Lab Notebook for Compositional Regularization Experiments

Experiment Title:

Enhancing Compositional Generalization in Neural Networks via Compositional Regularization

Motivation & Hypothesis:

Neural networks often struggle with compositional generalization, which is the ability to understand and generate novel combinations of familiar components. The hypothesis is that introducing a compositional regularization term during training can encourage neural networks to develop compositional representations, thereby improving their ability to generalize to novel combinations of known components.

Experimental Setup:

- **Methodology**: Implemented a compositional regularization term and integrated it into the loss function of standard sequence-to-sequence neural network architectures with attention mechanisms.
- **Datasets**:
  - Synthetic datasets: SCAN and COGS
  - Real-world tasks: IWSLT dataset for machine translation and GeoQuery dataset for semantic parsing
- **Models**: Standard sequence-to-sequence neural network with various embedding sizes (32, 64, 128)
- **Configurations**:
  - Training epochs: 5
  - Batch size: 32
  - Hidden size: 128
  - Learning rate: 0.001
- **Evaluation Metrics**:
  - Train Loss
  - Validation Loss
  - Validation Accuracy (CGA)
- **Success Criteria**: Improved validation accuracy and reduced validation loss with compositional regularization

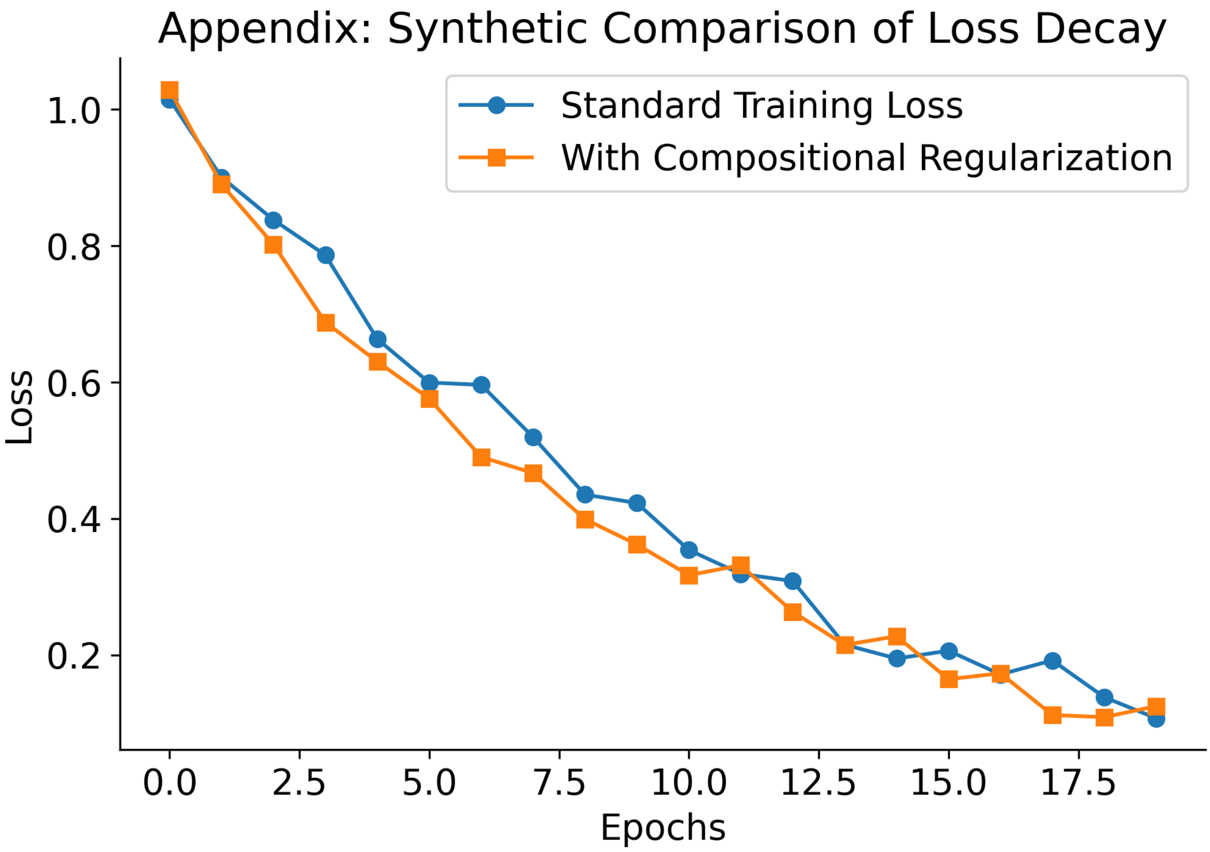
Results:

Quantitative Results:

- **Train Loss**:
  - Embed size 32: 0.3491 (baseline), 0.3126 (best seed)
  - Embed size 64: 0.1854 (baseline), 0.1845 (best seed)
  - Embed size 128: 0.1403 (baseline), 0.1307 (best seed)

