scenario



# Overall case scenario



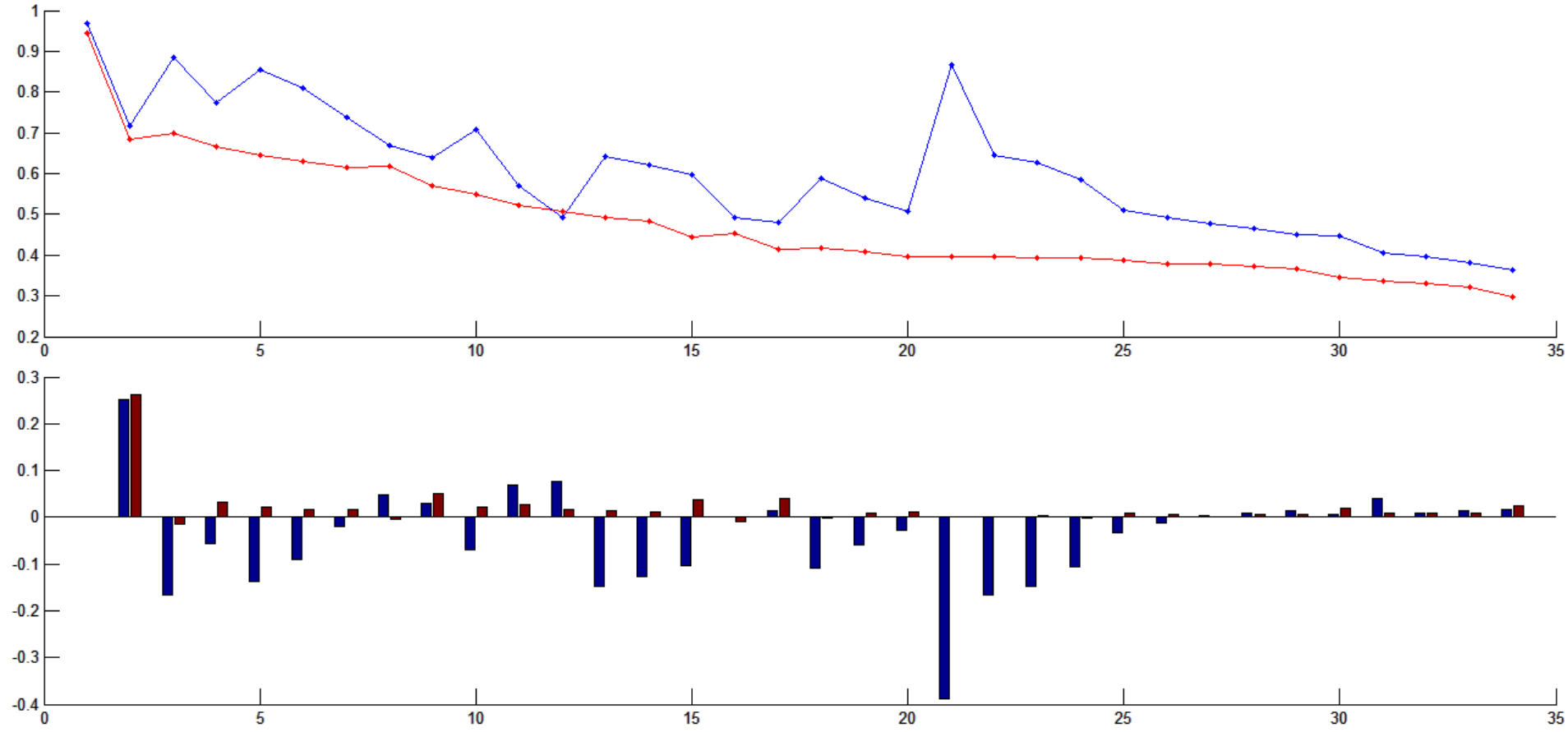
# Résultats (1/4)

