Optimizing Weighted Lower Linear Envelope Potentials Within Latent-SVM Framework

A Story

Figure 1.1 The original classroom

Figure 1.2 Classroom with people

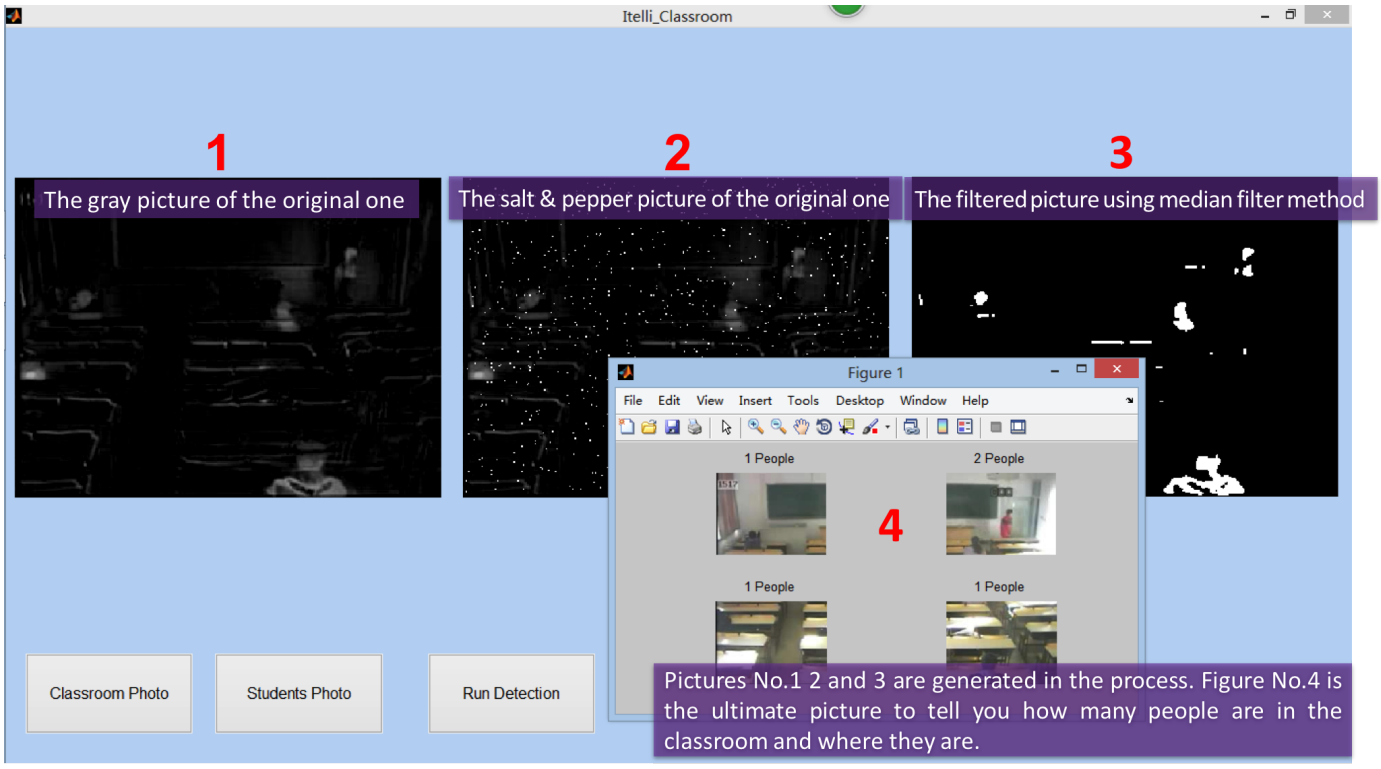

Figure 1.3 Result

Large Margin Framework

