

A GENERAL FRAMEWORK FOR COST-SENSITIVE BOOSTING

Author: Iago Landesa Vázquez

Supervisor: José Luis Alba Castro

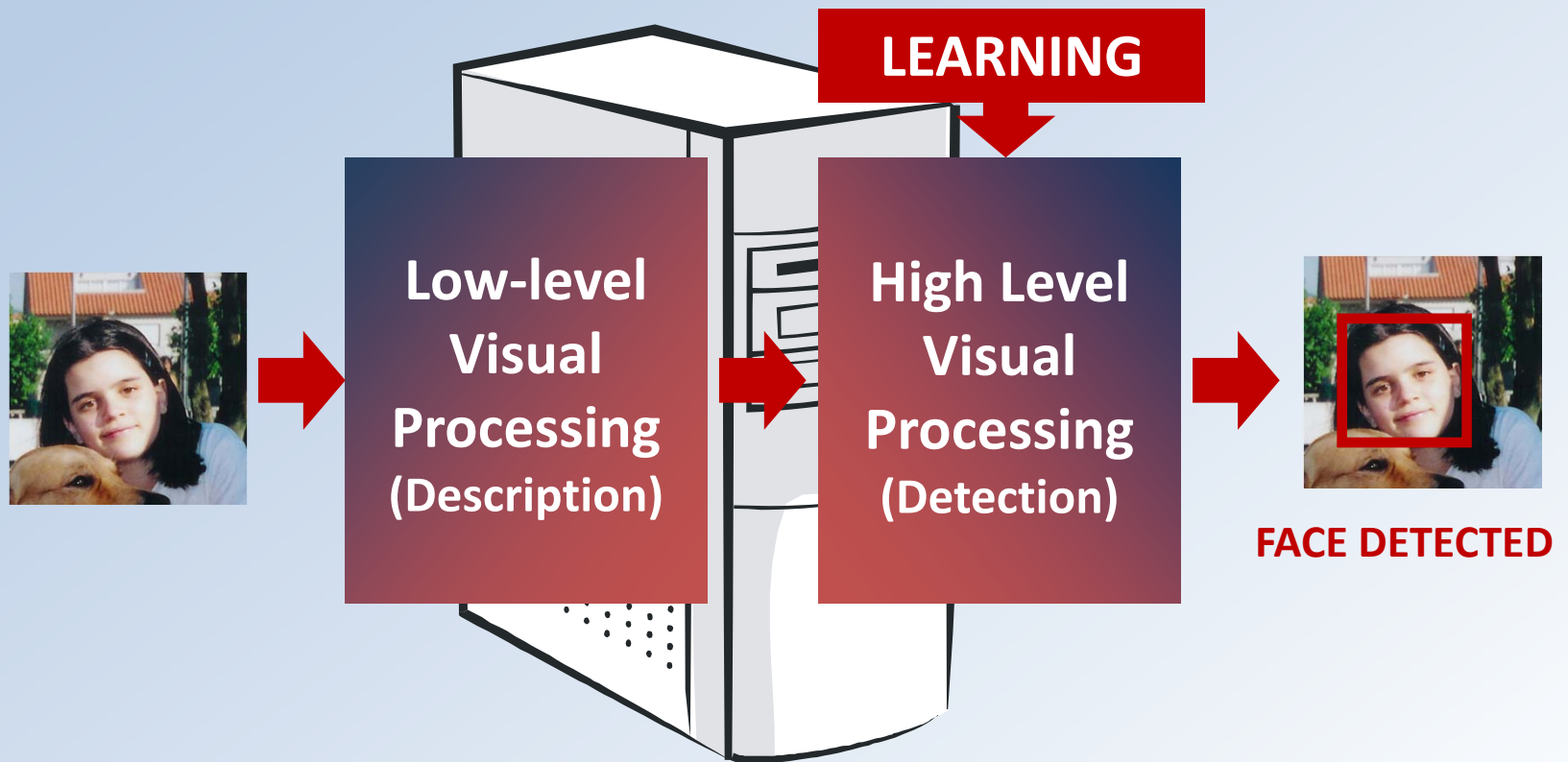
Overview

- Motivation
- PhD Thesis
- Current work

MOTIVATION

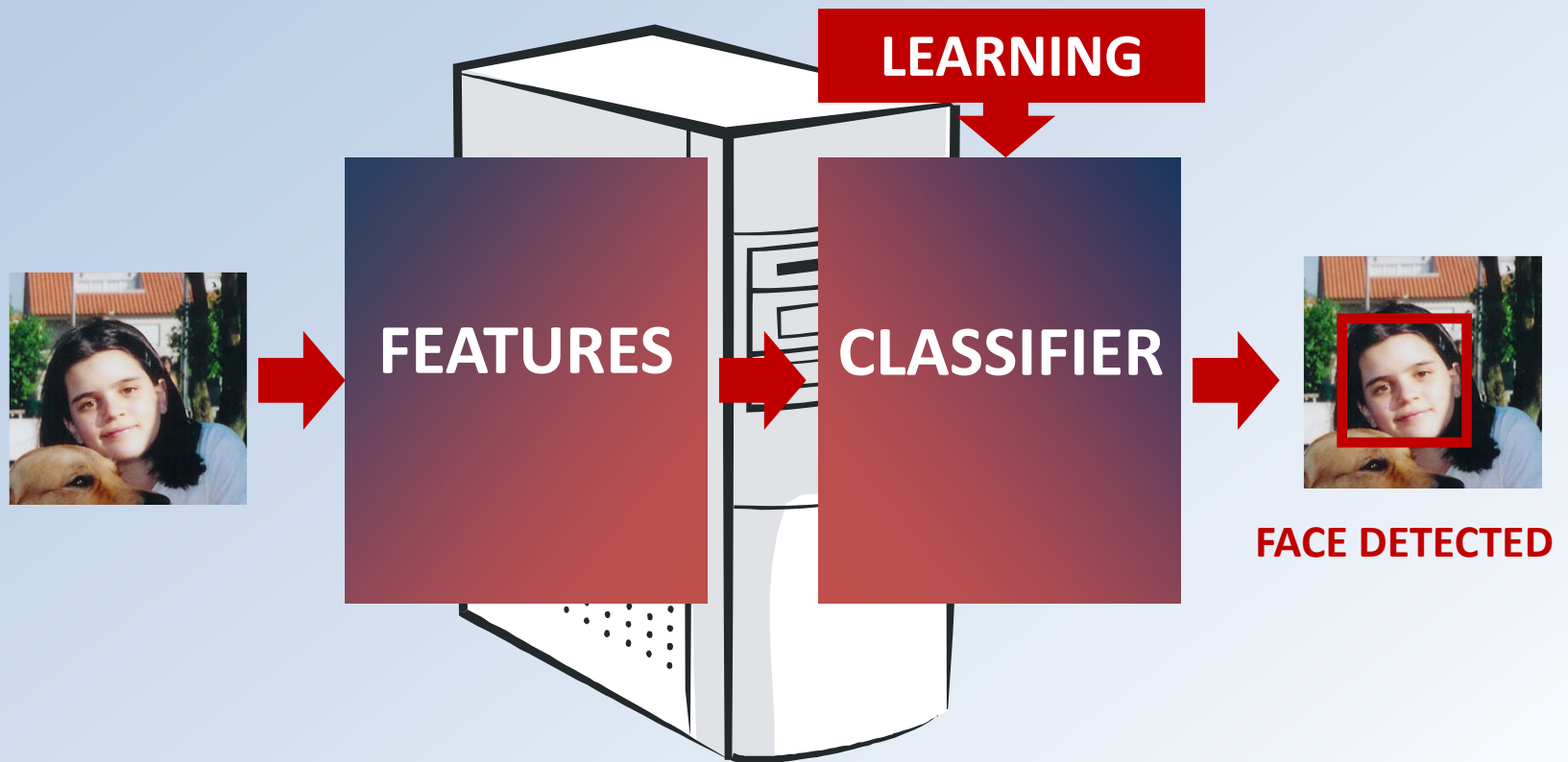
Face Detection in Computers

- MOTIVATION
- PHD THESIS
- CURRENT WORK



Face Detection in Computers

- MOTIVATION
- PHD THESIS
- CURRENT WORK



Reference model

- MOTIVATION
- PHD THESIS
- CURRENT WORK

- Viola and Jones Face Detector*. They succeeded, for the first time, to detect faces in images in real-time.
- One of the milestones in Computer Vision of the last decade.

* Viola, P., Jones, M., 2004. **Robust real-time face detection**. International Journal of Computer Vision 57, 137–154.

