Multimedia Indexing and Retrieval

Classical machine Learning for multimedia indexing

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Learning

- Machine learning: learning from data.
- Unsupervised learning:
  - Without human intervention,
  - Simple data,
  - Automatic class extraction (clustering).
- Supervised learning:
  - With human intervention (annotation),
  - Labeled (or annotated) data
  - Classification (predefined classes),
  - Regression (continuous values).

Supervised learning

- A machine learning technique for creating a function from training data.
- The training data consist of pairs of input objects (typically vectors) and desired outputs.
- The output of the function can be a continuous value (regression) or a class label (classification) of the input object.
- The task of the supervised learner is to predict the value of the function for any valid input object after having seen a number of training examples (i.e. pairs of input and target output).
- To achieve this, the learner has to generalize from the presented data to unseen situations in a “reasonable” way.
- The parallel task in human and animal psychology is often referred to as concept learning (in the case of classification).
- Most commonly, supervised learning generates a global model that helps mapping input objects to desired outputs.

(http://en.wikipedia.org/wiki/Supervised_learning)

Supervised learning

- Target function: $f : X \rightarrow Y$

$$x \rightarrow y = f(x)$$

  - x : input object (typically vector)
  - y : desired output (continuous value or class label)
  - X : set of valid input objects
  - Y : set of possible output values

- Training data: $S = (x_i, y_i)_{(1 \leq i \leq I)}$
  - I : number of training samples

- Learning algorithm: $L : (X \times Y)^* \rightarrow Y^X$

$$S \rightarrow f = L(S)$$

- Regression or classification system: $y = f(x) = [L(S)](x) = g(S,x)$

$$((X \times Y)^* = \cup_{n \in N} (X \times Y)^n)$$

Model based supervised learning

- Two functions, “train” and “predict”, cooperating via a Model

- General regression or classification system:

$$y = [L(S)](x) = g(S,x)$$

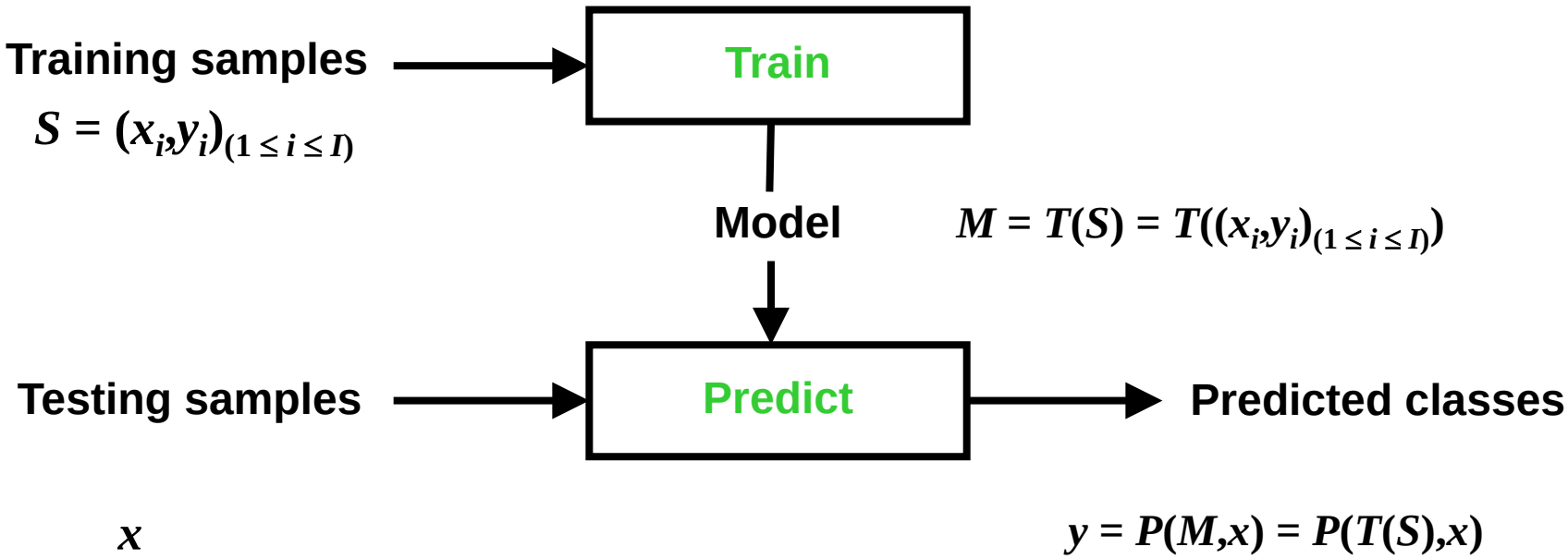
- Building of a model (train):

$$M = T(S)$$

- Prediction using a model (predict):

$$y = [L(S)](x) = g(S,x) = P(M,x) = P(T(S),x)$$

Supervised learning
Classification problem



Classification methods

- Gaussian Mixture Models
- Hidden Markov Models
- Decision trees
- Genetic algorithms
- Artificial neural networks
- K-nearest neighbor
- Linear discriminant analysis
- Support vector machines
- Minimum message length
- And many more.

