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Proxy Attention : Comparing and Combining Augmentation with Attention

Graduation Project
(Computational Intelligence and Robotics)

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CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

CHAPTER 2

BACKGROUND

2.1 Interpretability

- Need for Interpretability

2.2 Gradient Based Explanations

- Taxonomy

2.3 Augmentation

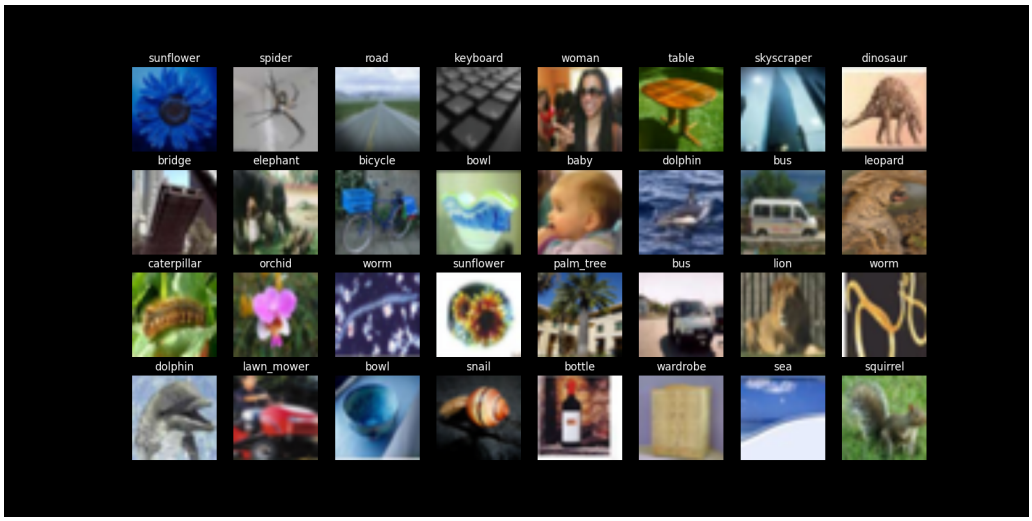
- Taxonomy

2.4 Datasets

To test Proxy Attention, the following datasets were used. Note: Images are resized to 224x224 pixels for consistency. These batch visualizations are generated by the author using the torchvision and matplotlib libraries.

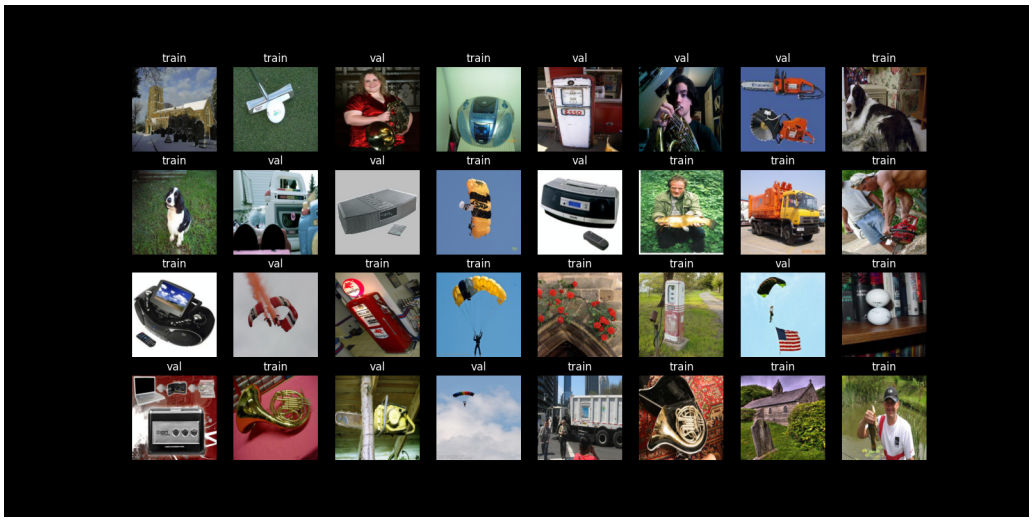
2.4.1 CIFAR 100

The CIFAR 100 dataset, introduced by [1] is an image dataset with 60000 color images with dimensions 32x32 pixels. As the name suggests, the dataset has 100 unique classes. Each of these classes have 500 training images. Some of the classes are - airplane, bird, truck, ship, deer and dog. This dataset is used as a coarse grained classification dataset in this project.

