Pattern Recognition from One Example by Chopping

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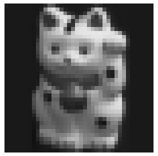
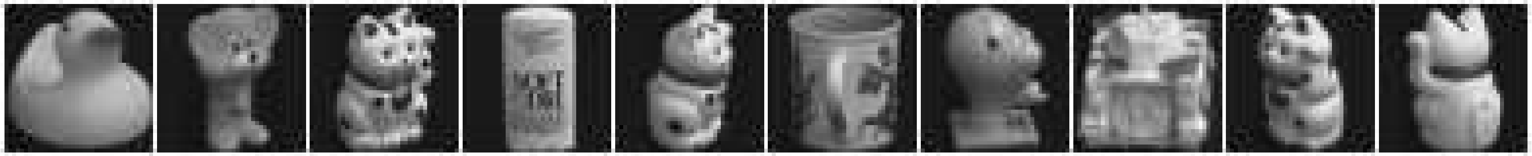
RECOGNITION FROM ONE EXAMPLE

Given a single training example, find the same object in the test images:

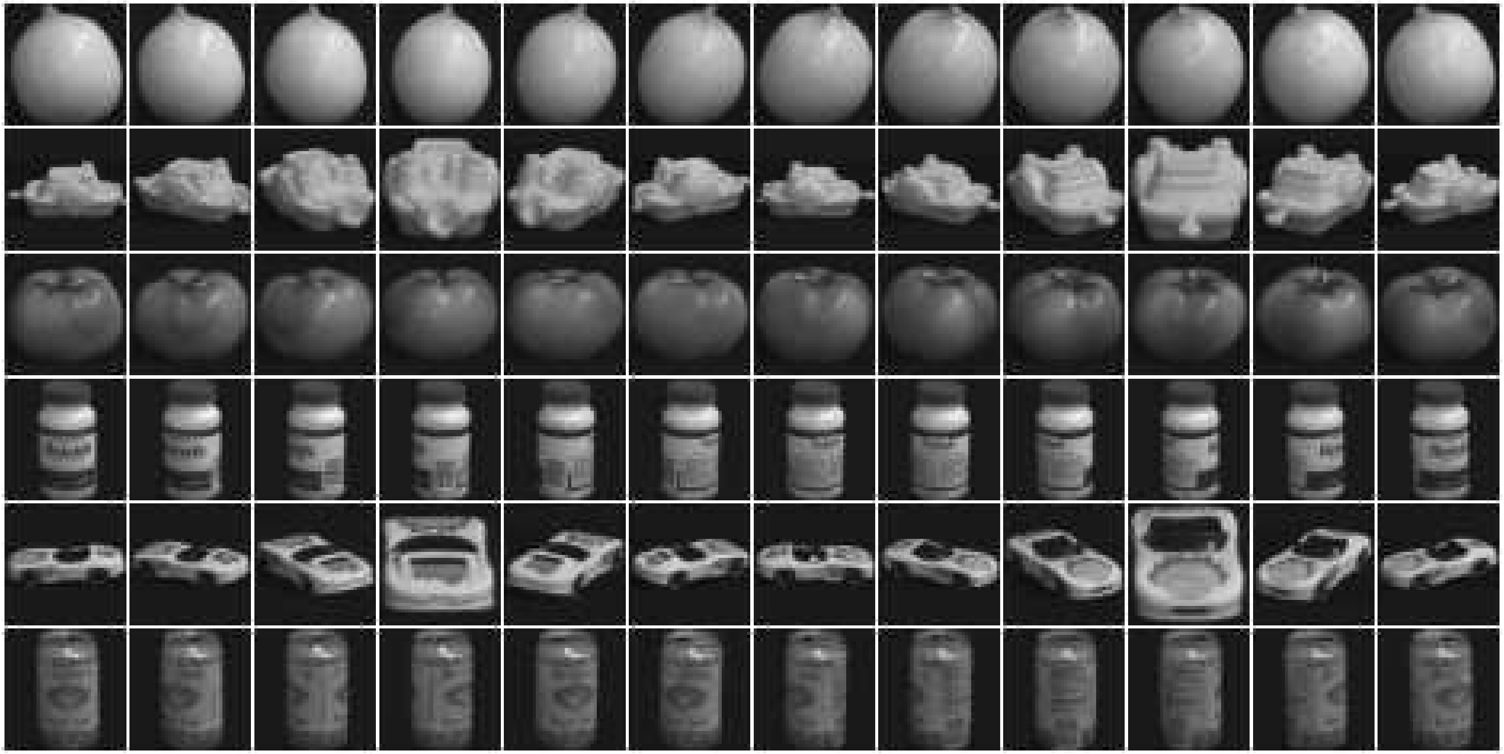


?

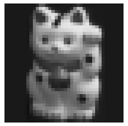
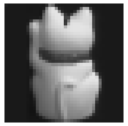


If we average the test on a large number of trials, an equivalent formulation is: given two images I_1 and I_2, are they showing the same object ?

❶ Learning invariance with a large number of objects



❷ Recognizing from one example

 =  ?

