Large Scale Image Classification Based on a Multi-Class Logistic Regression Model

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Outline

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Motivation

Challenges

- Massive training examples
- High feature dimension
- High class diversity

• Why Logistic?

- Flexibility in No. of examples involved in each iteration
- No. of parameters increases with feature dimension and class diversity

Multi-Class Logistic Regression

Binary Case

$$\ln \frac{p(y_i = 1|\mathbf{x}_i)}{p(y_i = -1|\mathbf{x}_i)} = \mathbf{w}^T \mathbf{x}_i \tag{1}$$

Multi-Class Case

$$\ln p(y_i|\mathbf{x}_i) \propto \mathbf{w}_{y_i}^T \mathbf{x}_i \tag{2}$$

Probability Constrain

$$\sum_{y_i=1}^K p(y_i|\mathbf{x}_i) = 1 \tag{3}$$

Multi-Class Logistic Regression-cont'

Formal Representation

$$p(y_i|\mathbf{x}_i) = \frac{1}{Z}e^{\mathbf{w}_{y_i}^T\mathbf{x}_i} \tag{4}$$

with

$$Z = \sum_{j=1}^{K} e^{\mathbf{w}_{j}^{T} \mathbf{x}_{i}}$$
 (5)

Multi-Class Logistic Regression-cont'

MLE Optimization

$$\max_{\mathbf{W}} \mathcal{L}(\mathbf{W}) = \max_{\mathbf{W}} \sum_{i=1}^{N} \ln p(y_i | \mathbf{x}_i)$$

$$= \max_{\mathbf{W}} \sum_{i=1}^{N} \ln \frac{e^{\mathbf{w}_{y_i}^T \mathbf{x}_i}}{\sum_{j=1}^{K} e^{\mathbf{w}_j^T \mathbf{x}_i}}$$
(6)

Multi-Class Logistic Regression-cont'

Gradient Calculation

$$\frac{\partial \mathcal{L}(\mathbf{W})}{\partial \mathbf{w}_{k}} = \sum_{i=1}^{N} \mathbf{x}_{i} \left(I(y_{i} = k) - \frac{e^{\mathbf{w}_{k}^{T} \mathbf{x}}}{\sum_{j=1}^{K} e^{\mathbf{w}_{j}^{T} \mathbf{x}}} \right)
= \sum_{i=1}^{N} \mathbf{x}_{i} (I(y_{i} = k) - p(y_{i} = k | \mathbf{x}_{i}))$$
(7)

Iteration Formula

$$\mathbf{w}_{k,t+1} = \mathbf{w}_{k,t} + \eta_t \frac{\partial \mathcal{L}(\mathbf{W})}{\partial \mathbf{w}_k}$$
 (8)

Training Example Sampling

- Involve all the training examples in each iteration?
 - No!!! Computationally expensive.
- Sampling Only a very small amount of memory needed to accommodate these sampled examples.
 - How many training examples in each iteration? Experimentally $N_s=250$ is chosen.
 - How many iterations needed?
 - How to implement fast sampling?
 Text documents—>Binary documents: replace the time-consuming sequential access with random access

Experimental Results

Cross Validation Accuracy and Mean Average Precision

Table 1: Cross Validation Report on the Proposed Approach Under Different Numbers of Iterations

No. of	ACCURACY	TRAINING	TESTING	
ITERATION	/MAP	TIME	TIME	
100	29.11%/22.40%	4MIN 57 S	30s	
200	30.29%/25.23%	9min9s	38s	
500	31.53%/30.53%	18min57s	35s	
1000	32.40%/35.56%	37min46s	32s	
2000	32.99%/39.37%	1H7MIN31s	31s	
5000	33.74%/44.31%	1H 54 MIN 28 S	30s	
10000	34.03%/47.98%	3H 5 8MIN 20 S	31s	
20000	34.40%/49.94%	6H37MIN15s	30s	

Experimental Results-cont'

Time and Memory Cost of the Final Training and Prediction

Table 2: Time and Memory Cost of the Final Training and Prediction

No. of	Training	PREDICTION	PEAK
ITERATIONS	TIME	TIME	MEMORY
5000	3H27MIN43S	49s	$1.764 \mathrm{MB}$

MATLAB Profile Report

Profile Summary Generated 16-Apr-2013 10:28:53 using cpu time.								
<u>Function Name</u>	Calls	<u>Total Time</u>	Self Time*	Allocated Memory	Freed Memory	Self Memory	Peak Memory	
main	1	415.952 s	0.015 s	58992112.00 Kb	58991952.00 Kb	-1156.00 Kb	1764.00 Kb	

Extra Efforts

- Smart Sampling Untested.
 - Unbalanced class distribution.
 - Equal chance of being sampled for each class.
- Principal Component Analysis (PCA) Failed.
- Bad Data Elimination Failed.
 - Assumption: Some data are abnormal and misleading.
 - Methodology: Judge by their deviation from the centroid.
- Feature Vector Expansion Failed.
 - Assumption: Some data are undistinguishable under a low degree.
 - Methodology: Expand the feature vectors in a polynomial way.

