Meta-Reinforced Synthetic Data for One-Shot Fine-Grained Visual Recognition

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Introduction
Quiz: Hawk or Falcon?
- Fine-grained visual recognition
  - HARDER THAN NORMAL CLASSIFICATION.
  - DIFFICULT TO COLLECT DATA.
  - NEED one-shot learning.

Our Ideas
- Want to use Generative Adversarial Networks (GANs).
- Challenge: GAN training itself needs a lot of data.
- Fine-tune GANs trained on ImageNet.
- Challenge: Generated images decreased accuracy.
- Learn to reinforce generated images with original images.
- Use meta-learning to learn best mixing strategy.

Answer to the quiz: Hawk is left, and Falcon is right.

Key Idea 1: Fine-tune BigGAN generator with a single image
- Transfer generative knowledge from one million generic images in ImageNet to a domain specific image [2].
- Instead of unstable adversarial training, we minimize both the noise and the difference between the input and output.

\[ L_z \left( G(z); I \right) + \lambda_1 L_{perc}(G(z); I) + \lambda_2 L_{EM}(z; I), \]

where \( z \) is a noise, \( G \) is the generator, \( I \) is an image, \( G(z) \) is a generated image, \( L_z \) is L1 loss, \( L_{perc} \) is perceptual loss, \( L_{EM} \) is an earth mover distance between \( z \) and random noise \( r \sim \mathcal{N}(0, 1) \) to regularize \( z \) to be sampled from a Gaussian, and \( \lambda_1 \) and \( \lambda_2 \) are coefficients of each term.

To avoid overfitting, we update batch normalization layers only. Specifically, only the \( \gamma \) and \( \beta \) of each batch normalization layer are updated in each layer,

\[ \hat{z} = \frac{z - E(z)}{\sqrt{\text{Var}(z) + \epsilon}}, \quad h = \gamma \hat{z} + \beta, \]

where \( z \) is the input feature from the previous layer, and \( E \) and \( \text{Var} \) indicate the mean and variance functions, respectively. Intuitively and in principle, updating \( \gamma \) and \( \beta \) only is equivalent to adjusting the activation of each neuron in a layer.

Key Idea 2: Reinforce generated image with the original.
- Linearly combine with a 3 x 3 block [1].
- Weights are learned by meta-learning.

Framework

Some examples:

<table>
<thead>
<tr>
<th>Original</th>
<th>Generated</th>
<th>Fused</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fine-tune z only</td>
<td>Fine-tune all layers</td>
<td>Fine-tune z + BatchNorm</td>
<td>Perturbate input z</td>
</tr>
<tr>
<td>Fine-tune z + BatchNorm + Perceptual loss</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Experiments
- Code: http://vision.soc.indiana.edu/metairenet/.
- Base one-shot classifier is Prototypical Networks (ProtoNet [3]), backbone is ImageNet-pre-trained ResNet18 or Conv4.
- Datasets:
  - Caltech UCSD Birds (CUB).
  - Train:val:test = 5,885 (100 classes):2,950 (50 classes):2,950 (50 classes)
  - North American Birds (NAB).

Results:

<table>
<thead>
<tr>
<th>Method</th>
<th>Data Augmentation</th>
<th>CUB Acc.</th>
<th>NAB Acc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nearest Neighbor</td>
<td>-</td>
<td>79.00 ± 0.62</td>
<td>80.58 ± 0.59</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>-</td>
<td>81.17 ± 0.60</td>
<td>82.70 ± 0.57</td>
</tr>
<tr>
<td>Softmax Regression</td>
<td>-</td>
<td>80.77 ± 0.60</td>
<td>82.38 ± 0.57</td>
</tr>
<tr>
<td>ProtoNet</td>
<td>FisntuneGAN</td>
<td>81.73 ± 0.63</td>
<td>87.01 ± 0.52</td>
</tr>
<tr>
<td>ProtoNet</td>
<td>Flip</td>
<td>82.66 ± 0.61</td>
<td>88.55 ± 0.50</td>
</tr>
<tr>
<td>ProtoNet</td>
<td>Gaussian</td>
<td>81.75 ± 0.63</td>
<td>87.89 ± 0.52</td>
</tr>
<tr>
<td>MetaIRNet (ours)</td>
<td>FisntuneGAN</td>
<td>84.13 ± 0.59</td>
<td>89.19 ± 0.51</td>
</tr>
<tr>
<td>MetaIRNet (ours)</td>
<td>FisntuneGAN, Flip</td>
<td>84.80 ± 0.56</td>
<td>89.57 ± 0.49</td>
</tr>
</tbody>
</table>

Visualization:
- Plot t-SNE of two classes, blue and red.
- Generated images are closer to real ones.
- Reinforced images are distinctive from others.

Conclusions:
- Composites of real and synthetic training images improve fine-grained one-shot recognition.
- Future work should explore other mixing strategies, and theoretical results on why it works.

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