No object is common to ❶ and ❷

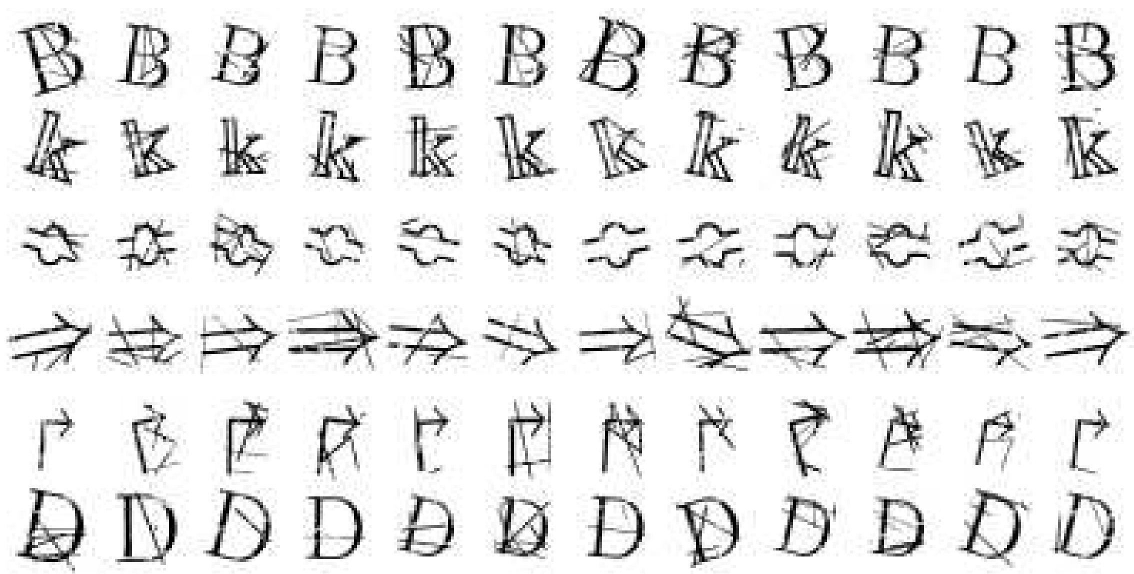
Remark

- ❷ Non-generative approach, no explicit model of the space of deformations
- ❷ Proof of concept

Databases

❶ The COIL-100 database (100 objects, 72 images of each)

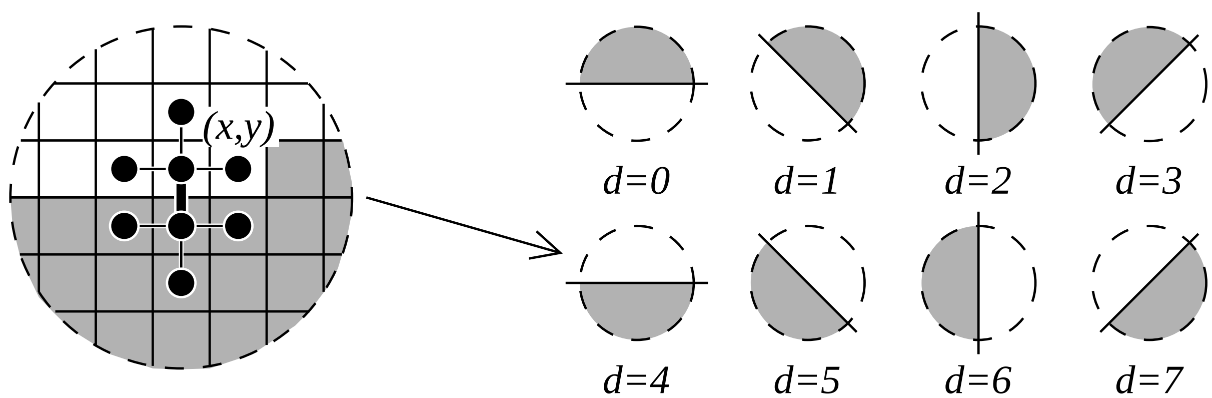
❷ Our $\LaTeX$ symbol database (150 symbols, 1,000 images of each)



Boolean Features

We denote by $\mathcal{I}$ the image space and by $f_1, \ldots, f_K$ a set of binary features $f_k : \mathcal{I} \rightarrow \{0,\, 1\}$.

Each one is a disjunction of a simple edge-detectors of orientation d over a rectangular areas (x_0, y_0, x_1, y_1).



No invariance to 3D transformation, moderate invariance to scaling, rotation and translation.

SPLITS

We denote by X an image (random variables on $\mathcal{I}$) and C its class (random variables on $\{1, \ldots, M\}$).

We call split a mapping $\psi : \mathcal{I} \rightarrow \{0, 1\}$ which splits the set of objects in two equilibrated halves:

- $P(\psi(X) = 0) = \frac{1}{2}$
- $P(\psi(X) = 0 \,|\, C)$ is 0 or 1

Let C^1 and C^2 denote the classes of two images X^1 and X^2, with an equilibrated prior $P(C^1 = C^2) = \frac{1}{2}$.

- $P(C^1 = C^2 \,|\, \psi(X^1) = \psi(X^2)) \simeq \frac{1}{2}$
- $P(C^1 = C^2 \,|\, \psi(X^1) \neq \psi(X^2)) = 0$

With several independent splits, we could do a very good job.