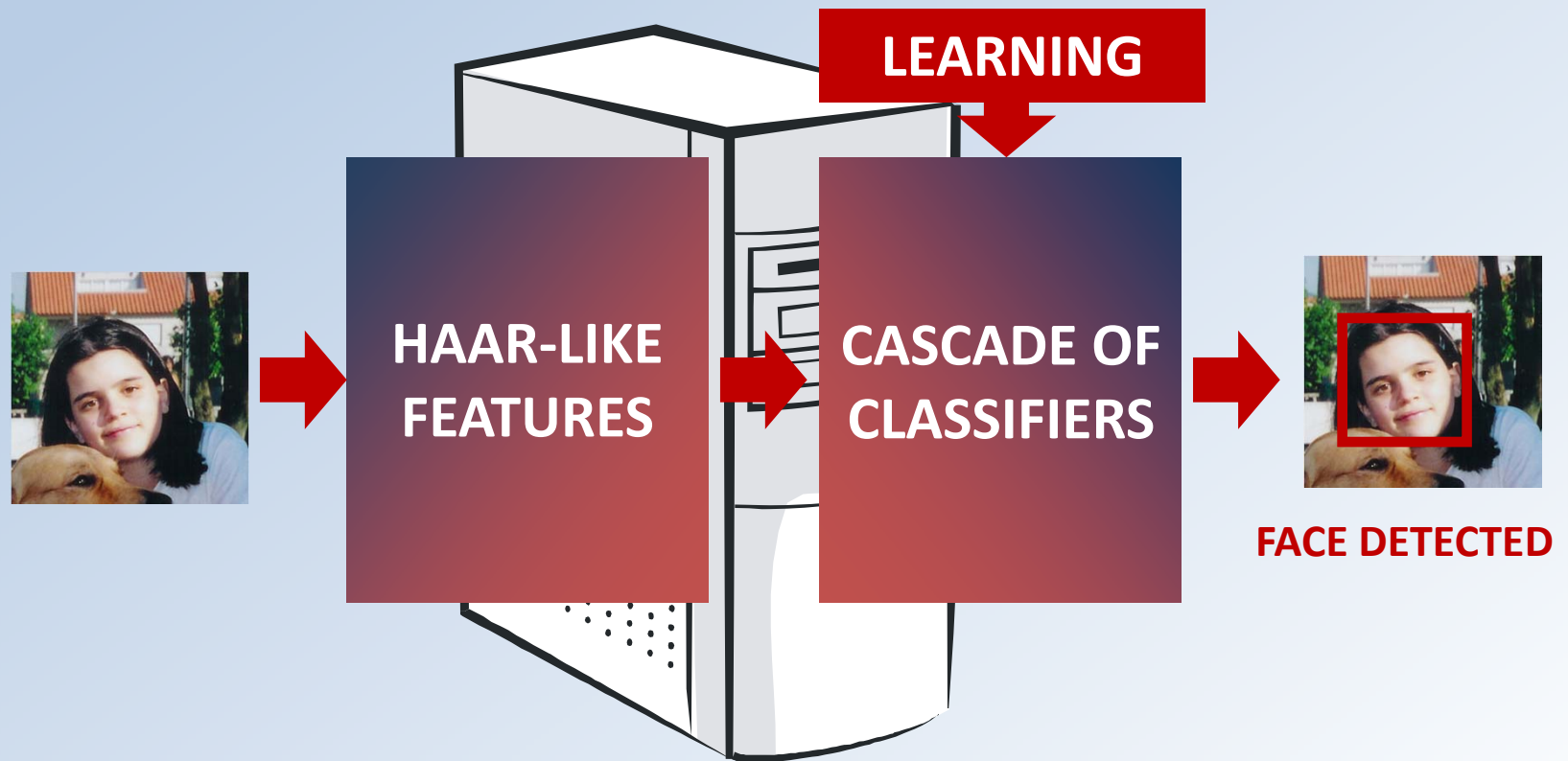
Viola and Jones Detector Framework

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- PHD THESIS
- CURRENT WORK

- It is based on three key ideas...
 - Haar-like as features (efficiently computable using Integral Images)
 - AdaBoost as learning algorithm
 - Cascaded architecture to improve efficiency

Viola and Jones Detector Framework

- MOTIVATION
- PHD THESIS
- CURRENT WORK



Early stages of the work

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- PHD THESIS
- CURRENT WORK

- Thorough **study** of the Viola-Jones face detector and related works.
- **Implementation**, from scratch, of our own Viola-Jones training platform.
- Collect **databases** of faces and non-faces, with enough generalization capability.
- **Train** several face detectors, with different parameters.
- Extension to **eye**, **nose** and **mouth** localizers.