k nearest neighbors (k-NN)

- No training : $M = T(S) = S$
- Compute the distances from the unknown sample x to all the training samples x_i,
- Select the k closest x_i,
- Compute the class of *x* from the classes of the closest x_i's:
  - k = 1 : the class of x is the class of the closest x_i,
  - k is odd and there are only two classes : majority vote.
- k-NN is a non linear classifier and can easily model classes with very irregular shapes,

k nearest neighbors (k-NN)

- 1-NN is a simple and quite often excellent classifier, it is often chosen as a baseline for comparison across systems,
- 3-NN is more robust against isolated outliers,
- Improvement: weight class values according to the (inverse) distance to the query point
- May be slow for classification because of the need to compute the distances with all the training samples
- However a single NN search may be performed for many classifications at once
- May be used for indexing (off line) or for search (on line, “similarity search”)

Computation of distance for k-NN

- Euclidian distance, angle between vectors,
- Comparison between a query vector to all the vectors in the database (no pre-selection),
- “Small” number of dimensions (< 10) : clustering techniques, hierarchical search,
- “Medium” number of dimensions (~ 10+) : methods based on space partitioning,
- “Large” number of dimensions(>> 10) : no known method faster that a full linear scan,
- Reduction of the number of dimensions by Principal Component Analysis.
- Approximate Nearest Neighbors: LSH

Locality Sensitive Hashing (LSH)

- Hashing: store many data samples into a table of fixed length; data placed into “buckets”
- “Regular” Hashing: avoid collision for faster access, polynomial and multiples XOR functions; any type of data
- Locality preserving hashing: favor collisions of “close” samples into the same buckets; data from highly dimensional Euclidean space, multiple projection functions

LSH: Multiple projection functions

- Set of random directions
- Projection on the axes $\rightarrow$ one component per direction
- Split values on axes according to a data distribution (two, four, eight … intervals)
- One or more bits per direction (generally one)
- Concatenation for producing the bucket index
- Multiple projections: matrix vector multiplication

LSH: Use of multiple tables

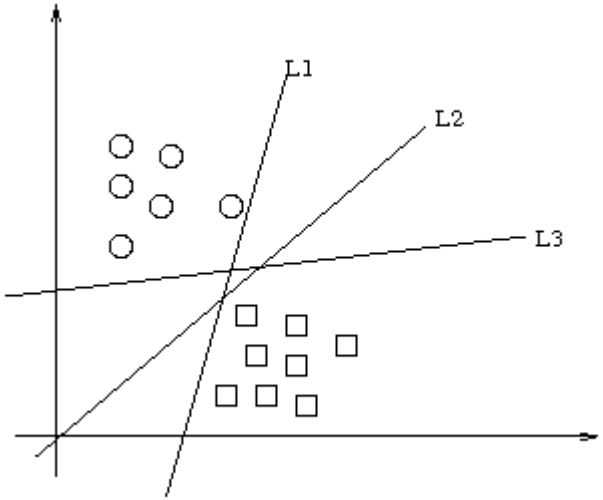
- Build many LSH tables
- For each table, select all the test samples that fall in the same bucket than the query sample
- Compute the Euclidean distance only for those samples
- Sort the test samples according to the Euclidean distances
- Euclidean distances are not approximate but some samples close to the query may not fall in the selected buckets
- The size and number of tables must be chosen so that enough and not too many samples are found for a query

LSH: Use of hamming distance

- Build binary codes (bucket index) as for one LSH table
- Hamming distance: number of bit locations in which the binary values differ: bitwise XOR followed by a count on 1 bits; modern processors have this as a single instruction
- Compute the Hamming distance between the query and all test samples: much faster than Euclidean distance
- Select samples with closest Hamming distance
- Compute the Euclidean distance only for those samples
- Similar to multiple tables from there

Support Vector Machines (SVM)