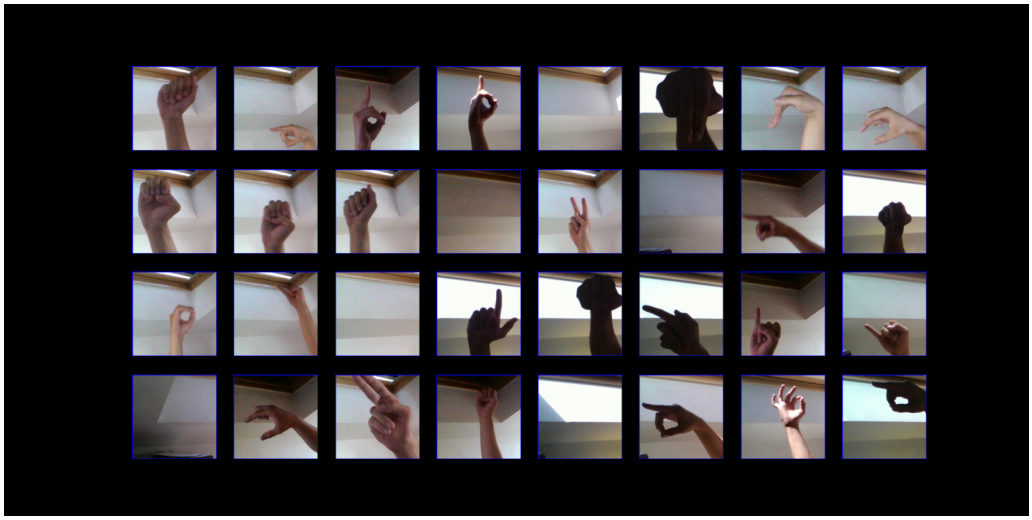


2.4.2 Stanford dogs

2.4.3 Imagenette



2.4.4 ASL



2.4.5 Food-101

Plant Village

CHAPTER 3

STATE OF THE ART

3.1 Gradient Based Explanations

Beware Of Inmates
Interpretation Is Fragile
Sanity Checks
The Unreliability Of Saliency Methods
There And Back Again
Influence Of Image Class Acc On Saliency Map Estimation
Deconvnet
Deep Inside Conv Nets
Cam
Gradcam++
Guided Backprop
In another paper, the authors propose a score weighted approach (ScoreCAM) to create saliency maps [2]. Like many other methods, the images are first passed through the network and the corresponding activations are obtained from the final convolutional layer. These activation maps are then upsampled and normalized to the range of [0,1]. The portions of the activation maps that were highlighted are then passed through a CNN with a SoftMax layer to obtain the score for each of the current classes. These scores are used to find the relative importance of all the activation maps. Finally the sum of all these maps is computed using a linear combination with the corresponding target score and then passed through a ReLU operation. These operations can be mathmaticaly represented as $L^c_{ScoreCAM} = ReLU(\sum_k w^c_k A^k)$, where k represents the index considered, c represents the current class and S_k represents the outputs of the aforementioned SoftMax layer. The authors find that the maps obtained using ScoreCAM are less noisy and using this method removes dependancy on unstable gradients as compared to other methods.
Guided Gradcam
Salience Map
Noise Tunnel
Integrated Gradients
Sam Resnet
Conductance
Deep Fool
Deep Lift
Generalizing Adversarial Exp With Gradcam
Shap
Smooth Grad
Smooth Grad Square
Lime

Sp Lime
Summit
Rise
Lrp
Var Grad
Visualizing Impact Of Feature Attribution Baselines
Adaptive Whitening Saliency
Bayesian Rule List
Deep Visual Explanations
Dynamic Visual Attention
Embedding Knowledge Into Deep Attention Map
Graph Based Visual Saliency