PHD THESIS

First Goals

- MOTIVATION
- PHD THESIS
- CURRENTWORK

- Main goal:
 - Detailed analysis on **each of the levels** of the Viola-Jones framework to propose novel improvements, applied to **different object** detection scenarios.

First goals

- MOTIVATION
- PHD THESIS
- CURRENT WORK

- We have studied the three main layers of the Viola-Jones framework.

CASCADE ARCHITECTURE

ADABOOST

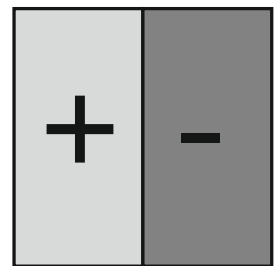
HAAR-LIKE FEATURES

Development

- MOTIVATION
- PHD THESIS
- CURRENT WORK

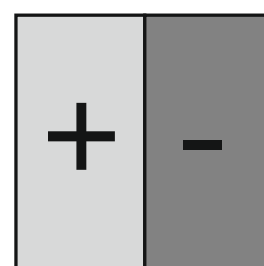
- **Feature Level:** New typologies of features with descriptive or computational advantages.
 - **Polarity invariant features** [1]

POLAR FEATURES



Brighter
↑
↓
Darker

NON-POLAR FEATURES



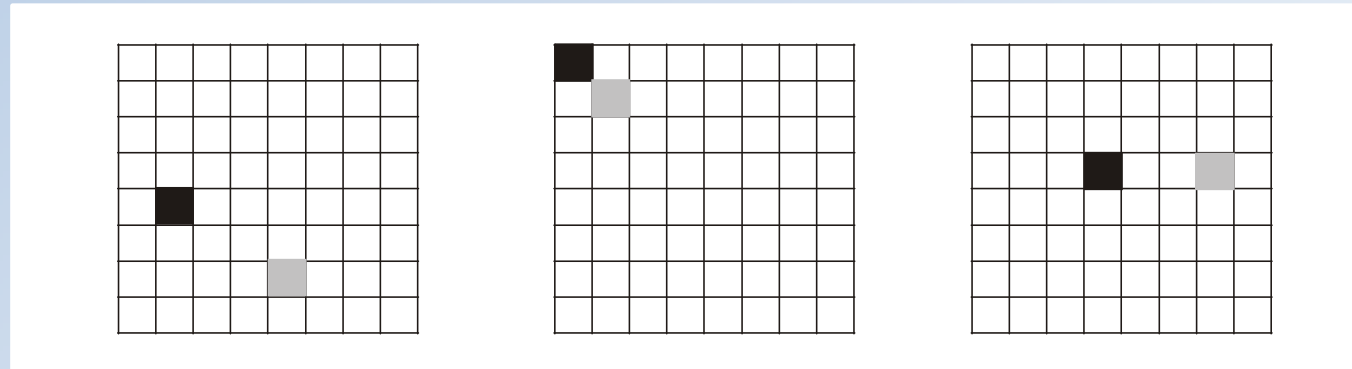
Different
↑
↓
Similar

[1] I. Landesa-Vázquez, J.L. Alba-Castro. *The Role of Polarity in Haar-like features for Face Detection*. XX International Conference on Pattern Recognition (ICPR 2010), 23-26 August 2010, Istanbul (Turkey)

Development

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- CURRENT WORK

- **Feature Level:** New typologies of features with descriptive or computational advantages.
 - Polarity invariant features [1]
 - Quantum features [2]



[2] I. Landesa-Vázquez, F. Parada-Loira, J.L. Alba-Castro. *Fast Real-time Multiclass Traffic Sign Detection Based on Novel Shape and Texture Descriptors*. XIII IEEE Conference on Intelligent Transportation Systems (ITSC 2010), 19-22 September 2010, Funchal (Portugal)

Development

- MOTIVATION
- PHD THESIS
- CURRENT WORK

- **Learning Level:** New theoretically motivated asymmetric AdaBoost algorithms.
 - **Cost Generalized AdaBoost [3]**
 - **AdaBoostDB [4]**