# Résultats (2/4)

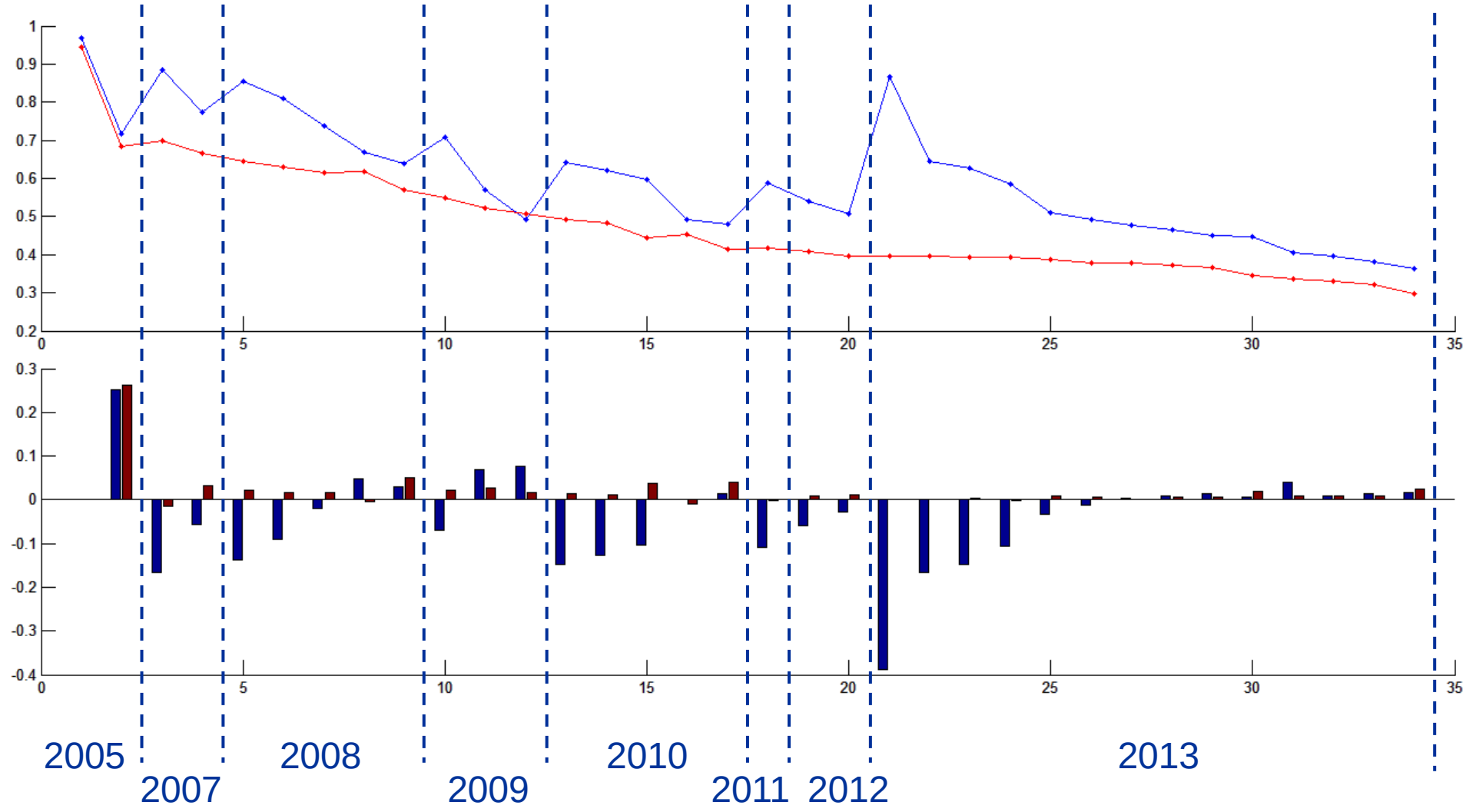
# Résultats (3/4)