- Empirical risk minimization
- Linear classifier with maximum margin



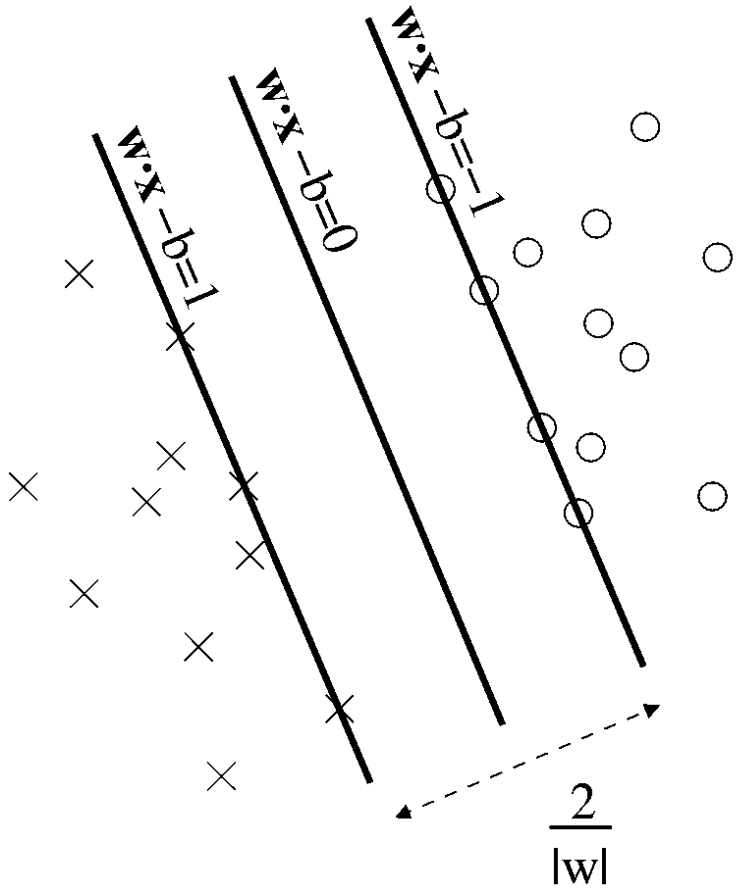
- The “kernel trick” permits non linear classification also with maximum margin and minimum empirical risk

SVM linear classification

- Maximum-margin hyperplanes for a SVM trained with samples from two classes.
- Samples along the hyperplanes are called the support vectors.
- The separated hyperplane is defined by:

$$w^T.x - b = 0$$

- The margin is $2/|w|$



SVM linear classification

- If the data is linearly separable:

  if $y_i = -1 : \; w^T.x_i - b \leq -1$ if $y_i = +1 : \; w^T.x_i - b \geq 1$

- This can be rewritten as:

$$y_i.(w^T.x_i - b) \geq 1$$

- SVM problem primal form:

  Minimize: $\frac{1}{2}\|w\|^2$ subject to: $y_i.\left(w^T.x_i - b\right) \geq 1, \quad 1 \leq i \leq n.$

- SVM problem dual form: $w = \sum_{i=1}^{n} \alpha_i y_i x_i$

  maximize: $\sum_{i=1}^{n} \alpha_i - \sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^T x_j$ subject to $\alpha_i \geq 0$

  α_i 's are non zero only for the support vectors.

SVM linear classification

- Soft margin, primal form:

$$y_i.\left(w^T.x_i - b\right) \geq 1 \quad \rightarrow \quad y_i.\left(w^T.x_i - b\right) \geq 1 - \xi_i$$

$$\min \frac{1}{2}\|w\|^2 \quad \rightarrow \quad \min\left(\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i\right)$$

- Dual form:

$$\alpha_i \geq 0 \quad \rightarrow \quad 0 \leq \alpha_i \leq C$$

- Allows for “misclassified” samples.

SVM non-linear classification

- Decision function:

$$f(x) = \langle w | x \rangle - b = \left\langle \sum_{i=1}^{n} \alpha_i y_i x_i \middle| x \right\rangle - b = \left(\sum_{i=1}^{n} \alpha_i y_i \langle x_i | x \rangle \right) - b$$

- Quadratic form maximization:

$$\sum_{i=1}^{n} \alpha_i - \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j \langle x_i | x_j \rangle$$

- Kernel trick: $\langle x_i | x_j \rangle \rightarrow \langle \Phi(x_i) | \Phi(x_j) \rangle = K(x_i, x_j)$

- Φ : possibly non-linear function, does not need to be computed, implicitly defined via the kernel (K) definition, linear separation in the im(Φ) space, may be non linear in the original space.

SVM non-linear classification

- Mercer condition : $K(x_i,x_j)$ must be definite positive.
- Common kernels:
  - Polynomial (homogeneous): $K(x,y)=(x.y)^d$
  - Polynomial (inhomogeneous): $K(x,y)=(x.y+1)^d$
  - Radial Basis Function: $K(x,y)=\exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right)$
  - Sigmoid: $K(x,y)=\tanh(\kappa x.y+c)$, for some (not every) $\kappa > 0$ and $c < 0$

Classification systems

- Classification at the global level:
  - Absence or presence of a concept,
  - Probability of presence of a concept,
  - No search for position in the image.
- Classification at the local level :
  - At the pixel level,
  - By block,
  - By region.
- Extraction of descriptors,
- Training and recognition,
- Systems with several levels: pipeline.