CHOPPING PRINCIPLE

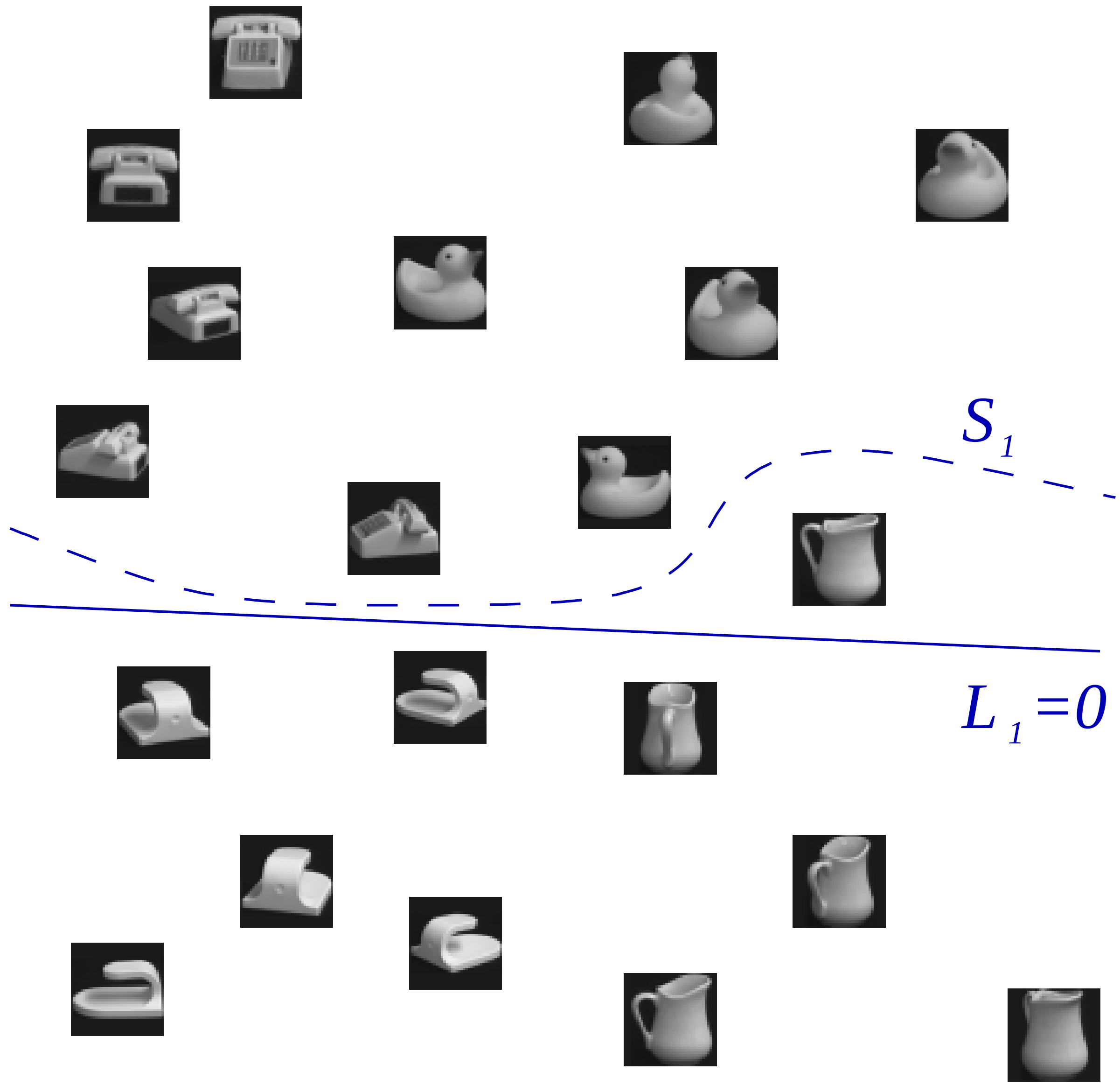
We can easily build independent splits on the training objects and we can extend them to the whole set $\mathcal{I}$ with machine learning methods.