Binary Support Vector Machine

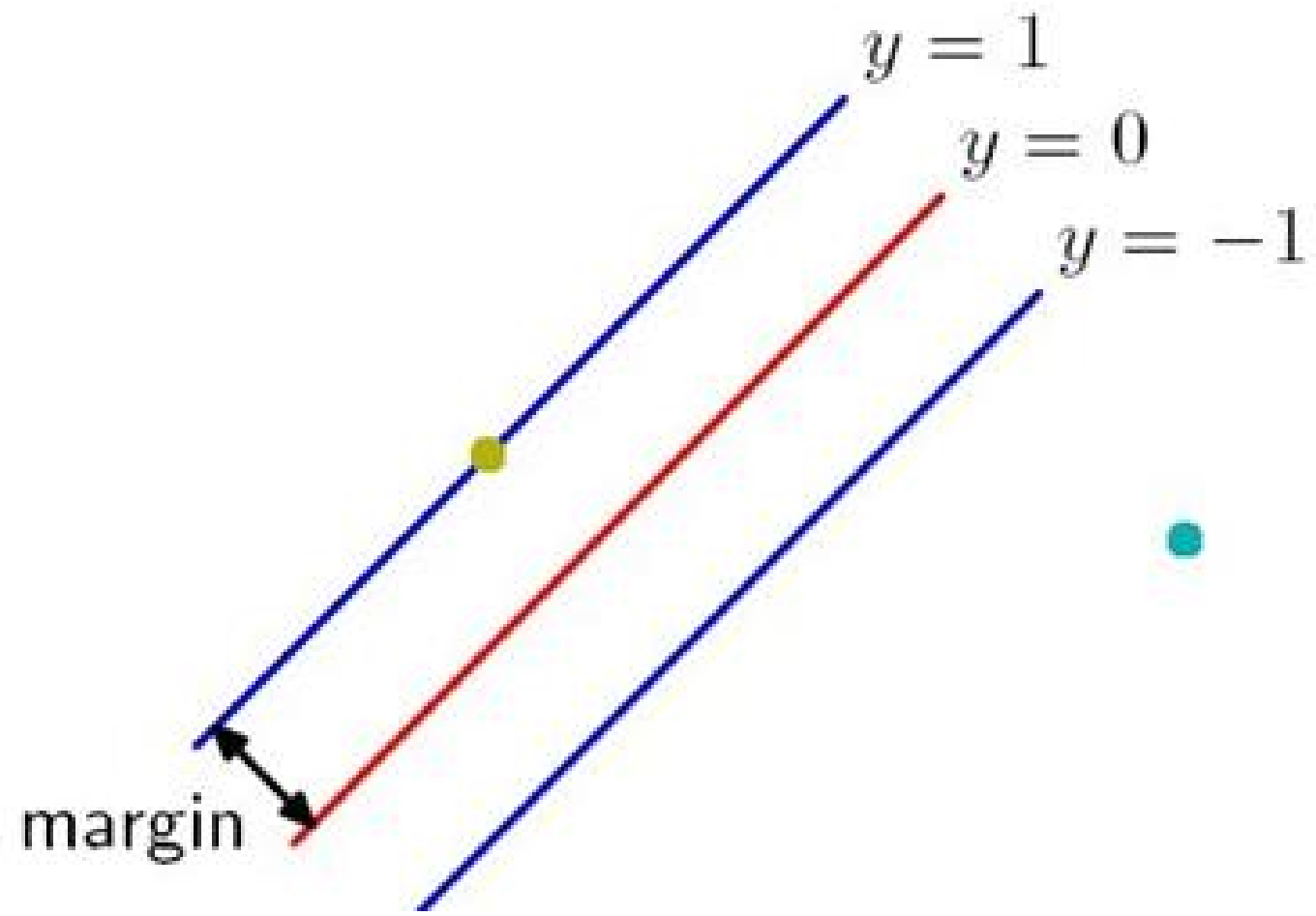

Figure 2.1 Linear Separable SVM

- Margin: perpendicular distance between the decision boundary and the closest data points.
- Support Vectors: Data points determine the location of this boundary.