Classification at the pixel level

- Color,
- Texture (frequential composition in the neighborhood),
- Gradients and similar (combinations of various spatial derivatives),
- Search for a small number (~15) of classes with a meaning at both the signal and semantic levels: sky, greenery, water, building, clouds, road/track, human skin, …
- Not much used for direct recognition because not very reliable and useful,
- Often used as “intermediate level material” for recognition at the region or image level :
  - Vector representing the proportions or probabilities of presence of the different classes at the level of the considered area,
  - Useful and efficient even with poor local performances

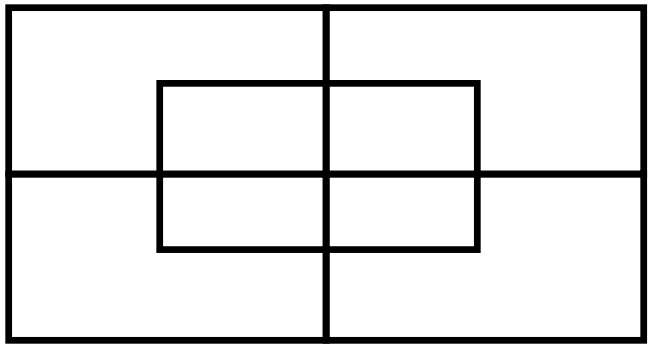
Classification at the block or region level

- Color : moments, histograms, corrélograms,
- Texture : Gabor transforms,
- Histograms of gradient directions,
- Statistics on classes recognized at the pixel level.

- Search for a small number (~15) of classes with a meaning at both the signal and semantic levels,
- Not much used for direct recognition,
- Often used as “intermediate level material” for recognition at the image scale level.

Classification at the block or region level

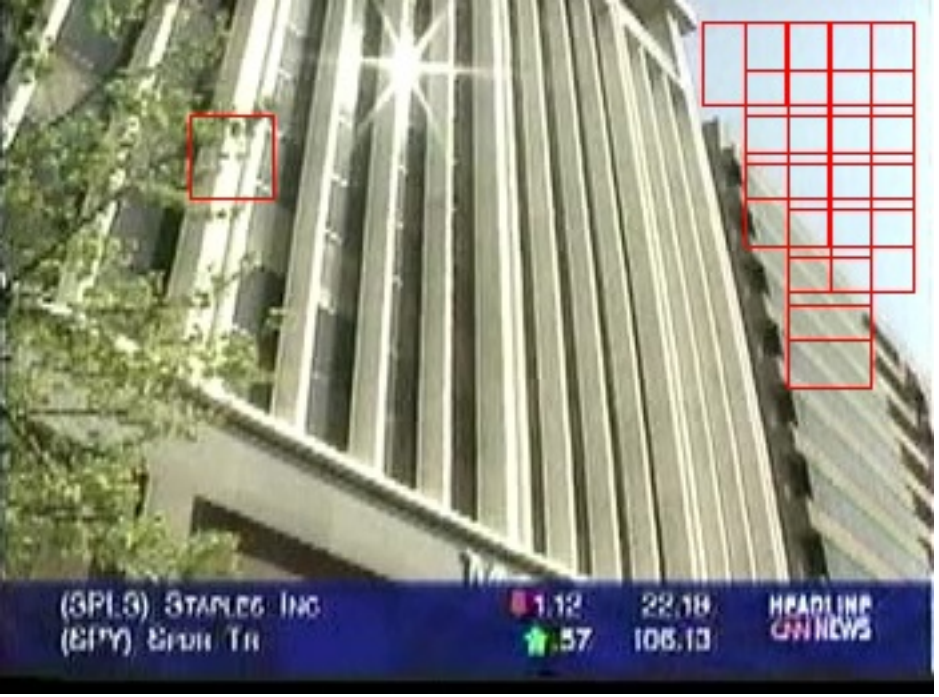
- Choice of regions : segmentation algorithms based on descriptors or classes associated to the pixels (targets a natural segmentation).
- Selection of blocks :
  - Regular grids, overlapping or non-overlapping blocks,
  - Window functions (2D Hamming, overlapping blocks),
  - Heuristical segmentations (center is more important)

