Non-I.I.D. Image Classification

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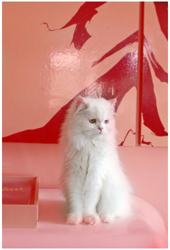
2020 年 5 月 31 日

Basic Ideas

- Working on NicoDataset[HSC19]
- Human perception
  - Foreground, background
  - Instance segmentation[MUBE18]
  - **Attention**[VSP+17]
- Non-IIDness comes largely from contexts



(a) at Home

(b) in the Tree

图 1: Cats in Different Contexts

Architecture

- **Residual** Attention[HZRS16]: residual connection keeps the capability of identity mapping
- Classifier: vanilla classifier, features in, classes out
- Discriminator: outputs whether two images from the same class have the identical context
- **Discriminator** can be replaced with **Context Classifier** (for comparison)
- **Gradient Reversal**[GL15]: to be explained further

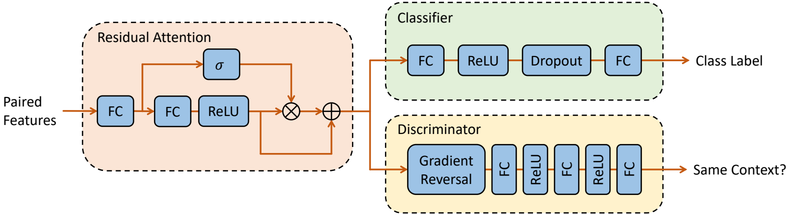


图 2: Architecture Illustration

About Loss Function

Attention module - θ_{att}, Classifier - θ_{cls}, Discriminator - θ_{dis}
$\theta = \{\theta_{att}, \theta_{cls}, \theta_{dis}\}$

- Legacy loss function: minimize the objective all together

$$\min_{\theta} \mathcal{L} = \mathcal{L}_{cls} + \lambda \mathcal{L}_{ctx} \tag{1}$$

- Better solution: optimize in an adversarial manner

$$\max_{\theta_{att}} \min_{\theta_{ctx}} \mathcal{L}_{ctx}, \quad \min_{\theta_{att}, \theta_{cls}} \mathcal{L}_{cls} \tag{2}$$

  - Discriminator: towards better discrimination; Attention: trying to obfuscate discriminator by making context features look more similar
  - How to optimize (2) ? Fix one parameter, optimize another?
  - **Gradient Reversal**[WJQ+17] to the rescue! You can still write loss as (1), and only need to add an additional layer before **Discriminator** branch
  - During back propagation, modify the gradient as follows

$$\frac{\partial \mathcal{L}}{\partial \theta_{ctx}} \rightarrow -\tau \cdot \frac{\partial \mathcal{L}}{\partial \theta_{ctx}}$$

Implementation Details

- Baselines
  - A simple two-layer MLP network
  - Attention classifier, with Discriminator substituted by a Context Classifier
- `NicoPairedDataset`
  - For each image, pair it with those having the same class label but different context label (randomly select one per context) –> N images
  - Pair the aforementioned image within the same context and class (randomly select N images) –> for equilibrium
- Parameters
  - $\lambda = 1$, $\tau = 1$, lr$= 10^{-5}$, weight decay$= 5 \times 10^{-4}$, batch size$= 16$

Performance

- 6/1 train/validation context split
- Best performance on validation set
- Comparing with baselines

Name	Accuracy
Classifier	61.82%
Attention Context Classifier	72.30%
Attention Discriminator	**74.49%**

- Ablation study

Attention	Residual Attention	Gradient Reversal	Accuracy
✓			73.48%
✓		✓	73.65%
	✓		74.16%
	✓	✓	**74.49%**

- Stability test (4 contexts for training, the rest for validating/testing)

Dataset	train	val	test1	test2
Accuracy	93.94%	66.89%	75.49%	77.47%

Collaboration & Contribution

- 张翔: Core algorithm design and implementation, such as `GradientReversal`, `AttentionResidualBlock`, `AttentionClassifier` and `NicoPairedDataset`
- 李家昊: Baseline implementation (MLP network `Classifier`) and framework construction (`NicoDataset`, `Metrics`)
- 宋浩轩: Core design, tuning and stability test
- 李浩源: Hyperparameters tuning, baseline comparison and ablation test

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Thanks!