[3] I. Landesa-Vázquez, J. L. Alba-Castro. *Shedding Light on the Asymmetric Learning Capability of AdaBoost*. Pattern Recognition Letters 33, pp. 247-255, 2012

[4] I. Landesa-Vázquez, J. L. Alba-Castro. *Double Base Asymmetric AdaBoost*. Neurocomputing 18, pp. 101-114, 2013

Development

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- CURRENT WORK

- **Cascade Architecture Level:** We have designed several changes
 - **Optimal/automatical sizing**
 - **Inter-stage information repechage**
 - **Data source fusion**

Final focus

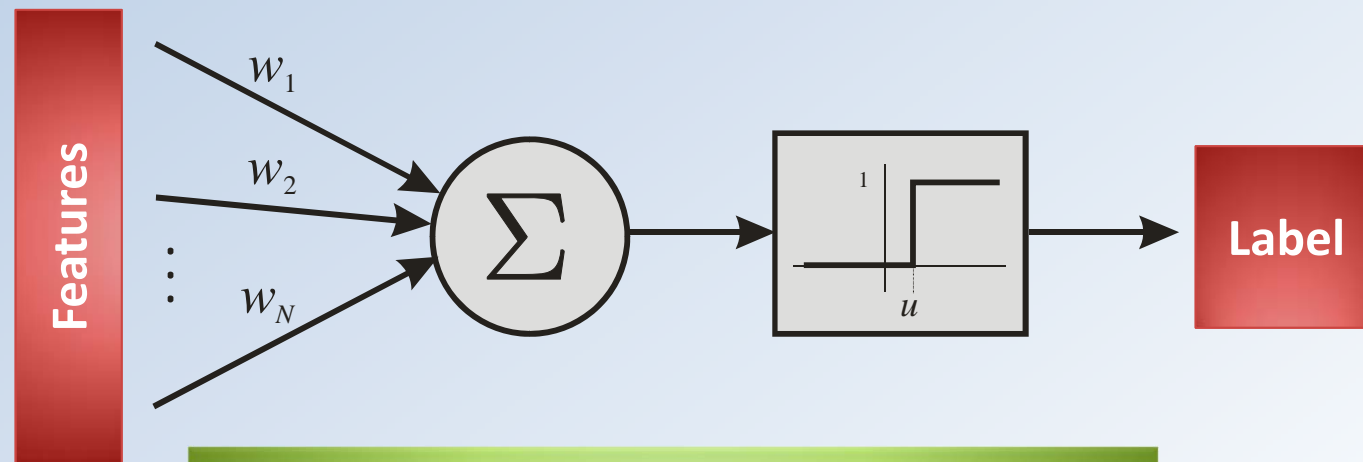
- MOTIVATION
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- CURRENT WORK

- Most of our efforts have been focused on the **Learning Level**, the most theoretical part.
- Final title : *“A General Framework for Cost-Sensitive Boosting”*

AdaBoost

- MOTIVATION
- PHD THESIS
- CURRENT WORK

- AdaBoost is a learning algorithm which selects **weak classifiers** from a pool, and combine them into a final **strong classifier**.



SELECT AND COMBINE

AdaBoost

- MOTIVATION
- PHD THESIS
- CURRENT WORK

- AdaBoost is a learning algorithm which selects **weak classifiers** from a pool, and combine them into a final **strong classifier**.

$$H(x) = \text{sign} \left(\sum_{t=1}^T \alpha_t h_t(x) \right)$$

Diagram illustrating the AdaBoost equation:

- $H(x)$ is labeled as the **Strong Classifier**.
- T is labeled as **Selection**.
- $\alpha_t h_t(x)$ is labeled as **Weak Classifiers**.
- The summation $\sum_{t=1}^T$ is labeled as **Combination**.

SELECT AND COMBINE

Asymmetric Learning

- MOTIVATION
- PHD THESIS
- CURRENT WORK

- **Object detection** in images is a paradigmatic **asymmetric problem**:
 - Positives are extremely **scarce** and valuable.
 - Negatives have a huge **variability** compared to that of positives.
 - To be feasible (real-time), negatives must be **rejected** as soon as possible.