# Résultats (4/4)

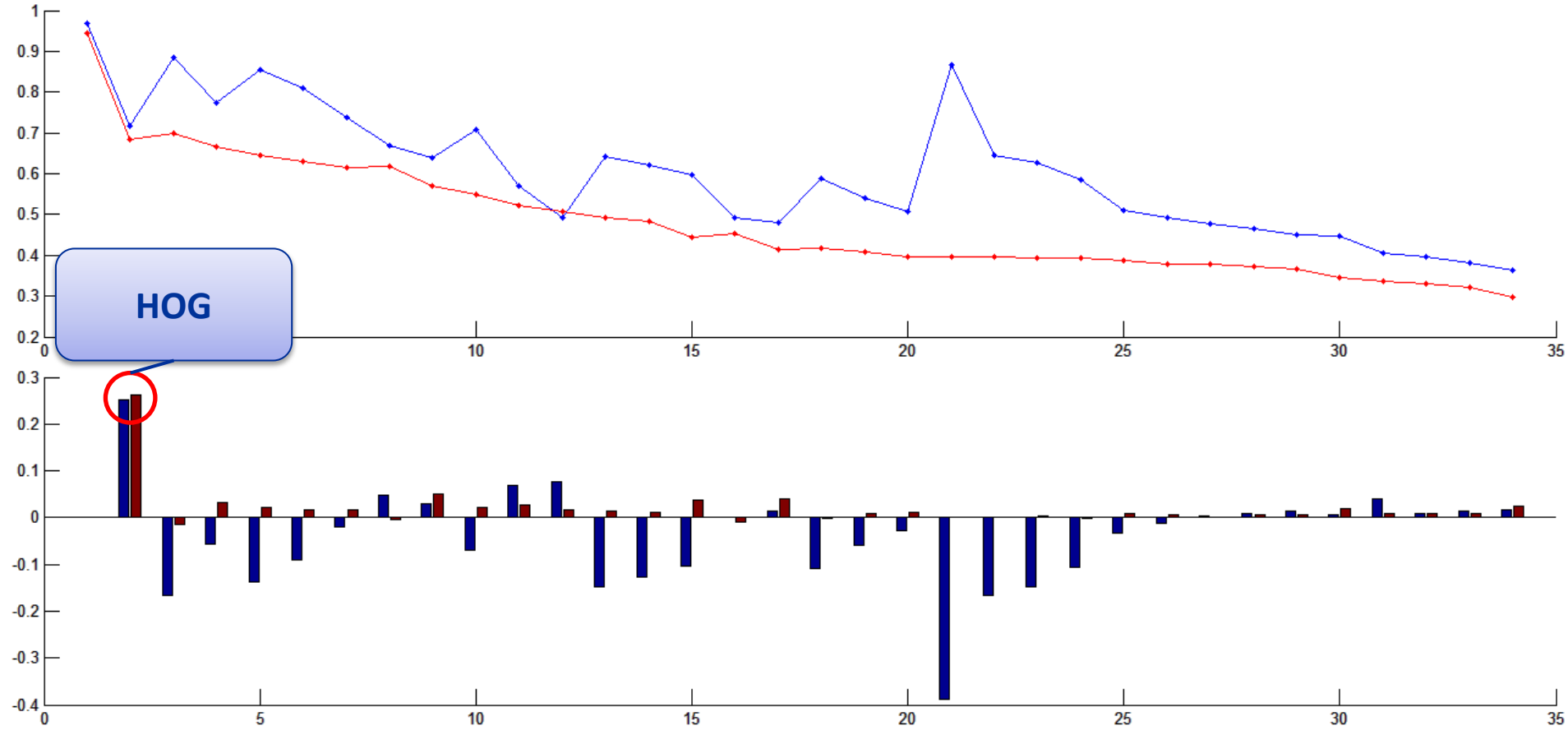
# Gain over time



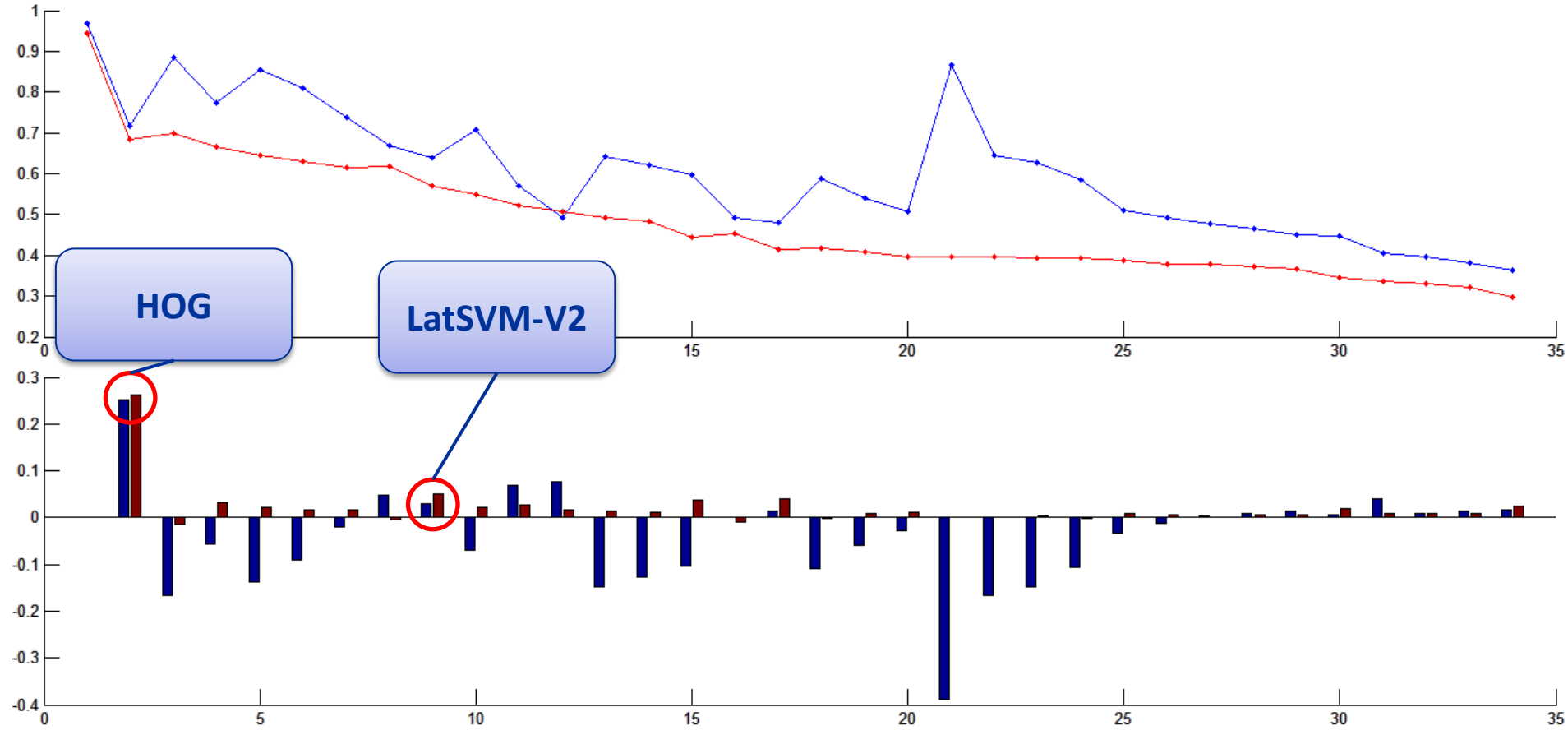