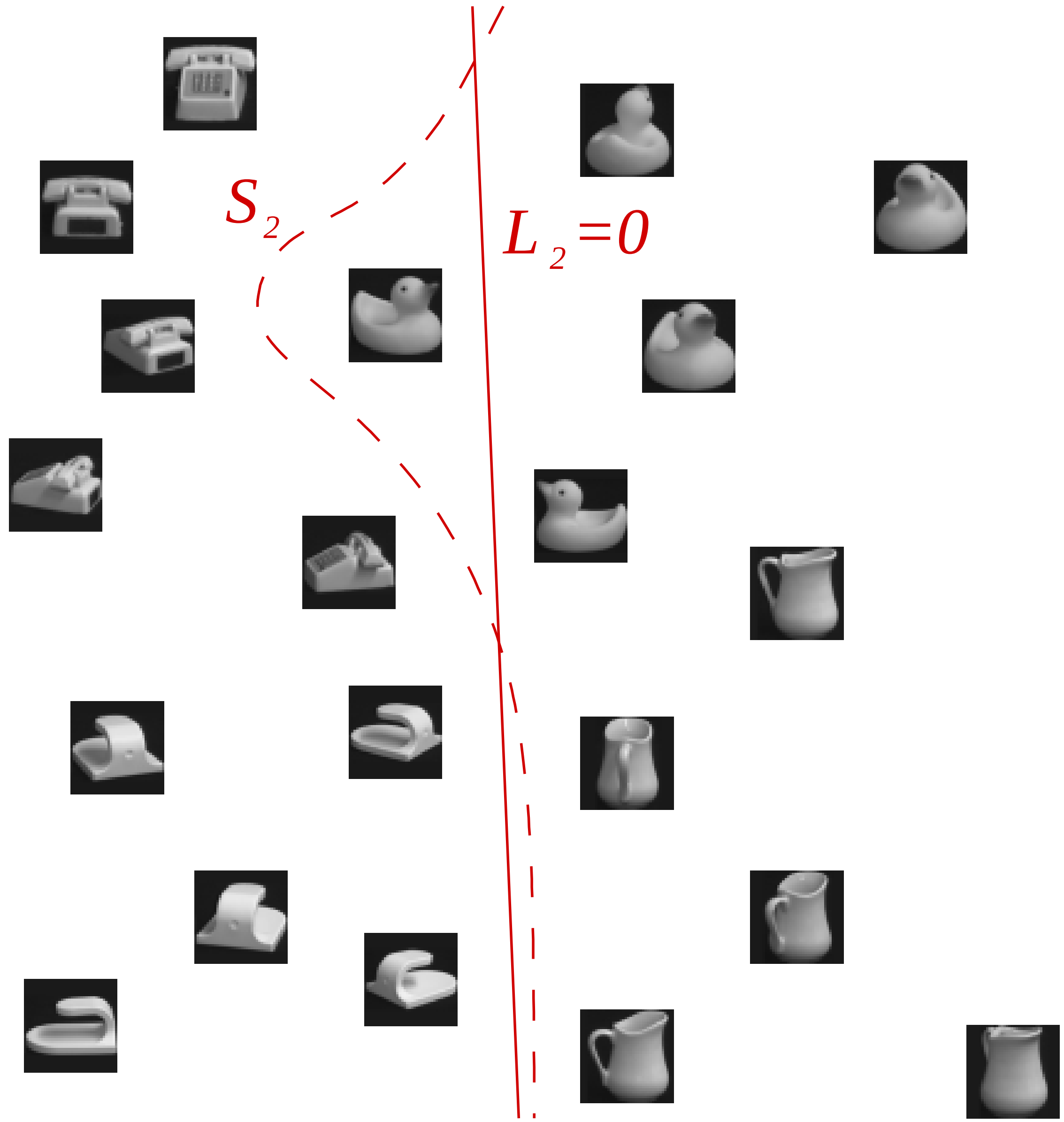
Chopping

We consider arbitrary splits of the training object set $S_1, \ldots, S_N$, and extend them to $\mathcal{I}$ by training predictors $L_1, \ldots, L_N$:

$$\forall n, \ L_n : \mathcal{I} \rightarrow \mathbb{R}$$

Those learners are feature-selection + linear perceptron without threshold.


