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R&D Project Proposal

Implementing Group Normalization in CNNs for Improved Training Stability and Performance

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1 Introduction

This project aims to explore the implementation of Group Normalization (GN) as an alternative to Batch Normalization (BN) in Convolutional Neural Networks (CNNs). By replacing BN with GN, we intend to overcome the limitations associated with BN, particularly its dependency on large batch sizes, which can hinder training stability and performance in scenarios constrained by memory and computational resources [2].

2 Background and Motivation

Batch Normalization has significantly advanced deep learning by normalizing the mean and variance of features within a batch, facilitating smoother optimization and faster convergence. However, BN's effectiveness diminishes with small batch sizes due to inaccurate batch statistics estimation, leading to increased error rates. This limitation is particularly critical in tasks like object detection, segmentation, and video classification, where high-resolution images necessitate smaller batch sizes. Group Normalization, introduced by Yuxin Wu and Kaiming He from Facebook AI Research, addresses this issue by dividing channels into groups and normalizing the features within each group. GN's computation is independent of batch sizes, maintaining stable accuracy across varying batch sizes and providing consistent performance from pre-training to fine-tuning stages.

3 Objectives

1. Implement Group Normalization in CNNs: Modify existing CNN architectures to incorporate GN instead of BN.

2. Evaluate Performance: Compare the performance of GN-implemented CNNs against their BN counterparts on various tasks, including image classification, object detection, and segmentation.

3. Analyze Training Stability: Investigate the stability and convergence rates of GN-implemented models across different batch sizes.

4. Optimize GN Hyperparameters: Explore the impact of varying the number of groups (G) on model performance and identify optimal configurations.

4 Methodology

1. Literature Review: Conduct an in-depth review of existing normalization techniques and their applications in deep learning, with a focus on GN and its benefits over BN.

2. Dataset Selection: Use standard datasets such as ImageNet and Plant Seedling Dataset [1] for image classification, COCO for object detection and segmentation, and Kinetics for video classification to ensure comprehensive evaluation.

3. Model Implementation: Integrate GN into popular CNN architectures like ResNet, Mask R-CNN, and 3D Convolutional Networks using deep learning frameworks such as PyTorch and TensorFlow, leveraging automatic differentiation for efficient computation.

4. Training and Evaluation: Train GN-implemented models using varying batch sizes and compare their performance with BN-implemented models. Assess metrics such as accuracy, loss, and error rates to determine the effectiveness of GN. Conduct ablation studies to understand the impact of different group configurations on model performance.

5 Analysis and Reporting

Analyze training stability by monitoring convergence rates and variance in performance across epochs. Compile results into comprehensive reports, highlighting the advantages and any limitations of GN over BN.

6 Expected Outcomes

1. Improved Training Stability: Demonstrate that GN provides stable training performance across a wide range of batch sizes, overcoming the limitations of

BN.

2. Enhanced Model Performance: Show that GN-implemented models achieve comparable or superior performance to BN-implemented models in various tasks.

3. Robustness to Small Batches: Prove that GN maintains accuracy and efficiency even with small batch sizes, making it suitable for memory-constrained environments.

4. Guidelines for GN Implementation: Provide best practices and guidelines for integrating GN into different CNN architectures, including recommendations for optimal group configurations.

7 Dataset Assignments

- Gaurav Shetty will work on the Kinetics Dataset.
- Ayusee Swain will handle the COCO Dataset.
- Akhilan Ashokan will focus on the ImageNet Dataset.
- Pratik Adhikari will explore the Plant Seedlings Dataset.

8 Conclusion

This project seeks to advance the field of deep learning by leveraging Group Normalization to enhance training stability and performance in CNNs. By addressing the limitations of Batch Normalization, we aim to provide robust and efficient normalization techniques suitable for a variety of computer vision tasks, ultimately contributing to the development of more resilient and high-performing neural networks.

References

[1] Thomas Mosgaard Giselsson, Rasmus Nyholm Jørgensen, Peter Kryger Jensen, Mads Dyrmann, and Henrik Skov Midtiby. A public image database for benchmark of plant seedling classification algorithms. *arXiv preprint arXiv:1711.05458*, 2017. URL `https://arxiv.org/abs/1711.05458`.

[2] Yuxin Wu and Kaiming He. Group normalization. *arXiv preprint arXiv:1803.08494v3*, 2018. URL `https://arxiv.org/pdf/1803.08494v3`.