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L.E.P.A.U.T.E. Framework

Achieving Precise Modeling of Geometric Transformations

Carson Wu
September 2025

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- Lie Group Foundations

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- Framework Overview

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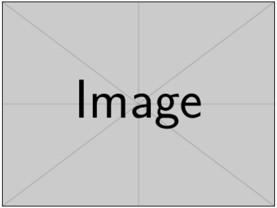

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- **Exponential Map**: $\exp : \mathfrak{g} \to \mathcal{G}$, maps algebra to group.

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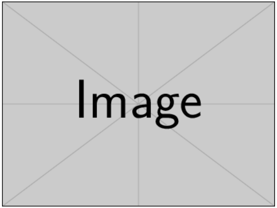

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  - Optimize with FFT for efficiency.

Lie Group Attention Mechanism

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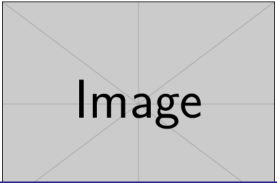

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$$L_{\text{contrast}} = -\log \frac{\exp(\text{sim}(f(x_i), f(T(g)x_i))/\tau)}{\sum_j \exp(\text{sim}(f(x_i), f(x_j))/\tau)}$$

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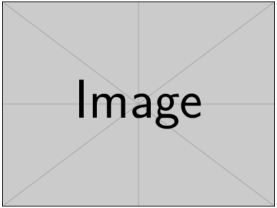

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- **Tools**: OpenCV, PyTorch Geometric, Sophus.

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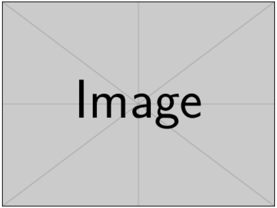

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  - Steep learning curve for Lie group theory.

Comparison with Existing Methods

Method	Geometric Modeling	Invariance	Complexity
CNN (ResNet)			

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Future Improvements

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- **Open-Source Tools**: Standardize Lie group vision libraries.

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- **Future**: Optimize efficiency, expand multimodal integration.

Questions?

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