3.2 Augmentation

Attentive Cutmix
Attributemix
Augmentaiton with curriculum leanring
Augmix Another augmentation strategy proposed by [3] first applies multiple transformations randomly and in parallel chains to each image. These transformations can include combinations of Translation, Rotation, Shearing etc. The outputs of these combinations are then mixed to form a new image, which is then further mixed with the original image to form the new image. This combination is done to improve performance in cases where data shifts are encountered in production. Once the images are mixed, a skip-connection is used to combine the results of the chains. AugMix also uses the Jensen-Shannon Divergence consistency loss [4] to ensure that the images are stable across a range of inputs. Considering KL to be Kullback-Leibler Divergence, the Jensen-Shannon Divergence can be defined as $JS(p_{orig}; p_{augmix1}; p_{augmix2}) = \frac{1}{3}(KL[p_{orig}||M||] + KL[p_{augmix1}||M||] + KL[p_{augmix2}||M||])$, where M is the mean of the three distributions $p_{orig}, p_{augmix1}, p_{augmix2}$.
Devries et al. in their paper [5] propose an augmentation method they call Cutout. In this method, random sized square patches are removed from the images by replacing the corresponding pixels with a constant value (usually 0). Selecting the region involves picking a random pixel value and then creating a uniform sized square around the chosen pixel. The authors also find that Cutout performs better in combination with other methods rather than just being used by itself. Cutout can be expressed as an element-wise multiplication operation $x_{cutout} = x \odot M$, where x is the original image, M is a binary mask of the same size as x with randomly chosen coordinates of a square patch of pixels to be cut out, and $\odot$ denotes element-wise multiplication.
Co mixup
Unlike Cutout [5], where the chosen patch is replaced with zero pixels, in CutMix [6] the chosen patch is replaced with a randomly chosen patch from a different region of the same image. Yun et al. propose this approach as multiple class labels can be learned with a single image. CutMix can be defined by the following operations $\widetilde{x} = M \odot x_A + (1-M) \odot x_B$; $\widetilde{y} = \lambda y_A + (1-\lambda) y_B$. where x is an RGB image, y is the respective label, M is a binary mask of the patch of the image that will be dropped and $\odot$ represents element wise multiplication. The new training sample $\widetilde{x}, \widetilde{y}$ is created by combining two other training samples x_A, y_A and x_B, y_B. To control the combination ratio λ, a sample from the $\beta(1,1)$ distribution is chosen. This combination is quite similar to [7] but differs in the sense that CutMix focuses on generating locally natural images. In their paper Singh et al. [8] propose a data augmentation method that takes an image as an input, and divides it into a grid. Each of the sub-grids are then turned off with a given probability. These sub-grids can be connected or independant of each other and the turned off grids are replaced by the average pixel value of all the images in the dataset.
GridMask
Image Mixing and deletion
Intra class part swapping
Keep augment

Latent space interpo
Puzzle mix
Randaugment
Random Erasing
Random distortion
Remix
Resizemix
Ricap
Saliencymix
Sample pairing
Smooth mix
Smote
Snap mix
Spec augment
Visual context Augmentation

3.3 Architectures

Resnet 18, 50
VGG
Vision Transformer

3.4 Summary and Limitations

CHAPTER 4

PROPOSED APPROACH

4.1 Design Decisions

Efficient Computation Updating Dataloaders Batched Implementation Callbacks Training Resumption Logging

4.2 Hyper Parameters

4.2.1 Clear Every Step

4.2.2 Gradient Threshold Considered

4.2.3 Multiply Weight

4.2.4 Proxy Steps

4.2.5 Subset Of Wrongly Classified

4.2.6 Gradient Method

4.2.7 Architectures

CHAPTER 5

IMPLEMENTATION

5.1 Overview

5.2 Hyper parameters

5.2.1 Clear Every Step

5.2.2 Gradient Method

5.2.3 Gradient Threshold Considered

5.2.4 Multiply Weight

5.2.5 Proxy Steps

5.2.6 Subset Of Wrongly Classified

5.3 Data Loading and Pre Processing

5.3.1 Directory structure

5.3.2 Label function

5.3.3 Clearing proxy images

5.3.4 Encode, Stratify, Kfold

5.3.5 train and test, val separate

5.3.6 Augmentations

Imagenet Normalize Tensor Num workers

5.4 Training Details

5.5 Grid Search

5.6 Optimizations

5.6.1 Mixed Precision

5.6.2 Gradient Scaling

5.6.3 No grad

5.6.4 Batched Proxy step

5.6.5 Trial Resumption

5.6.6 Models

TIMM

5.7 Gradient Based Methods

5.8 Proxy Attention

5.8.1 Callback Mechanism

5.9 Tensorboard

5.10 Transfer learning

5.11 Optimizer

5.12 LR scheduler

5.13 Loss function

5.14 Batch sizer finder

5.15 Result Aggregation

5.16 Inference

CHAPTER 6

EVALUATION

6.1 Metric Based Analysis

6.2 Visual Based Analysis

6.3 Summary

CHAPTER 7

CONCLUSION

7.1 Contributions

7.2 Lessons Learned

7.3 Future Work

CHAPTER 8

APPENDIX

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