# Gain over time



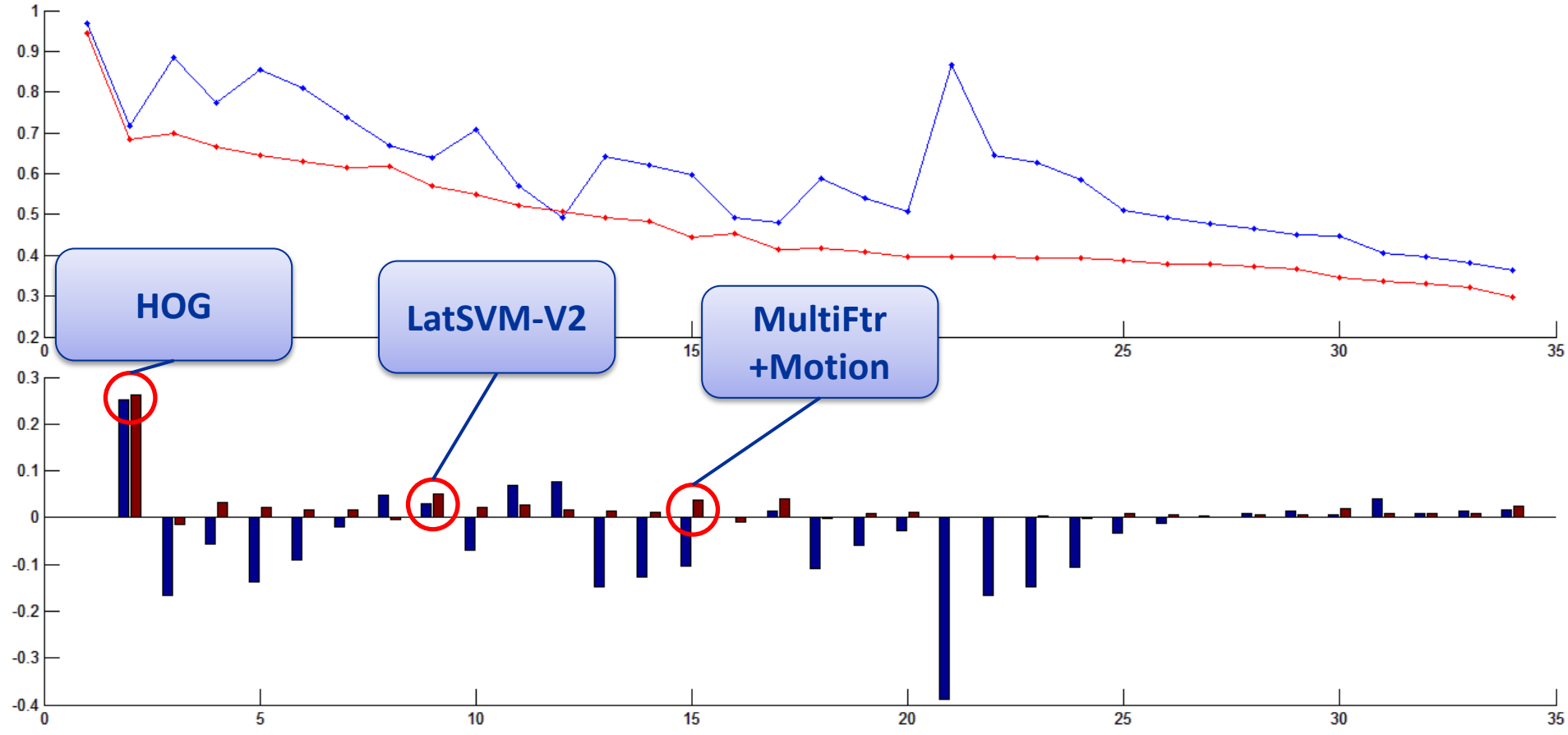
# Gain over time



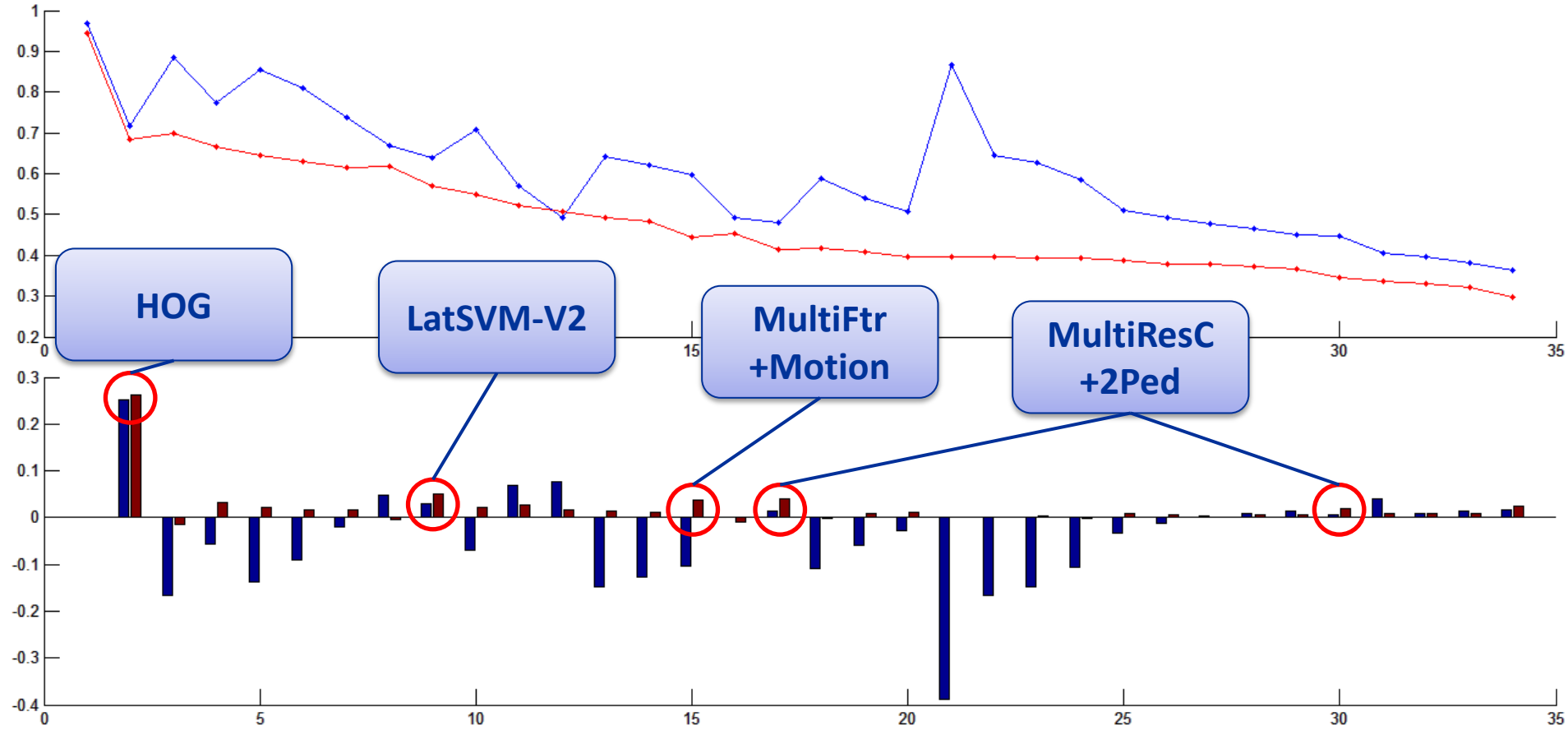
# Gain over time