Multi-classes Support Vector Machine

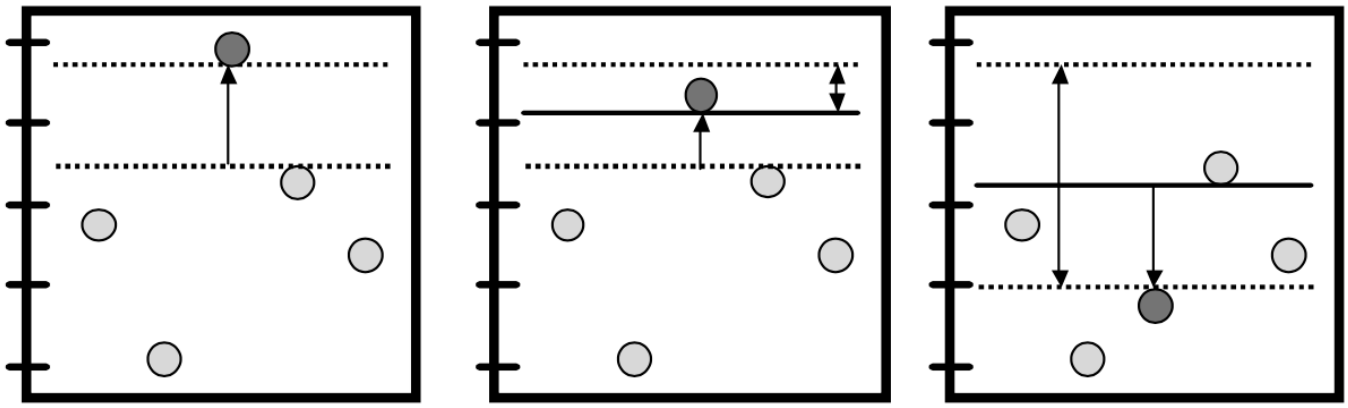

Figure 2.2 Multi-classes SVM

$$\max_r \{\mathbf{M_r} \cdot x + 1 - \delta_{y,r}\} - \mathbf{M_y} \cdot x$$

Where $y \in 1, \ldots, k$ is label of x and $\mathbf{M_r}$ is a $k \times n$ size matrix. $\delta_{p,q}$ equals 1 if $p == q$ and 0 otherwise.

Structral Support Vector Machine

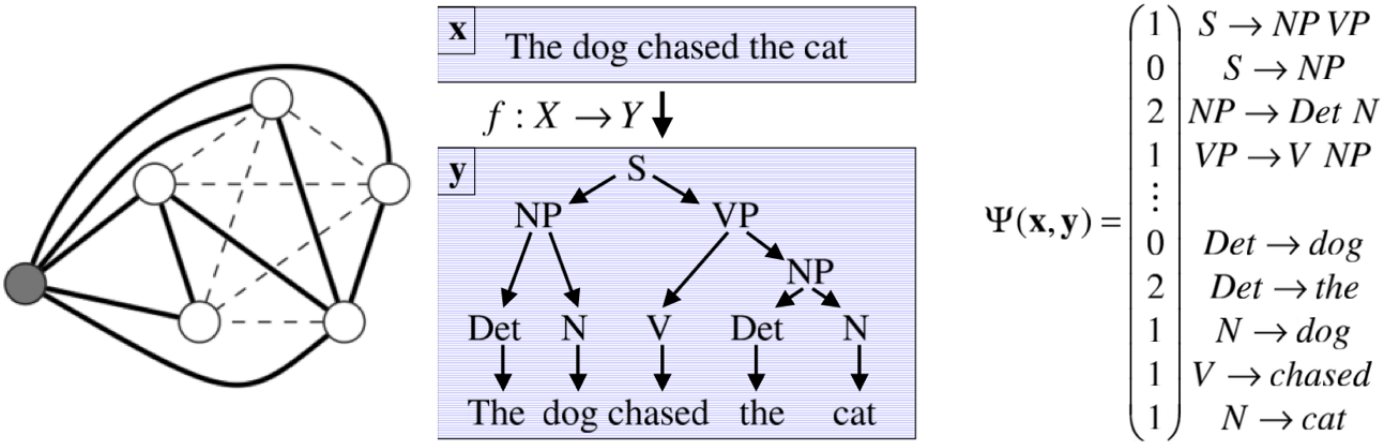

Figure 2.3 Structured SVM

Latent Structral SVM

$$f_w(x) = \arg\max_{(\mathbf{y} \times \mathbf{h}) \in \mathcal{Y} \times \mathcal{H}} w \cdot \Psi(\mathbf{x}, \mathbf{y}, \mathbf{h})$$