S_1
$L_1=0$



S_2
$L_2 = 0$

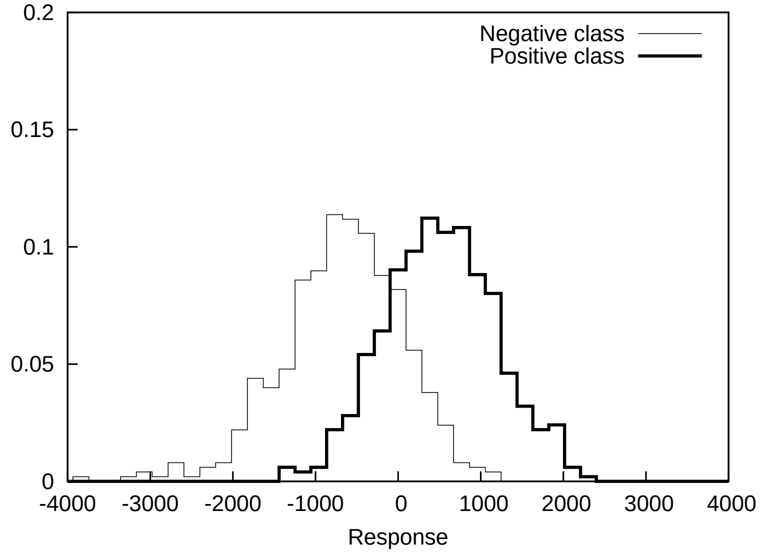
COMBINING SPLITS

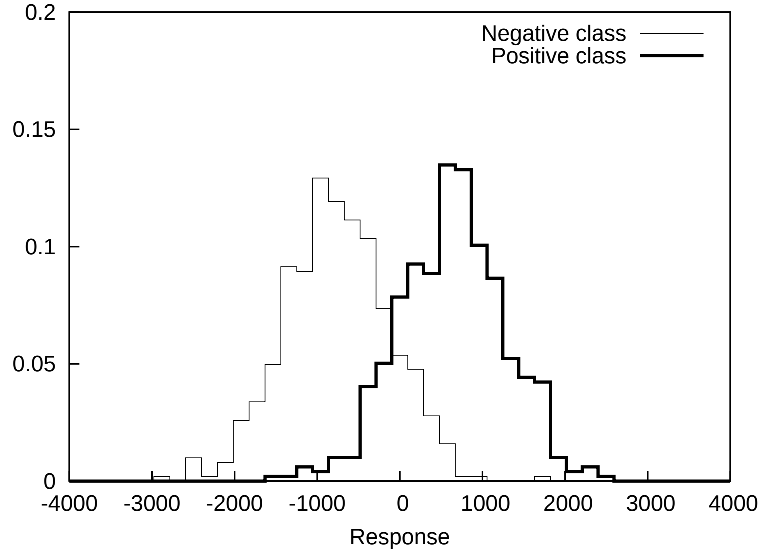
To predict if two images show the same object, we estimate how many splits keep them together.

The algorithm relies on the split predictors and takes into account their estimated reliability.

SPLIT PREDICTOR RELIABILITY

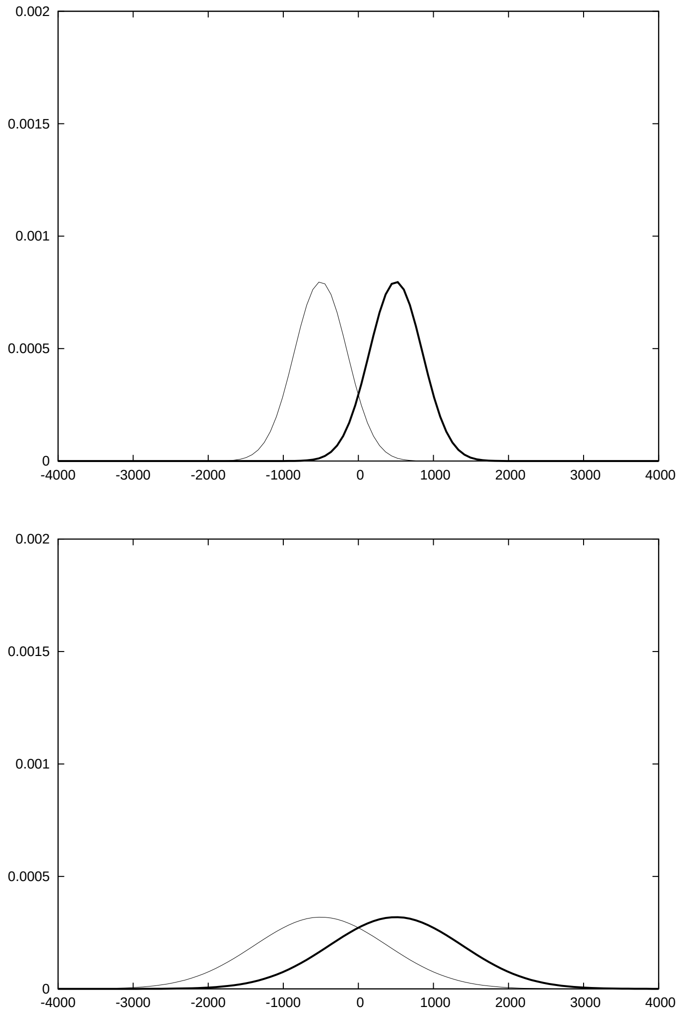
Since we have lot of images of the training objects, we can use a validation set to estimate $P(L_n \mid S_n)$