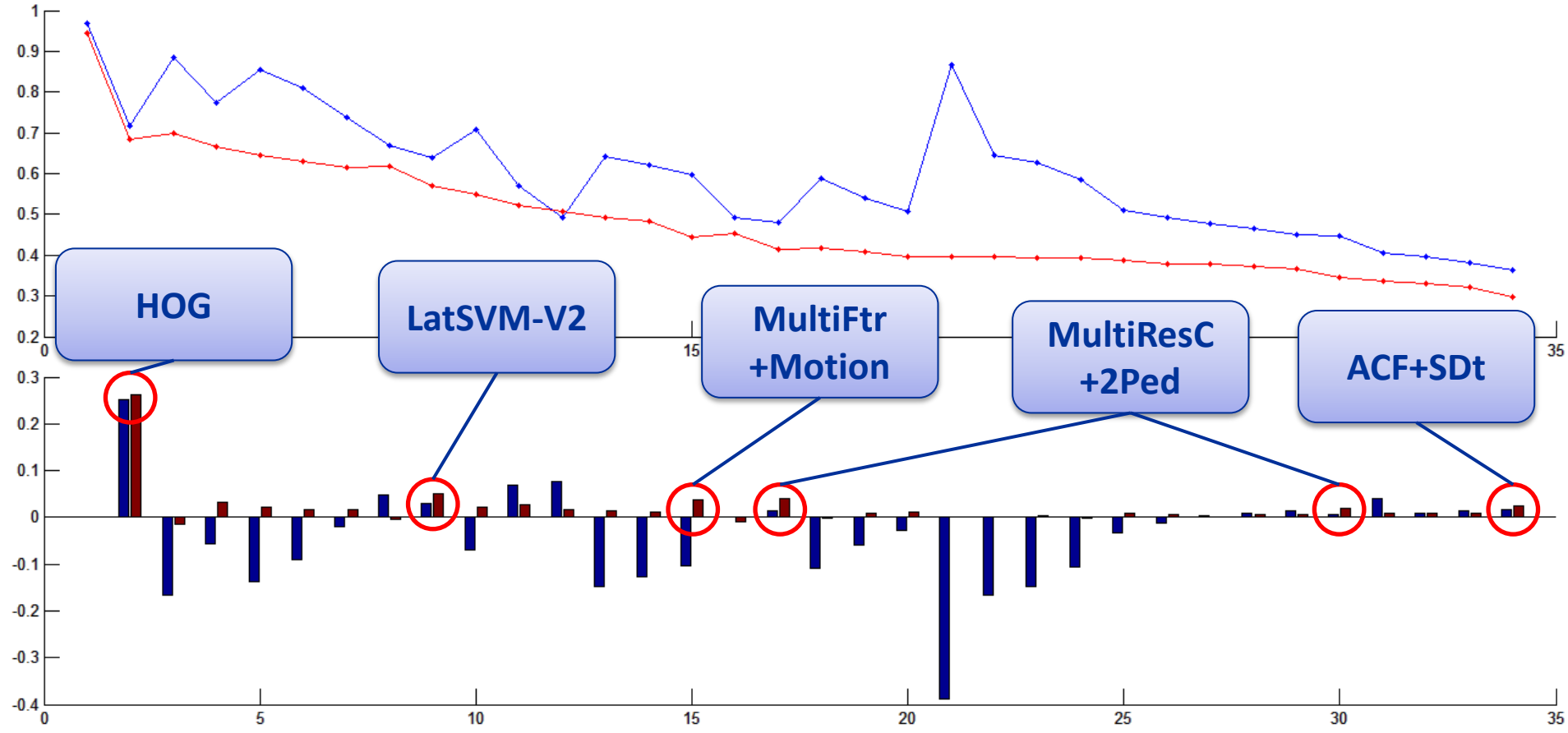
# Gain over time



# Gain over time



# Gain over time



# Conclusion

- **Evidential combination performs better than probabilistic combination**
- **New detectors can be easily added**
- **The contribution of new method can be measured compared to the combination of existing methods**

# Thank you!

# Matlab code soon available at:

www.hds.utc.fr/~xuphilip/dokuwiki/en/data