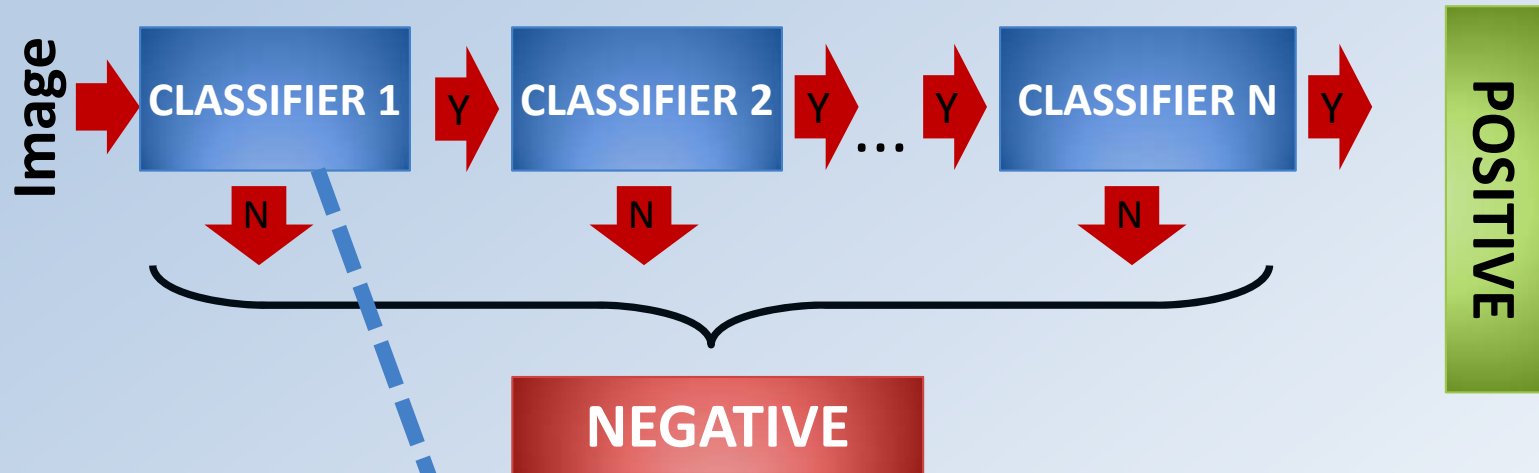
Asymmetric Learning in the Viola-Jones Framework

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- CURRENT WORK

- However, as originally stated, **AdaBoost** is a **cost-insensitive learning algorithm**.
- In the Viola and Jones framework, the threshold of every boosted classifier is modified **“*a posteriori*”** (after training) to get an asymmetric result → **Non-optimal solution**.

Viola-Jones Strategy

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$$H(x) = \text{sign} \left(\sum_{t=1}^T \alpha_t h_t(x) \right)$$

$$H(x) = \text{sign} \left(\sum_{t=1}^T \alpha_t h_t(x) - T \right)$$

Asymmetric AdaBoost variants

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- CURRENT WORK

- Several “asymmetric AdaBoost” variants have been proposed in the literature...

- AdaCost
- AsymBoost
- AdaC1, AdaC2, AdaC3
- CSB0, CSB1, CSB2
- Cost-Sensitive AdaBoost

Heuristics
No theoretical guarantees

Too complex

Our proposals

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- We have followed two different ways:
 - **Cost-generalized AdaBoost**
 - **AdaBoostDB**

Cost-Generalized AdaBoost

- ORIGIN
- MOTIVATION
- PHD THESIS
- CURRENT WORK

- Several papers claim that, AdaBoost remains being cost-insensitive even when initialized with an uneven (asymmetric) weight distribution.

Cost-Generalized AdaBoost

- MOTIVATION
- PHD THESIS
- CURRENT WORK

- We have **refuted that a**firmation, proving [3] theoretically and practically, that **asymmetric weight initialization** is an effective way to reach **boosted cost-sensitive behaviors**.
- It preserves **all the theoretical guarantees** of original boosting, but for asymmetric problems.

AdaBoostDB

- MOTIVATION
- PHD THESIS
- CURRENT WORK

- Another way is defining a **Double-Base exponential bound** (different base for different classes), and minimize it.
- It can be modeled by a polynomial, and allows a **very efficient** search method.
- Results are equivalent to “Cost-Sensitive Boosting” but **200 times faster**.

CURRENT WORK

Current Work

- MOTIVATION
- PHD THESIS
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- We are **writing** a final **comparative framework** of all cost-sensitive boosting algorithms in the literature with **Cost-Generalized AdaBoost** and **AdaBoostDB**.
- Defense of the PhD scheduled for the beginning of 2014.

Thank you for
your attention!!