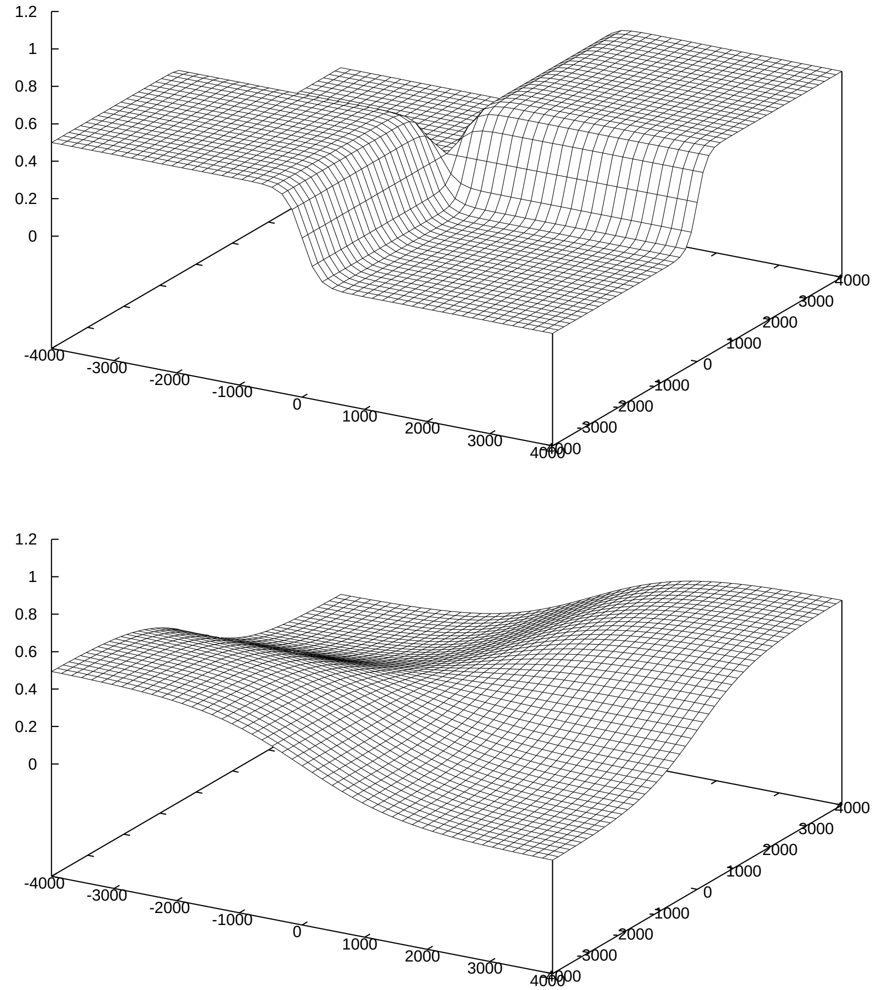


It makes sense to model $P(L_n \mid S_n = s)$ as a Gaussian.

PREDICTION WITH ONE SPLIT



$P(L_n \mid S_n = 0)$ and $P(L_n \mid S_n = 1)$



$P(C^1 = C^2 \mid L_n^1,\, L_n^2)$

The rule is similar with several splits under reasonable assumptions of conditional independence:

$$\begin{tikzcd}
L_1^2 \arrow[r, dash] & S_1^2 \arrow[dr, dash] & & & S_1^1 \arrow[r, dash] & L_1^1 \\
L_2^2 \arrow[r, dash] & S_2^2 \arrow[r, dash] & C^2 \arrow[r, dash] & C^1 \arrow[ur, dash] \arrow[r, dash] \arrow[ddr, dash] & S_2^1 \arrow[r, dash] & L_2^1 \\
\cdots & \cdots & & & \cdots & \cdots \\
L_N^2 \arrow[r, dash] & S_N^2 \arrow[uur, dash] & & & S_N^1 \arrow[r, dash] & L_N^1
\end{tikzcd}$$

Final Rule

We have

$$\log \frac{P(C^1 = C^2 \,|\, \mathbf{L}^1, \mathbf{L}^2)}{P(C^1 \neq C^2 \,|\, \mathbf{L}^1, \mathbf{L}^2)} \quad = \quad \log \frac{P(\mathbf{L}^1, \mathbf{L}^2 \,|\, C^1 = C^2)}{P(\mathbf{L}^1, \mathbf{L}^2 \,|\, C^1 \neq C^2)} + \log \frac{P(C^1 = C^2)}{P(C^1 \neq C^2)}$$

If we denote by $\alpha_i^j = P(S_i^j = 1 \,|\, L_i^j)$, we end up with the following expression

$$\boxed{\log \frac{P(C^1 = C^2 \,|\, \mathbf{L}^1, \mathbf{L}^2)}{P(C^1 \neq C^2 \,|\, \mathbf{L}^1, \mathbf{L}^2)} = \sum_i \log \left(\alpha_i^1 \alpha_i^2 + (1 - \alpha_i^1)(1 - \alpha_i^2)\right) + \rho}$$

REMARKS

❶ Splits correctly learnt are balanced, thus optimally informative

❷ Splits which are “unlearnable” are naturally ignored in the Bayesian formulation since $P(S = 1 \mid L = l)$ does not depend on l