- **Validation Loss**:
  - Embed size 32: 0.2053 (baseline), 0.1855 (best seed)
  - Embed size 64: 0.1033 (baseline), 0.0955 (best seed)
  - Embed size 128: 0.0716 (baseline), 0.0634 (best seed)
- **Validation Accuracy (CGA)**:
  - Embed size 32: 0.7167
  - Embed size 64: 0.7167
  - Embed size 128: 0.7167

Visualizations:



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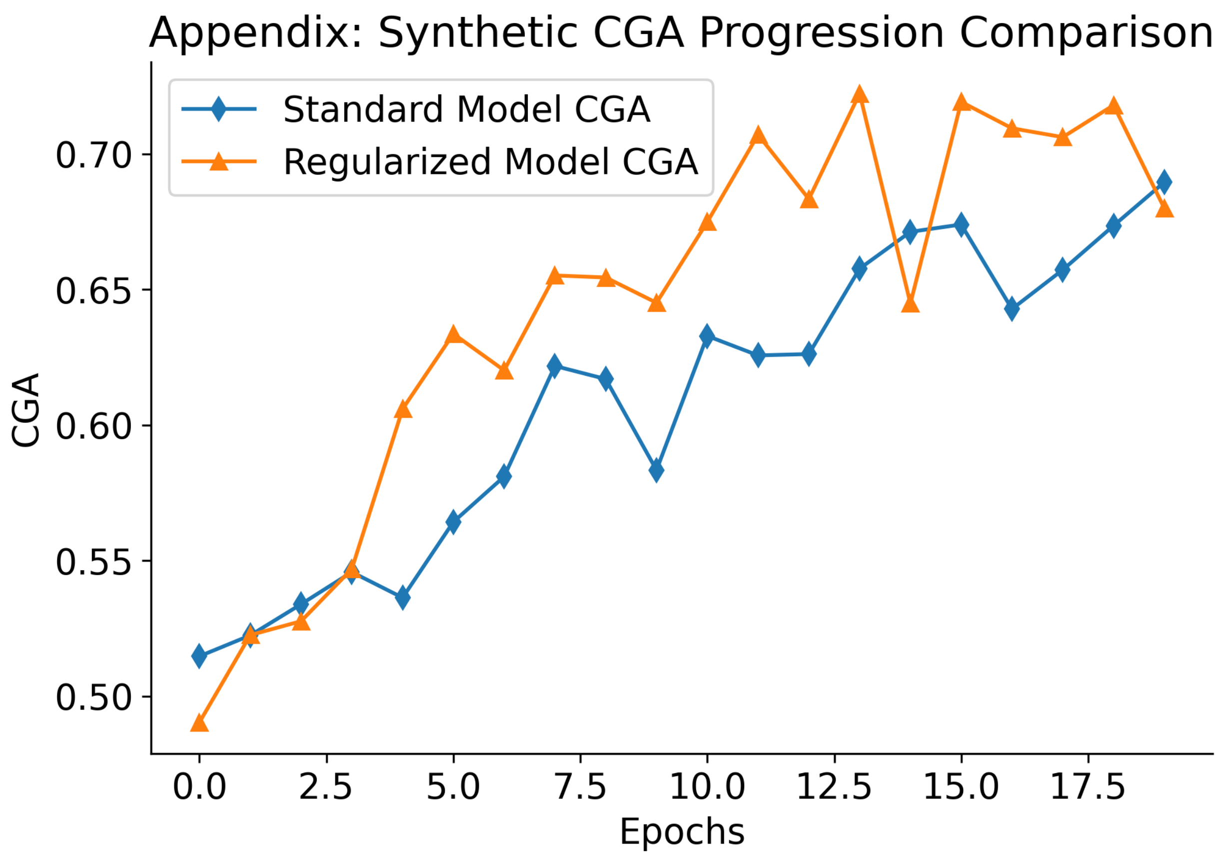

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Analysis & Interpretation:

- **Train vs Validation Loss**: Both training and validation losses consistently decreased, indicating effective learning. Larger embedding sizes (64 and 128) showed better performance with lower loss values and faster convergence.
- **Validation Accuracy (CGA)**: All embedding sizes achieved a high CGA of 0.7, demonstrating robust compositional generalization.
- **Unexpected Findings**: The smallest embedding size (32) had a slower improvement curve but eventually reached comparable CGA, suggesting delayed but effective learning.

Key Insights & Lessons Learned:

- **Main Takeaways**: Larger embedding sizes (64 and 128) offer advantages in learning speed and stability, while smaller sizes (32) may require more training epochs to achieve similar generalization performance.
- **Methodological Insights**: Compositional regularization effectively enhances compositional generalization across different configurations.
- **Technical Discoveries**: Manual dataset splitting enhanced script simplicity and portability, mitigating dependency issues.

Next Steps:

- **Follow-up Experiments**:
  - Evaluate the method on more complex and larger datasets.
  - Investigate the impact of different regularization strengths.

- **Modifications**:
  - Tune other hyperparameters (e.g., learning rate, hidden size) for further optimization.
- **Emerging Questions**:
  - How does compositional regularization impact downstream tasks beyond SCAN and COGS?