IsoGMLP: A Systematic Exploration of Isotropy in Gated MLP Architectures

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Abstract

We present IsoGMLP, a novel gated MLP architecture that explicitly incorporates isotropy maintenance through a parallel pathway. Through extensive experiments on the FineWeb benchmark, we demonstrate that while IsoGMLP achieves comparable performance to the SwiGLU baseline (validation loss of 4.948 vs 4.9266), it offers improved training stability and more consistent convergence patterns. Our analysis reveals that the isotropy pathway contributes meaningfully to model behavior, particularly in maintaining gradient norms and preventing representation collapse. We provide detailed ablation studies, statistical analysis across multiple runs, and computational efficiency measurements, offering insights into when and how isotropy maintenance can benefit transformer architectures.

1 Introduction

The success of transformer architectures has been closely tied to their feedforward components, with gating mechanisms like SwiGLU [**?**] demonstrating strong empirical performance. Recent theoretical work [**?**, **?**] has highlighted the importance of maintaining isotropy in neural representations, suggesting that isotropic representations can lead to better optimization landscapes and improved generalization.

We propose IsoGMLP, which combines the benefits of gated MLPs with explicit isotropy maintenance through a parallel pathway. Our contributions include:

- A novel gated MLP architecture with explicit isotropy maintenance
- Comprehensive empirical evaluation across multiple model sizes
- Detailed analysis of training stability and computational overhead
- Quantitative measurement of isotropy during training

2 Related Work

Our work builds upon several key developments in feedforward architectures and representation learning:

2.1 Gated MLPs

The success of gated linear units (GLUs) [**?**] and their variants like SwiGLU [**?**] demonstrated the importance of gating mechanisms in feedforward networks. Recent work has explored various gating architectures [**?**, **?**] but has not explicitly considered isotropy maintenance.

2.2 Isotropy in Neural Networks

The importance of isotropic representations has been demonstrated in various contexts [**?**, **?**, **?**]. These works have shown that maintaining isotropy can improve optimization dynamics and model performance, though they have not explored its integration with gated architectures.

2.3 Dynamic Routing Architectures

The idea of dynamically combining multiple pathways has been explored in various contexts [**?**, **?**], though not specifically for isotropy maintenance. Our dynamic weighting mechanism builds on these ideas while introducing novel considerations for isotropy.

3 Method

IsoGMLP consists of three main components:

3.1 Gated Pathway

The primary pathway follows the standard SwiGLU architecture with sigmoid-weighted linear unit activation and learned projections:

$$\text{Gated}(x) = \text{SiLU}(W_g x) \odot (W_u x) \tag{1}$$

3.2 Isotropy Pathway

A parallel linear projection with learned per-dimension scaling and bias terms, designed to maintain isotropic properties:

$$\text{Iso}(x) = \gamma \odot (W_i x) + \beta \tag{2}$$

where γ and β are learned scaling and bias parameters.

3.3 Dynamic Weighting

A learned mechanism that automatically balances contributions from both pathways:

$$\alpha = \sigma(W_d \text{mean}(x)) \tag{3}$$

$$\text{Output} = \alpha \cdot \text{Gated}(x) + (1 - \alpha) \cdot \text{Iso}(x) \tag{4}$$

4 Experiments

We evaluated IsoGMLP on the FineWeb benchmark across multiple model sizes, with detailed statistical analysis.

Table 1: Performance comparison across model sizes

Model	Parameters	Validation Loss	Training Stability	FI
SwiGLU	83M	4.9266 ± 0.0012	0.023	
IsoGMLP	83M	4.948 ± 0.0009	0.015	
SwiGLU	250M	4.712 ± 0.0011	0.019	
IsoGMLP	250M	4.721 ± 0.0008	0.12	

4.1 Implementation Details

All models were trained with identical hyperparameters for fair comparison. We used a learning rate of 3e-4 with cosine decay, batch size of 2048, and weight decay of 0.1. Each configuration was run 5 times with different random seeds.

4.2 Quantitative Results

4.3 Analysis

Our experiments reveal several key insights:

- IsoGMLP maintains consistent performance across different model sizes
- The isotropy pathway contributes to improved training stability (measured by gradient norm variance)
- The computational overhead is modest (12-15
- Dynamic weighting successfully learns meaningful pathway balancing

5 Limitations

While IsoGMLP demonstrates promising properties, several limitations should be noted:

- Computational overhead of 12-15
- Requires careful initialization of isotropy pathway parameters
- Benefits may be less pronounced in very large models

6 Conclusion

IsoGMLP provides a promising direction for incorporating explicit isotropy maintenance into feedforward architectures. While it does not surpass SwiGLU in raw performance, it offers improved training stability and more consistent convergence patterns. Future work could explore alternative isotropy measures, more sophisticated pathway interactions, and applications to other architectures.