

Slides adapted from Prof Carpuat and Duraiswami



CMSC 422 Introduction to Machine Learning

Lecture 12 Reductions

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Reductions for Multiclass Classification

TASK: MULTICLASS CLASSIFICATION

Given:

1. An input space $\mathcal{X}$ and number of classes K
2. An unknown distribution $\mathcal{D}$ over $\mathcal{X} \times [K]$

Compute: A function f minimizing: $\mathbb{E}_{(x,y) \sim \mathcal{D}} [f(x) \neq y]$

TASK: BINARY CLASSIFICATION

Given:

1. An input space $\mathcal{X}$
2. An unknown distribution $\mathcal{D}$ over $\mathcal{X} \times \{-1, +1\}$

Compute: A function f minimizing: $\mathbb{E}_{(x,y) \sim \mathcal{D}} [f(x) \neq y]$

Reduction 1: OVA

- “One versus all” (aka “one versus rest”)
 - Train K-many binary classifiers
 - classifier k predicts whether an example belong to class k or not
- At test time,
 - If only one classifier predicts positive, predict that class
 - Break ties randomly

Algorithm 12 ONEVERSUSALLTRAIN($\mathbf{D}^{multiclass}$, BINARYTRAIN)

```
1: for  $i = 1$  to  $K$  do
2:    $\mathbf{D}^{bin} \leftarrow$  relabel  $\mathbf{D}^{multiclass}$  so class  $i$  is positive and  $\neg i$  is negative
3:    $f_i \leftarrow$  BINARYTRAIN( $\mathbf{D}^{bin}$ )
4: end for
5: return  $f_1, \dots, f_K$ 
```

Algorithm 13 ONEVERSUSALLTEST($f_1, \dots, f_K, \hat{x}$)

```
1:  $score \leftarrow \langle 0, 0, \dots, 0 \rangle$  // initialize  $K$ -many scores to zero
2: for  $i = 1$  to  $K$  do
3:    $y \leftarrow f_i(\hat{x})$ 
4:    $score_i \leftarrow score_i + y$ 
5: end for
6: return  $\operatorname{argmax}_k score_k$ 
```

Time complexity

- Suppose you have N training examples, in K classes. How long does it take to train an OVA classifier
 - if the base binary classifier takes $O(N)$ time to learn?
 - if the base binary classifier takes $O(N^2)$ time to learn?

Error bound

- **Theorem:** Suppose that the average error of the K binary classifiers is ϵ , then the error rate of the OVA multiclass classifier is at most $(K-1) \epsilon$
- To prove this: how do different errors affect **the maximum ratio of the probability of a multiclass error to the number of binary errors (“efficiency”)**?

Error bound proof

1. If we have a **false negative** on one of the binary classifiers (assuming all other classifiers correctly output negative)

What is the probability that we will make an incorrect multiclass prediction?

$$(K - 1) / K$$

$$\text{Efficiency: } [(K - 1) / K] / 1 = (K - 1) / K$$

Error bound proof

2. If we have m **false positives** with the binary classifiers

What is the probability that we will make an incorrect multiclass prediction?

If there is also a false negative: 1

$$\text{Efficiency} = 1 / (m + 1)$$

Otherwise $m / (m + 1)$

$$\text{Efficiency} = [m / (m + 1)] / m = 1 / (m + 1)$$

Error bound proof

3. What is the worst case scenario?

False negative case: efficiency is $(K-1)/K$

Larger than false positive efficiencies

There are K -many opportunities to get false negative, **overall error bound is $(K-1) \epsilon$**

Reduction 2: AVA

All versus all (aka all pairs)

How many binary classifiers does this require?

Algorithm 14 ALLVERSUSALLTRAIN($\mathbf{D}^{multiclass}$, BINARYTRAIN)

```
1:  $f_{ij} \leftarrow \emptyset, \forall 1 \leq i < j \leq K$ 
2: for  $i = 1$  to  $K-1$  do
3:    $\mathbf{D}^{pos} \leftarrow$  all  $\mathbf{x} \in \mathbf{D}^{multiclass}$  labeled  $i$ 
4:   for  $j = i+1$  to  $K$  do
5:      $\mathbf{D}^{neg} \leftarrow$  all  $\mathbf{x} \in \mathbf{D}^{multiclass}$  labeled  $j$ 
6:      $\mathbf{D}^{bin} \leftarrow \{(\mathbf{x}, +1) : \mathbf{x} \in \mathbf{D}^{pos}\} \cup \{(\mathbf{x}, -1) : \mathbf{x} \in \mathbf{D}^{neg}\}$ 
7:      $f_{ij} \leftarrow$  BINARYTRAIN( $\mathbf{D}^{bin}$ )
8:   end for
9: end for
10: return all  $f_{ij}$ s
```

Algorithm 15 ALLVERSUSALLTEST(all f_{ij} , $\hat{\mathbf{x}}$)

```
1:  $score \leftarrow \langle 0, 0, \dots, 0 \rangle$  // initialize  $K$ -many scores to zero
2: for  $i = 1$  to  $K-1$  do
3:   for  $j = i+1$  to  $K$  do
4:      $y \leftarrow f_{ij}(\hat{\mathbf{x}})$ 
5:      $score_i \leftarrow score_i + y$ 
6:      $score_j \leftarrow score_j - y$ 
7:   end for
8: end for
9: return  $\operatorname{argmax}_k score_k$ 
```



Time complexity

- Suppose you have N training examples, in K classes. How long does it take to train an AVA classifier
 - if the base binary classifier takes $O(N)$ time to learn?
 - if the base binary classifier takes $O(N^2)$ time to learn?

Error bound

Theorem: Suppose that the average error of the K binary classifiers is ϵ , then the error rate of the AVA multiclass classifier is at most $2(K-1) \epsilon$

Question: Does this mean that AVA is always worse than OVA?

Extensions

Divide and conquer

Organize classes into binary tree structures

Use confidence to weight predictions of binary classifiers

Instead of using majority vote

Topics

Given an arbitrary method for binary classification, how can we learn to make multiclass predictions?

OVA, AVA

Fundamental ML concept: reductions



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