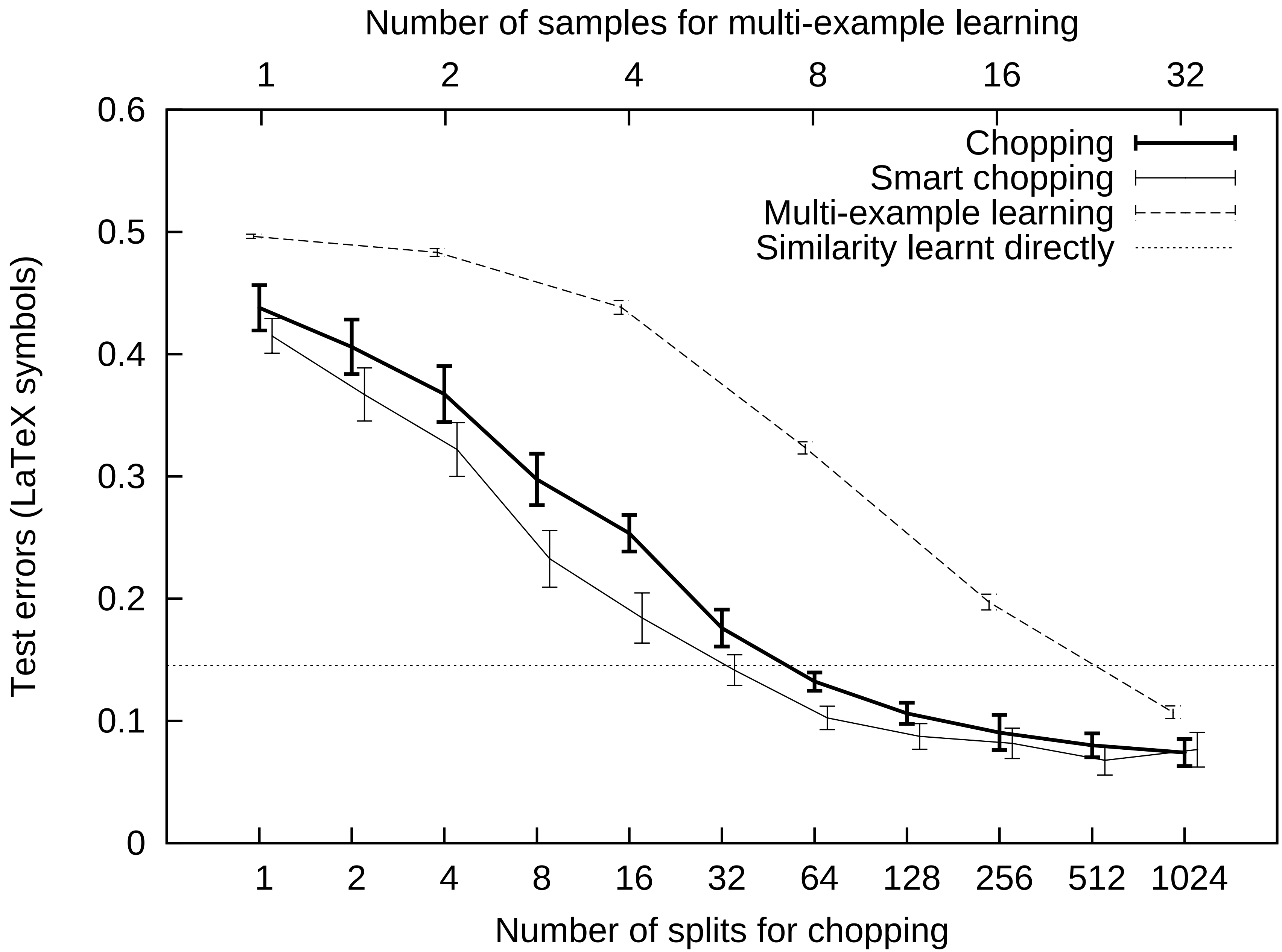
SMART CHOPPING

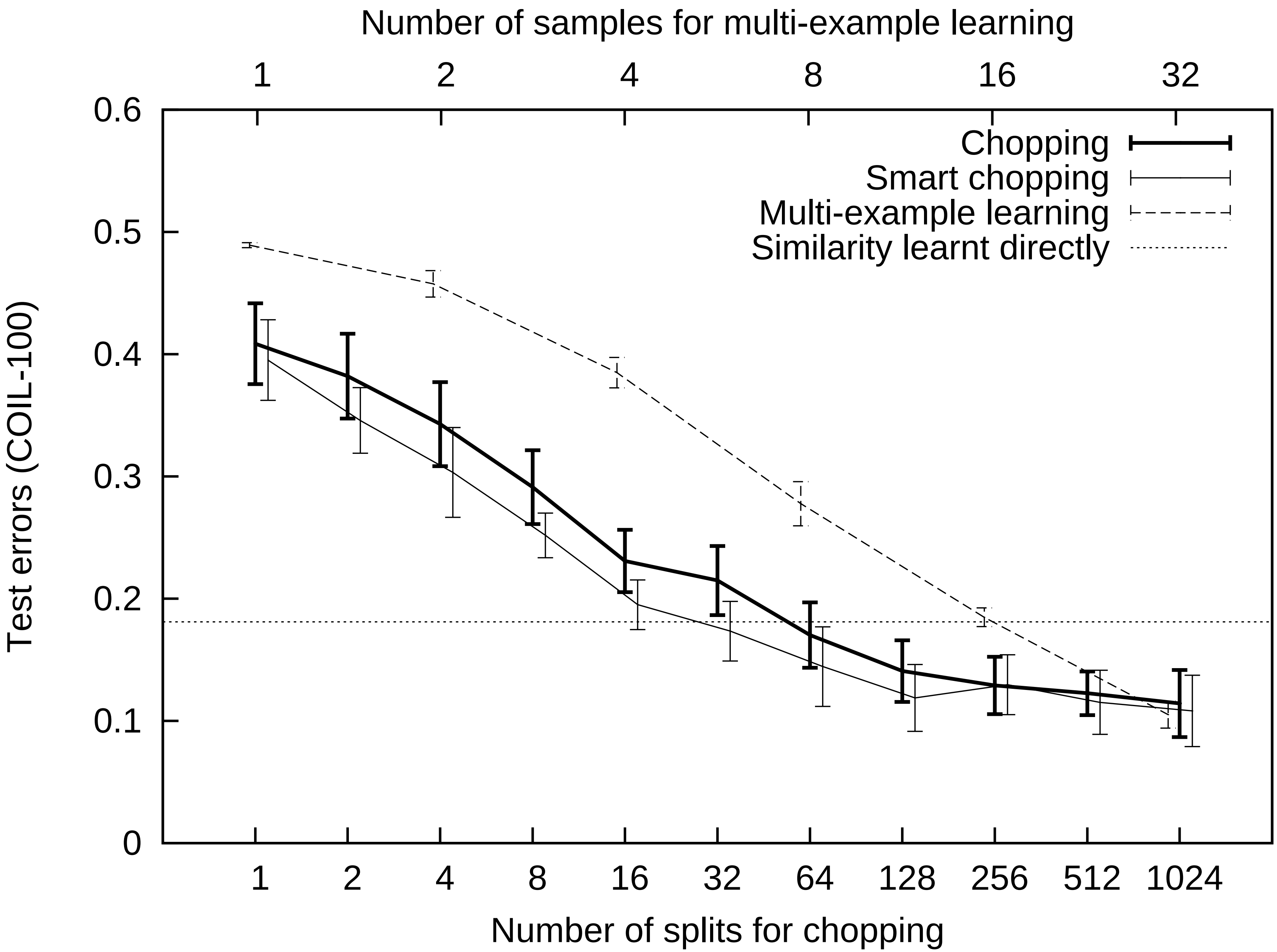
An arbitrary split can label differently very similar objects. We can improve performance by getting rid of objects difficult to learn, and re-building the predictor.