Markov Random Field

Markov Random Field

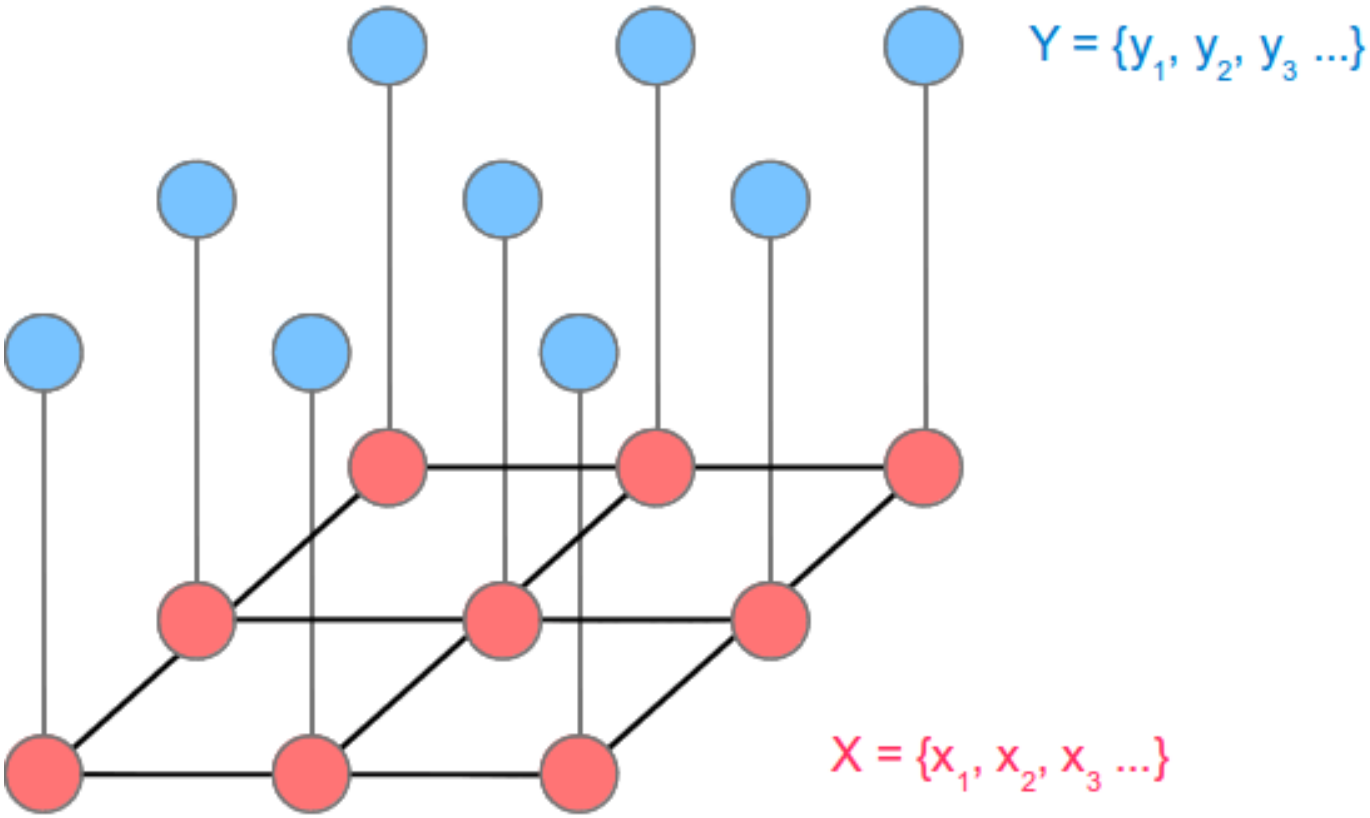

Figure 3.1 Markov Random Field

Figure 3.2 Restore Pictures

$$E(x, y) = h \sum_i x_i - \beta \sum_{i,j} x_i x_j - \eta \sum_i x_i y_i$$

Higher Order Energy using Linear Envelope

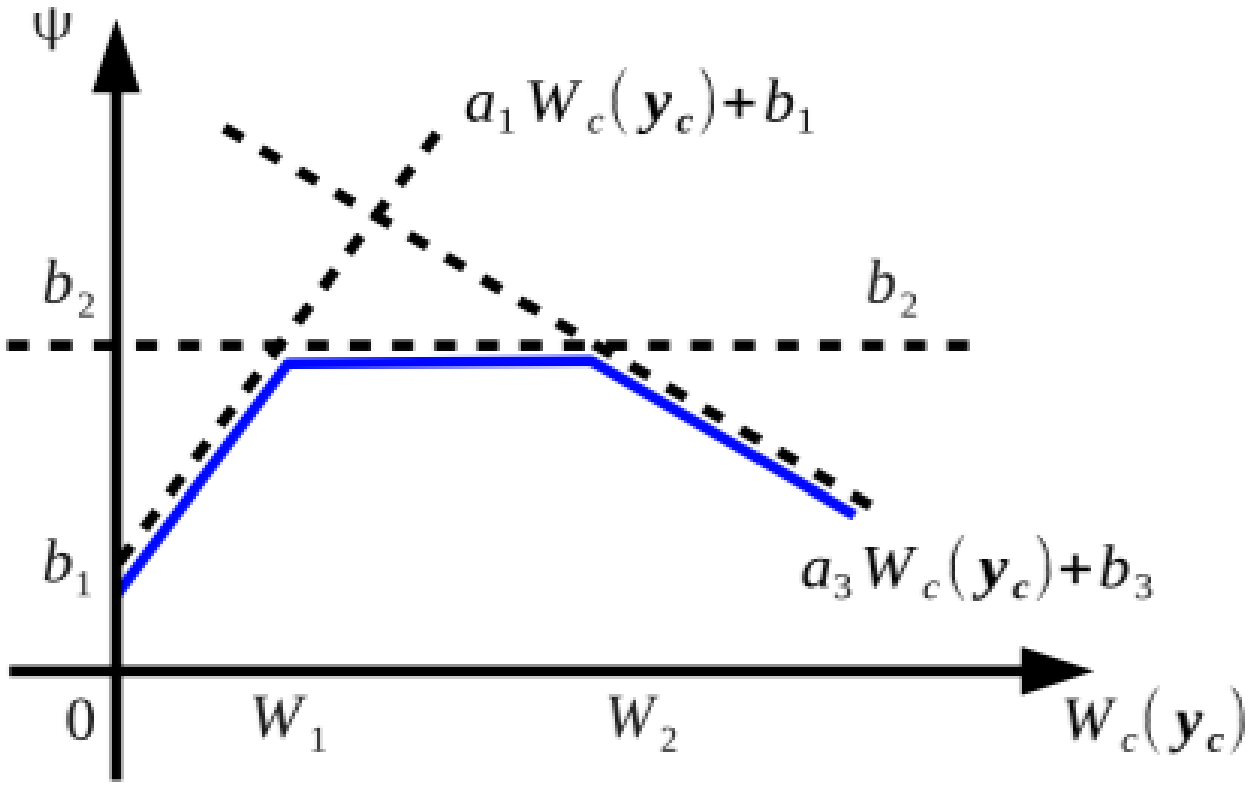

Figure 3.3 Linear Envelope

Current Work

Introducing Latent Variable into Linear Envelope

By introducing latent vector $\mathbf{h} = \{h_0, h_1, \dots, h_K\}$where $h_i \in [0, 1]$ into feature vector, we have $\phi_c^H(\mathbf{y}_c) = \boldsymbol{\theta}^T \boldsymbol{\psi}(\mathbf{y}, \mathbf{h})$ where,

$$\theta_k = \begin{cases} b_1 & \text{for } k = 0 \\ a_1 & \text{for } k = 1 \\ a_{k-1} - a_k & \text{for } k = 2, \dots, K+1 \end{cases}$$

$$\phi_k = \begin{cases} 1 & \text{for } k = 0 \\ W(\mathbf{y}) & \text{for } k = 1 \\ \Big(h_{k-1} - W(\mathbf{y})\Big)\Big[\Big[W(\mathbf{y}) > h_{k-1}\Big]\Big] & \text{for } k = 2, \dots, K+1 \end{cases}$$

Remaining Work

- Inference Algorithm
- Coding

Some Experiences

- A-ha moments keep you going.

- Be prepared for unexpected things.