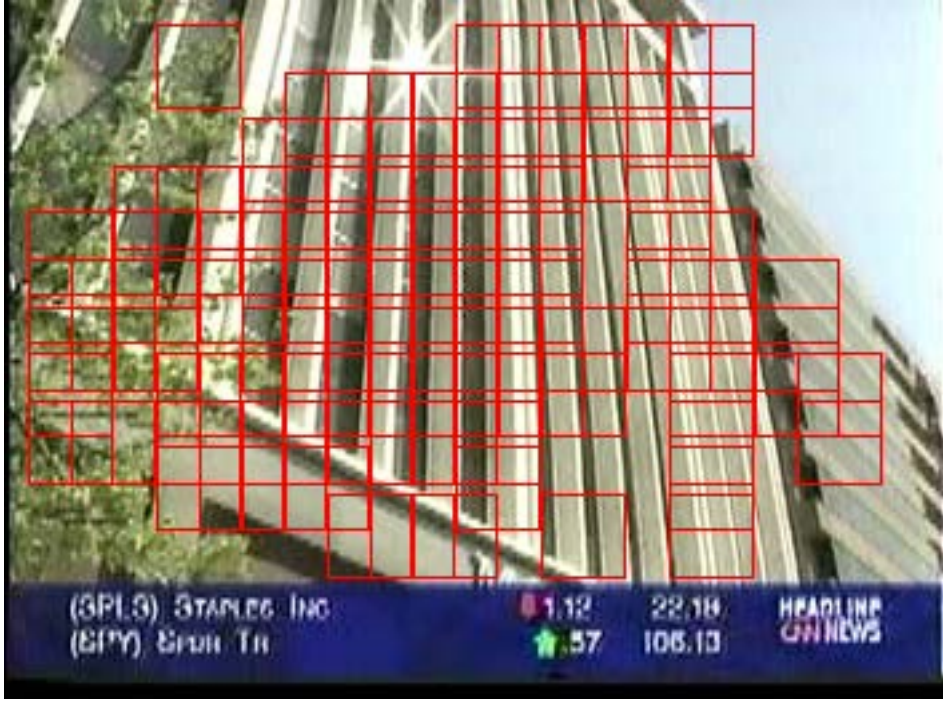


Classification at the image level

- Color : moments, histograms, correlograms,
- Texture : Gabor transforms,
- Histograms of gradient directions,
- Shapes (contours),
- Points of interest,
- Statistics on classes recognized at the pixel, regions or block level,
- Face detection.

- Classification of a large number of classes : from 10 (TRECVID 2003) to 850 (LSCOM Ontology)


(SPLS) STAPLES INC
1.12
22.19
.57
106.13
HEADLINE
CNN NEWS


(SPLS) STAPLES INC
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(SPLS) STAPLES INC
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CNN NEWS


(XCN) EXXON
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(AA) ALCOA
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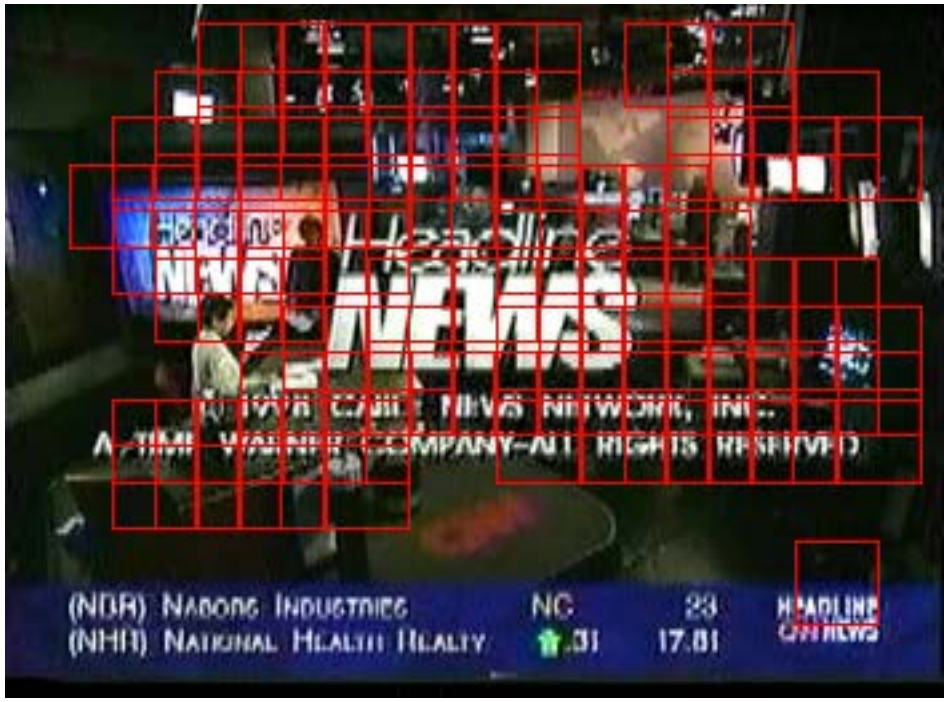
NEWS
(NBR) NABORS INDUSTRIES
NC
23
(NHR) NATIONAL HEALTH REALTY
.31
17.81


