# Trustworthy Localized Corrections-guided Mutual Learning for Multi-View Learning

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TABLE I DETAILS OF EACH DATASET

Dataset	Size	K	Dimensionality
Caltech101	8677	101	4096/4096
CUB	11788	10	1024/300
HandWritten	2000	10	240/76/216/47/64/6
PIE	680	68	484/256/279
Scene15	4485	15	20/59/40

### I. Proof 1

*Proof.* An upper bound, denoted by M, exists upon convergence. The inequation is given by:

$$0 \le (\log(S_f) - \log(S_{ww}))^2 \le M$$

Assume that  $S_f \geq S^{ww}$ , which then obtain the following formula:

$$0 \le log(S_f) - log(S_{ww}) \le \sqrt{M}$$

 $\Delta_S = S_f - S_{ww}$  is calculated as follows:

$$\Delta_S = S_{ww} \left( e^{\log(S_f) - \log(S_{ww})} - 1 \right)$$
  
 
$$\leq S_{ww} \left( e^{\sqrt{M}} - 1 \right)$$

Similarly, the lower bound of  $\Delta_S$  is calculated as:

$$\Delta_S \ge S_{ww} \left( 1 - e^{-\sqrt{M}} \right)$$

In summary, the scope of  $\Delta_S$  is determined by the following inequation:

$$S_{ww}\left(1 - e^{-\sqrt{M}}\right) \le \Delta_S \le S_{ww}\left(e^{\sqrt{M}} - 1\right)$$

## II. DATASETS

Details of each dataset is shown in Table I. **Caltech101** [1] comprises 8766 images across 11 categories, each represented by two views. **CUB** [2] comprises 11788 images, each paired with textual descriptions, spanning 200 different categories

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# Algorithm 1 TLCML algorithm

/\*Training\*/

**Input**: Multi-View dataset:  $D_N^M = \{\{\boldsymbol{x}_n^m\}^M, \boldsymbol{y}_n\}_N$ 

Output: Parameters of model

1: Initialize the parameters of model.

2: while not converged do

3: **for** m=1:M **do** 

4:  $e^m \leftarrow \text{view-specific MENN};$ 

Subjective opinion ← Dirichlet distribution;

6: Obtain the loss of view-specific MENN with Eq. 3;

7: end for

5:

8: Concatenate all of evidence;

9: Obtain joint opinion with TML module;

10: Obtain the joint loss of with Eq. 3;

11: Obtain the consistency loss with Eq. 7;

12: Obtain the boundary loss with Eq. 9;

13: Obtain the overall loss with Eq. 11;

14: Update the parameters;

15: end while

# /\*Test\*/

Calculate the decisions and corresponding uncertainty.

of birds. **HandWritten** [3] comprises 2000 samples, evenly distributed across 10 classes corresponding to the digits '0' to '9', with each class containing 200 samples. **PIE** [4] comprises 680 facial images from 68 distinct subjects. Three feature types, intensity, LBP, and Gabor, are extracted from each image. **Scene15** [5] comprises 4485 images spanning 15 categories, encompassing both indoor and outdoor scenes. Three types of features GIST, PHOG, and LBP are extracted from the dataset.

### III. ALGORITHM

The detailed procedure of our method had been comprehensively outlined in Algorithm 1.

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