Dual Loss for Manga Character Recognition with Imbalanced Training Data

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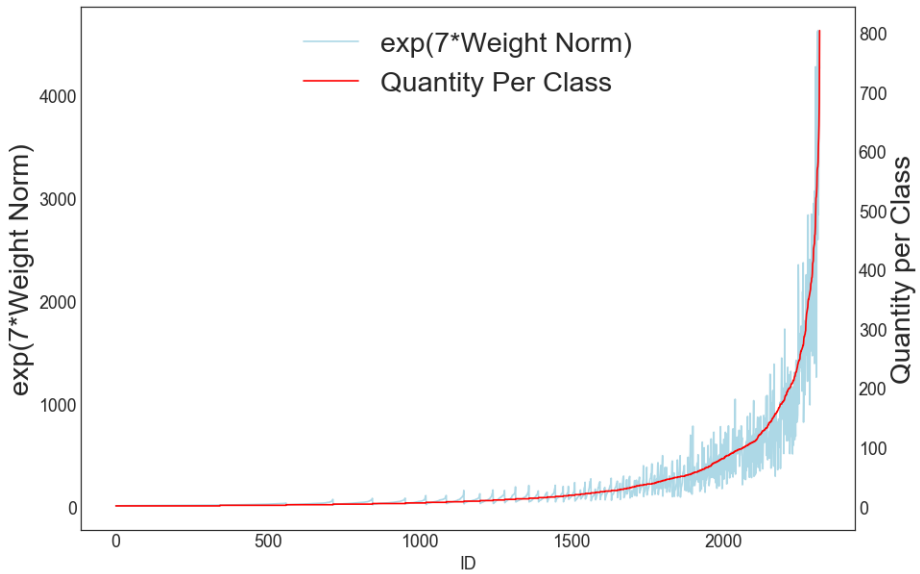
Outline

Manga Characeter Recognition

- Manga character recognition is a key technology for manga character retrieval and verification.
- Manga character images have a long-tailed distribution and large quality variations.
- Training models with cross-entropy softmax loss on such imbalanced data would introduce biases.

Data Imbalance



(a)

(b)

Figure: (a) The distribution of dataset sample quantity per class and the distribution of $e^{7 \cdot (weight\ norm)}$ per class. One can see that weight norm is exponentially correlated with the number of samples per class. (b) Illustration of the imbalance of sample quality. This imbalance is caused by the sample scale, pose, sharpness, and fineness.

Dual Loss

- We propose a novel dual loss which is the sum of two losses: dual ring loss and dual adaptive re-weighting loss
- The *dual ring loss* forces the deep model to learn with a similar norm for all feature vectors and class weight vectors respectively.
- The *dual adaptive re-weighting loss* assigns weights to softmax loss according to the inverse of the feature norm and class weight norm.
- These two losses can reinforce each other for *more balanced distributions of feature and class weight norm.*

Outline

Cross-Entropy Softmax Loss

Softmax loss, also known as cross-entropy softmax loss, is fundamental in the recognition task and formulated as:

$$p_{i,j} = \frac{e^{W_j^T x_i + b_j}}{\sum_{k=1}^{M} e^{W_k^T x_i + b_k}}, \tag{1}$$

$$\mathcal{L}_s = -\frac{1}{N} \sum_{i=1}^{N} \log p_{i,y_i}. \tag{2}$$

Dual Ring Loss (DRL)

To alleviate the imbalance of feature and weight norm, we combine the ring loss [1] and the under-represented term [2].

$$\mathcal{L}_{dr} = \frac{\lambda_1}{2N} \sum_{i=1}^{N} \left(\|x_i\|_2 - \alpha \right)^2 + \frac{\lambda_2}{2M} \sum_{i=1}^{M} \left(\|W_i\|_2 - \beta \right)^2, \tag{3}$$

$$\mathcal{L} = \mathcal{L}_s + \mathcal{L}_{dr}. \tag{4}$$

Dual Adaptive Re-Weighting Loss (DARL)