(MO) PHILIP MORRIS
(MOB) MORE GOOD
72.44


(MO) PHILIP MORRIS
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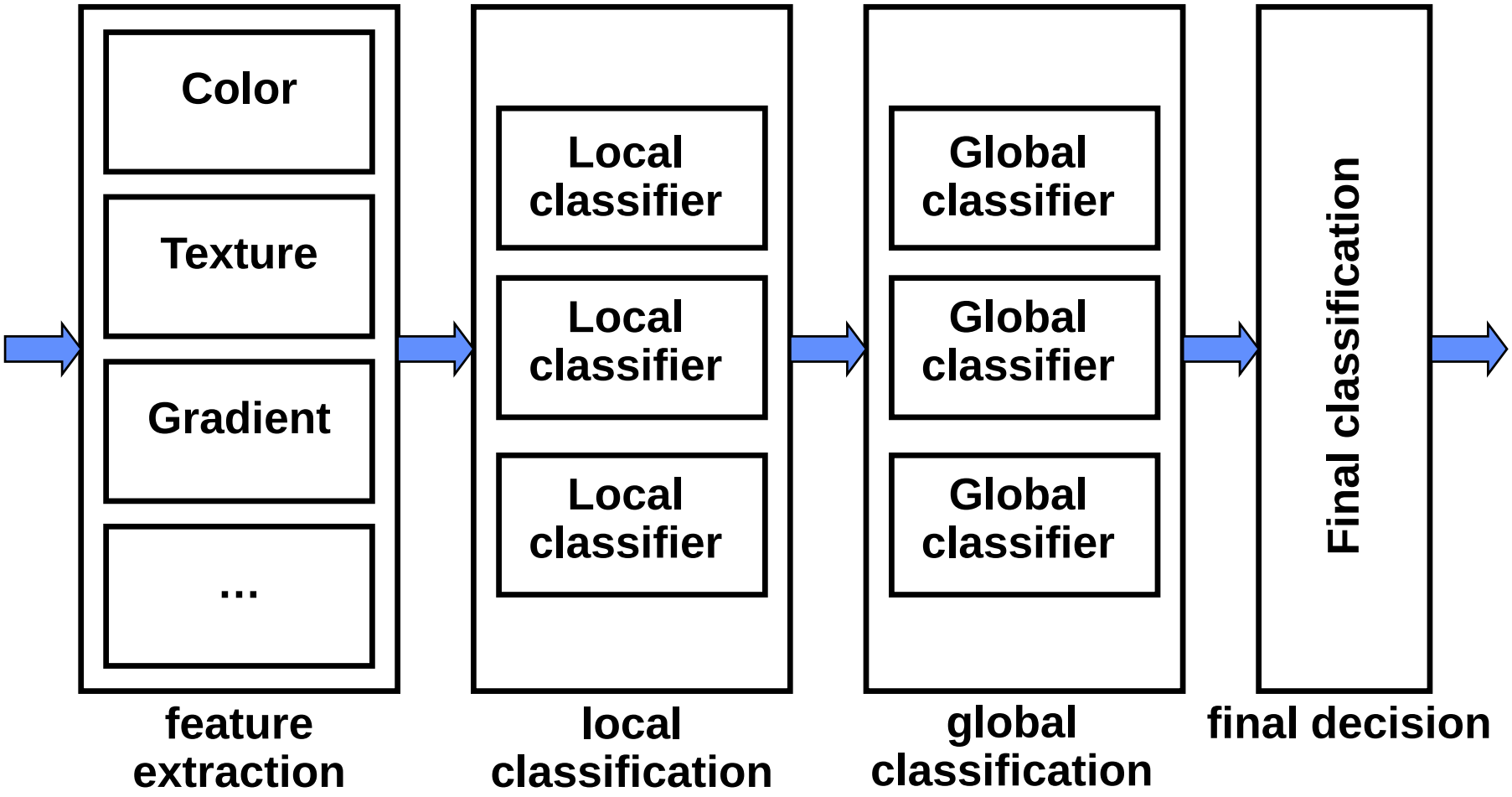
Classification at the image level

Pipeline architecture (IBM, CMU, MediaMill, LIG, …)



LSCOM
Large Scale Concept Ontology for Multimedia

- LSCOM: 850 concepts:
  - What is realistic (developers)
  - What is useful (users)
  - What makes sense to humans (psychologists)
- LSCOM-lite: 39 concepts, subset of LSCOM.
- Annotation of 441 concepts on ~65K subshots of the TRECVID 2005 development collection.
- 33,508,141 concept $\times$ annotations $\rightarrow$ About 20,000 hours or 12 man $\times$ years effort at 2 seconds/annotation.

