

Reducing Multiclass to Binary

LING572

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Highlights

- What?
 - Converting a k-class problem to a binary problem.
- Why?
 - For some ML algorithms, a direct extension to the multiclass case may be problematic.
 - Ex: Boosting, support-vector machines (SVM)
- How?
 - Many methods

Methods

- One-vs-all
- All-pairs
- Error-correcting Output Codes (ECOC)**:
see additional slides
- ...

One-vs-all

- Idea:
 - Each class is compared to all others.
 - K classifiers: one classifier for each class.
- Training time:
 - For each class c_m , train a classifier $cl_m(x)$
 - replace (x,y) with
 - $(x, 1)$ if $y = c_m$
 - $(x, -1)$ if $y \neq c_m$

An example: training

- $x_1 \ c_1 \ \dots$
- $x_2 \ c_2 \ \dots$
- $x_3 \ c_1 \ \dots$
- $x_4 \ c_3 \ \dots$

for c_1 -vs-all:

$x_1 \quad 1 \ \dots$
 $x_2 \quad -1 \ \dots$
 $x_3 \quad 1 \ \dots$
 $x_4 \quad -1 \ \dots$

for c_2 -vs-all:

$x_1 \quad -1$
 $x_2 \quad 1 \ \dots$
 $x_3 \quad -1 \ \dots$
 $x_4 \quad -1 \ \dots$

for c_3 -vs-all:

$x_1 \quad -1 \dots$
 $x_2 \quad -1 \dots$
 $x_3 \quad -1 \ \dots$
 $x_4 \quad 1 \ \dots$

One-vs-all (cont)

- Testing time: given a new example x
 - Run each of the k classifiers on x
 - Choose the class c_m with the highest confidence score $cl_m(x)$:
$$c^* = \arg \max_m cl_m(x)$$

An example: testing

- x1 c1 ...
- x2 c2 ...
- x3 c1 ...
- x4 c3 ...

→ three classifiers

Test data:

x ?? f1 v1 ...

for c1-vs-all:

x ?? 1 0.7 -1 0.3

for c2-vs-all

x ?? 1 0.2 -1 0.8

for c3-vs-all

x ?? 1 0.6 -1 0.4

=> what's the system prediction for x?

All-pairs

- Idea:
 - all pairs of classes are compared to each other
 - C_k^2 classifiers: one classifier for each class pair.
- Training:
 - For each pair (c_m, c_n) of classes, train a classifier cl_{mn}
 - replace a training instance (x, y) with
 - $(x, 1)$ if $y = c_m$
 - $(x, -1)$ if $y = c_n$
 - otherwise ignore the instance

An example: training

- $x_1 \ c_1 \ \dots$
- $x_2 \ c_2 \ \dots$
- $x_3 \ c_1 \ \dots$
- $x_4 \ c_3 \ \dots$

for c_1 -vs- c_2 :

$x_1 \quad 1 \ \dots$

$x_2 \quad -1 \ \dots$

$x_3 \quad 1 \ \dots$

for c_2 -vs- c_3 :

$x_2 \quad 1 \ \dots$

$x_4 \quad -1 \ \dots$

for c_1 -vs- c_3 :

$x_1 \quad 1 \ \dots$

$x_3 \quad 1 \ \dots$

$x_4 \quad -1 \ \dots$

All-pairs (cont)

- Testing time: given a new example x
 - Run each of the C_k^2 classifiers on x
 - Max-win strategy: Choose the class c_m that wins the most pairwise comparisons:
 - Other coupling models have been proposed: e.g., (Hastie and Tibshirani, 1998)

An example: testing

- $x_1 \ c_1 \ \dots$
- $x_2 \ c_2 \ \dots$
- $x_3 \ c_1 \ \dots$
- $x_4 \ c_3 \ \dots$

→ three classifiers

Test data:

$x \ \ ?? \ f_1 \ v_1 \ \dots$

for c_1 -vs- c_2 :

$x \ \ ?? \quad 1 \quad 0.7 \quad -1 \quad 0.3$

for c_2 -vs- c_3

$x \ \ ?? \quad 1 \quad 0.2 \quad -1 \quad 0.8$

for c_1 -vs- c_3

$x \ \ ?? \quad 1 \quad 0.6 \quad -1 \quad 0.4$

=> what's the system prediction for x ?

Summary

- Different methods:
 - Direct multiclass
 - One-vs-all (a.k.a. one-per-class): k -classifiers
 - All-pairs: C_k^2 classifiers
 - ECOC: n classifiers (n is the num of columns)
- Some studies report that All-pairs and ECOC work better than one-vs-all.