RESULTS

We compare:

1. Chopping with one example and several numbers of splits
2. Smart chopping with one example and several numbers of splits
3. Classical learning with several numbers of positive examples
4. Direct learning of the similarity with a perceptron


Number of samples for multi-example learning
1
2
4
8
16
32
0.6
0.5
0.4
0.3
0.2
0.1
0
Test errors (LaTeX symbols)
Chopping
Smart chopping
Multi-example learning
Similarity learnt directly
1
2
4
8
16
32
64
128
256
512
1024
Number of splits for chopping


Number of samples for multi-example learning
1
2
4
8
16
32
0.6
0.5
0.4
0.3
0.2
0.1
0
Test errors (COIL-100)
Chopping
Smart chopping
Multi-example learning
Similarity learnt directly
1
2
4
8
16
32
64
128
256
512
1024
Number of splits for chopping

WHY DOES IT WORK ?

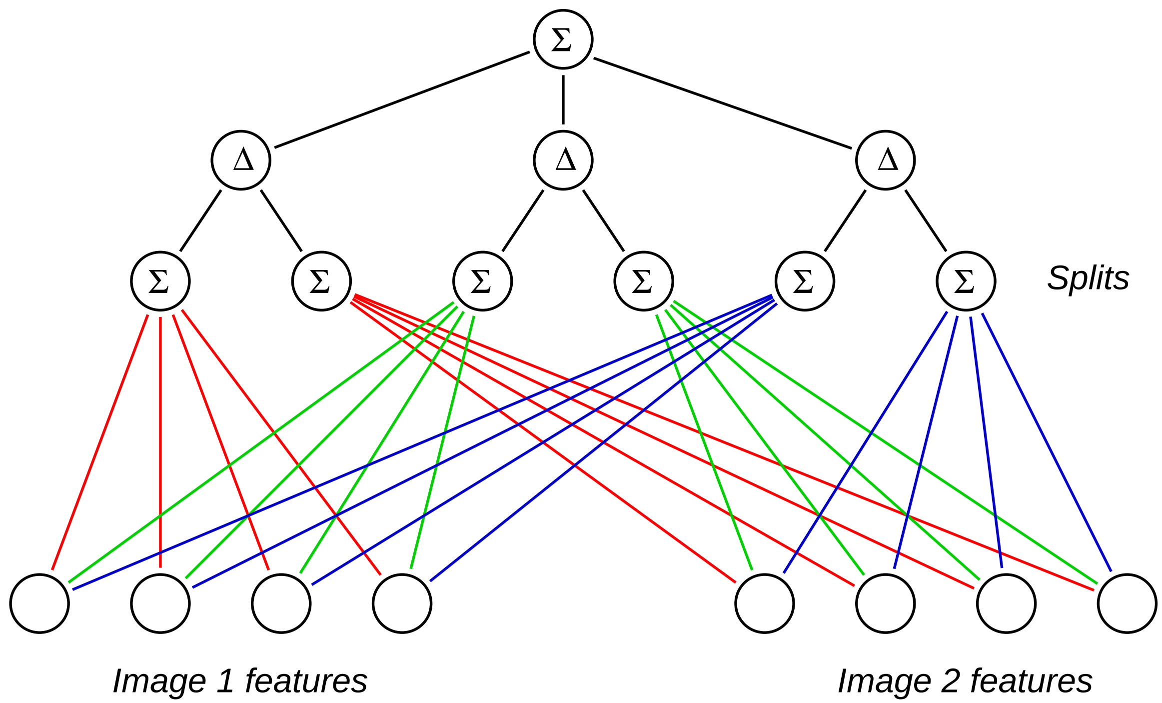
We are inferring functionals which are somehow arbitrary on the training examples.

However, we can expect that the training objects provide an exhaustive dictionary of invariant parts, even though they are not an exhaustive dictionary of the combined parts.

Note that since splits are built independently, we avoid over-fitting when their number increases.

Relation with ANNs

The Chopping structure can be seen as a one-hidden layer ANN with shared weights and an *ad hoc* output layer. If we define $\Delta(\alpha, \beta) = \log\left(\alpha\,\beta\, +\, (1-\alpha)(1-\beta)\right)$, we have



Can we globally learn the shared weights ?

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