Hyper-parameter tuning

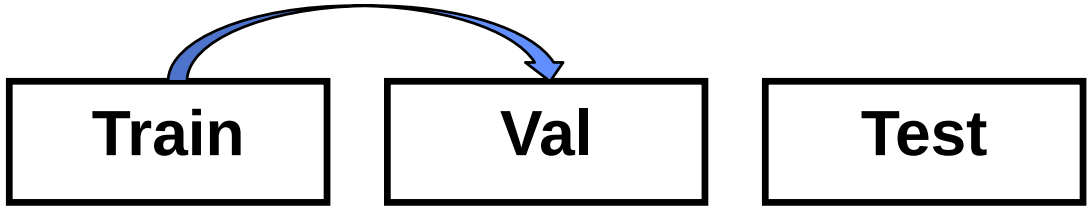
- Parameters:
  - Parameters of the model learnt from training data
  - e.g. values of the support vectors (x_i) and Lagrange coefficients (α_i) in SVMs
- "Hyper"-parameters:
  - Parameters that controls how the model (and "standard" parameters) are learnt
  - e.g. soft margin coefficient (C) in SVMs and the scale parameter in the RBF version (γ)
  - Possibly also class weights
  - Controls "how well" the classification algorithm generalizes from training data, especially the under fit versus over fit compromise

Hyper-parameter tuning, validation set

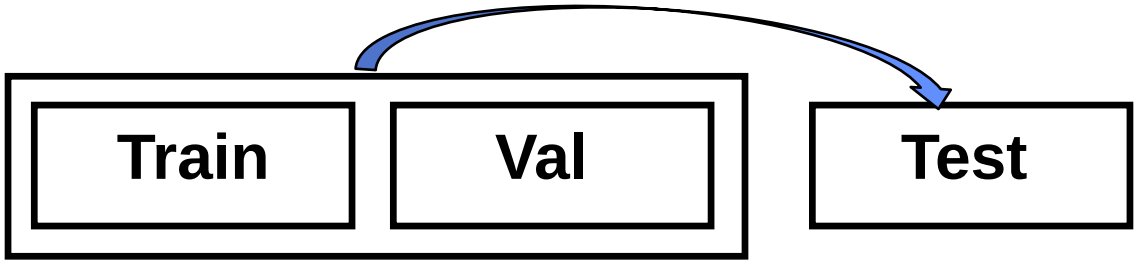
- A dataset used for training cannot be used for evaluation (over-fitting)
- Standard method: use different datasets for training and performance evaluation, each with annotated samples.
- Tuning of hyper-parameters on the test set is bad (over-fitting again)
- Good solution: use three datasets: train, val and test, all with annotated samples
- Train and evaluate several hyper-parameter values between train and val and then apply to test.

Hyper-parameter tuning, validation set

- Parameter tuning: selection of the optimal hyper-parameter combination by training on train and evaluating on test.

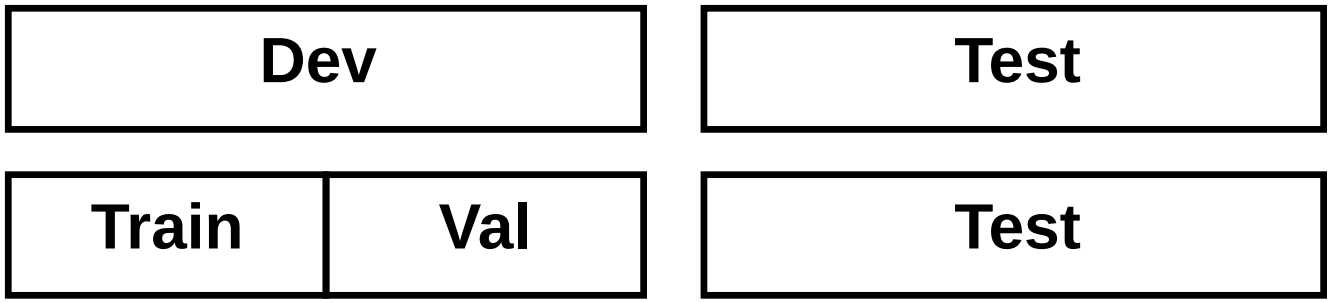


- Actual evaluation: keep the optimal hyper-parameter values, train on train+val and evaluate on test.

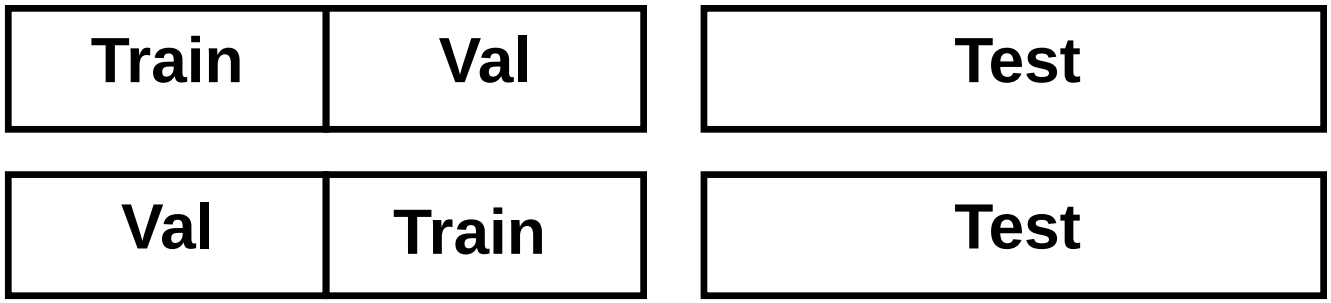


No validation set: split the training set

- Split into two equal parts, use first part as train and second part for validation (“one-fold” cross-validation)