Hw7

Q1: one-vs-all

- `q1.sh training_data test_data output_dir > acc_file`
- `training_data`, `test_data`: Mallet text format
 - `instanceName goldClass f1 v1 f2 v2 ...`
- `output_dir/`: see the next slide
- `acc_file`: same as the one in hw2-hw5

output_dir/

- class_map: classname class_index
 - gun 1 \n mid-east 2 \n misc 3 \n
- 1-vs-all/, 2-vs-all/, 3-vs-all/
 - “train” and “test”: like training_data and test_data, but goldClass is changed to 1 or -1
 - “sys_output”:
 - instanceName goldClass c1 p1 c2 p2
 - c1 and c2 are 1 and -1 (the order depends on prob)
 - $p_i = P(c_i | x)$
- final_sys_out: “instName goldClassName [cn1 prob1 cn2 prob2 ...]”
 - goldClassName and cn_i are classnames, not class index or 1, -1
 - prob_i is $P(1 | x)$ based the classifier i-vs-all
 - (cn_i, prob_i) pairs are sorted according to prob_i in descending order

Q2: all-pairs

- `q2.sh training_data test_data output_dir > acc_file`
- The file formats are the same except for the following under `output_dir/`:
 - 1-vs-2, 1-vs-3, 2-vs-3, not 1-vs-all, 2-vs-all, ...
 - `final_sys_output`:
 - `InstanceName goldClass sysClass 1:2 p(1,2) 1:3 p(1,3) ...
c1=n1 c2=n2 c3=n3`
 - `sysClass` is the class name that `q2.sh` predicts for the instance
 - `p(i,j)` is the $P(\text{class}=1 \mid x)$ based on `i-vs-j` classifier
 - `n_i` is the number of times that `c_i` wins

Additional slides

Error-correcting output codes (ECOC)

- Proposed by (Dietterich and Bakiri, 1995)
- Idea:
 - Each class is assigned a unique binary string of length n .
 - Train n classifiers, one for each bit.
 - Testing time: run n classifiers on x to get a n -bit string s , and choose the class which is closest to s .

An example

Class	Code Word					
	vl	hl	dl	cc	ol	or
0	0	0	0	1	0	0
1	1	0	0	0	0	0
2	0	1	1	0	1	0
3	0	0	0	0	1	0
4	1	1	0	0	0	0
5	1	1	0	0	1	0
6	0	0	1	1	0	1
7	0	0	1	0	0	0
8	0	0	0	1	0	0
9	0	0	1	1	0	0

Meaning of each column

Column position	Abbreviation	Meaning
1	vl	contains vertical line
2	hl	contains horizontal line
3	dl	contains diagonal line
4	cc	contains closed curve
5	ol	contains curve open to left
6	or	contains curve open to right

Another example: 15-bit code for a 10-class problem

Class	Code Word														
	f_0	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}
0	1	1	0	0	0	0	1	0	1	0	0	1	1	0	1
1	0	0	1	1	1	1	0	1	0	1	1	0	0	1	0
2	1	0	0	1	0	0	0	1	1	1	1	0	1	0	1
3	0	0	1	1	0	1	1	1	0	0	0	0	1	0	1
4	1	1	1	0	1	0	1	1	0	0	1	0	0	0	1
5	0	1	0	0	1	1	0	1	1	1	0	0	0	0	1
6	1	0	1	1	1	0	0	0	0	1	0	1	0	0	1
7	0	0	0	1	1	1	1	0	1	0	1	1	0	0	1
8	1	1	0	1	0	1	1	0	0	1	0	0	0	1	1
9	0	1	1	1	0	0	0	0	1	0	1	0	0	1	1

Hamming distance

- Definition: the **Hamming distance** between two strings of equal length is the number of positions for which the corresponding symbols are different.
- Ex:
 - 10111 and 10010
 - 2143 and 2233
 - Toned and roses

How to choose a good error-correcting code?

- Choose the one with large minimum Hamming distance between any pair of code words.
- If the min Hamming distance is d , then the code can correct at least $(d-1)/2$ single bit errors.

Two properties of a good ECOC

- Row separations: Each codeword should be well-separated in Hamming distance from each of the other codewords
- Column separation: Each bit-position function f_i should be uncorrelated with each of the other f_j .

All possible columns for a three-class problem

Class	Code Word							
	f_0	f_1	f_2	f_3	f_4	f_5	f_6	f_7
c_0	0	0	0	0	1	1	1	1
c_1	0	0	1	1	0	0	1	1
c_2	0	1	0	1	0	1	0	1

If there are k classes, there will be at most $2^{k-1} - 1$ usable columns after removing complements and the all-zeros or all-ones column.

Finding a good code for different values of k

- Exhaustive codes
- Column selection from exhaustive codes
- Randomized hill climbing
- BCH codes
- ...

Results