To further improve the performance of the deep model on the imbalanced data, we propose the dual adaptive re-weighting loss. It assigns different weights to the softmax loss of different samples or different categories.

$$w_w = 1 - \lambda_3 \frac{\|W_{y_i}\|_2 - \min \|W_j\|_2}{\max \|W_j\|_2 - \min \|W_j\|_2}, j \in [1, M], \tag{5}$$

$$w_x = 1 - \lambda_4 \frac{\|x_i\|_2 - \min \|x_j\|_2}{\max \|x_j\|_2 - \min \|x_j\|_2}, j \in [1, N], \tag{6}$$

$$\mathcal{L}_{dar} = -\frac{1}{N} \sum_{i=1}^{N} w_w w_x \mathcal{L}_s(x_i). \tag{7}$$

Dual Loss

The above two losses are both forcing the norm of the learned feature or the norm of class weight to be similar. Therefore, they can reinforce the learning of each other. We combine them to form the dual loss $\mathcal{L}_d$ and use it to supervise the training process of the deep model, as given by Equation (8).

$$\mathcal{L}_d = \mathcal{L}_{dr} + \mathcal{L}_{dar}. \tag{8}$$

Outline

Datasets and Settings

- Datasets
  - Manga109 [3]: the biggest manga dataset with character identity annotations
  - 109 manga volumes; 29845 image pages;
  - 80 volumes for training; 29 volumes for testing;[4]
  - Character Retrieval Test: 28138 head images as database; 2000 head images as queries;
  - Character Verification Test: 6000 head image pairs.
- Settings
  - For retrieval, rank-1, rank-5 matching accuracy, and mean Average Precision (mAP).
  - For verification, the verification accuracy using 10-fold cross-validation.

Results

Table: Experimental results using Manga109.

Methods	Retrieval			Verification
	rank-1(%)	rank-5(%)	mAP(%)	Accuracy(%)
Softmax	66.60	81.95	35.72	87.00
L2-Constrained	64.45	**81.35**	**35.10**	87.70
NormFace	64.00	80.25	33.66	**87.90**
CosFace	64.25	79.35	33.22	86.80
ArcFace	60.45	76.65	30.30	87.00
Am_Softmax	**64.50**	80.25	33.14	87.00
Range Loss	68.70	82.50	36.01	86.20
CB Loss	68.30	**83.50**	36.10	87.30
Focal Loss	67.85	83.35	36.70	87.50
CB Focal	68.65	83.25	36.58	87.60
Softmax + RL	68.70	**83.50**	**37.03**	87.40
Softmax + UP	**68.80**	83.00	36.23	**87.80**
Softmax + DRL	69.65	83.55	37.26	87.90
DARL	69.00	83.80	37.66	87.80
Dual Loss	**70.55**	**84.30**	**38.88**	**88.50**

Image Classification: CIFAR-10

Table: Test set error rate (%) of Long-Tailed CIFAR-10.

Dataset	Long-Tailed CIFAR-10				
Imbalance	200	100	50	20	10
Softmax	34.32	29.64	25.19	17.77	13.61
Sigmoid	34.51	29.55	23.84	16.40	12.97
Focal ($\gamma = 0.5$)	36.00	29.77	23.28	17.11	13.19
Focal ($\gamma = 1.0$)	34.71	29.62	23.29	17.24	13.34
Focal ($\gamma = 2.0$)	35.12	30.41	23.48	16.77	13.68
CB Focal	31.11	25.43	20.73	15.64	**12.51**
Dual Loss	**30.32**	**24.10**	**19.28**	**15.16**	**12.51**

Outline

Conclusions

- We propose the dual loss with two novel losses for manga character recognition with imbalanced training data.
- The dual ring loss adds regularization to the deep model and forces the model to learn a similarity norm for both feature and class weight vectors.
- The dual adaptive re-weighting loss assigns weights to the softmax loss term according to the norm of feature and class weight vectors.
- Experiment results on Manga109 dataset demonstrate that the effectiveness of dual loss.

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