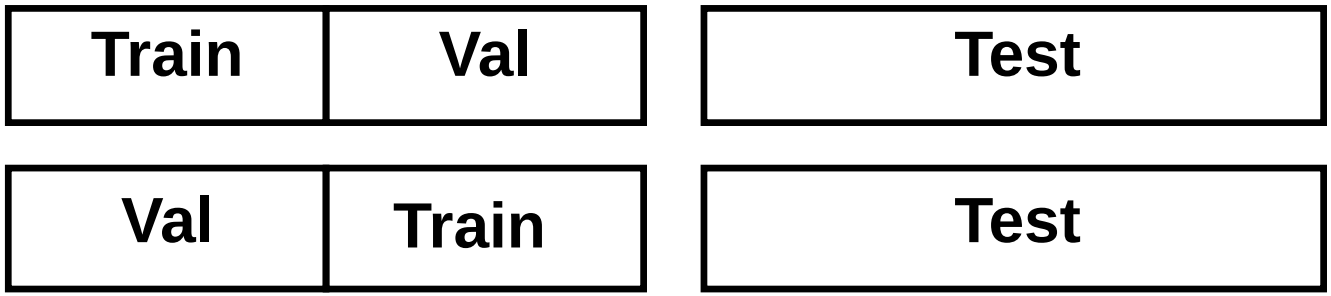


- Two-fold cross-validation



Two-fold cross-validation

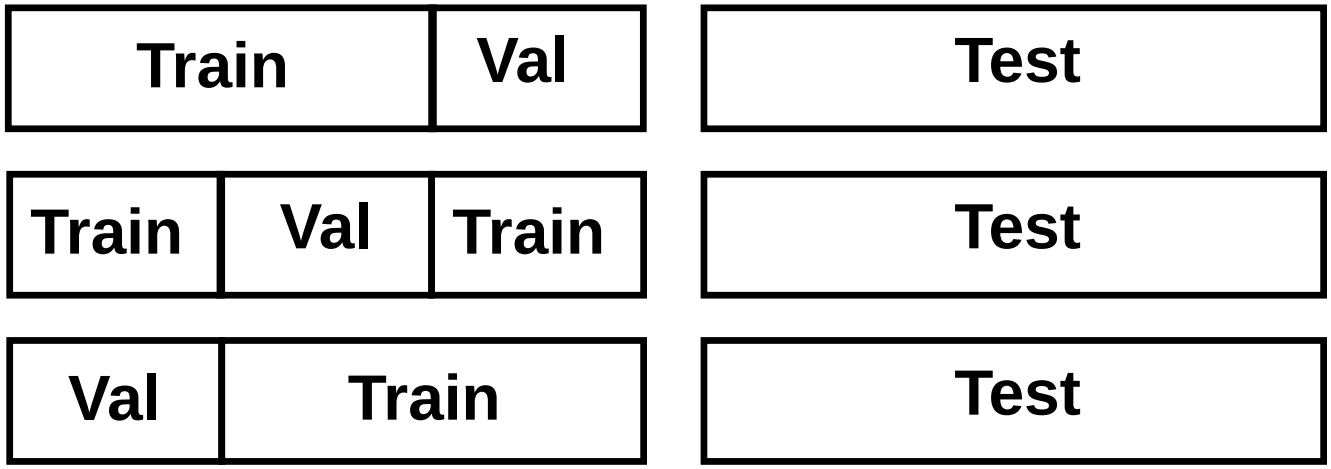
- Use two parts alternatively for training and validation



- The whole development set is used both for training and for evaluation during hyper-parameter tuning
- Tuning is done on MAP(hyper-parameters)
  - Either average the MAP on the two validations
  - Or compute a global MAP on the concatenated scores
- Training is done on half of the development set each time

N-fold cross-validation

- Use N parts of 1/N od the development set alternatively for validation and the complement ((N-1)/N) for training



- The whole development set is used both for training and for evaluation during hyper-parameter tuning
- Training is done on (N-1)/N of the development set each time, the greater N, the better.

Probabilized output

- SVM scores ranges from $-\infty$ to $+\infty$
- Probabilities are expected to range from 0 to 1
- Sigmoid transform: $p(score) = 1/(1+e^{(A*score+B)})$
- Additional hint: among the samples within a small interval around p, a fraction of about p would have positive labels
- Platt's method: learn A and B by cross-validation to optimally satisfy the above hint
- Probability normalized outputs better for late fusion