Affect2Act: Graph Attention Networks for Emotion-Informed Decision Making

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NEURAL INFORMATION PROCESSING SYSTEMS

Emotion-Informed AI: Moving Beyond Recognition to Reasoning

Introduction:

Current AI struggles to use recognized emotions for reasoning. Psychological models show emotions are interdependent, not flat features. We introduce Affect2Act, a Graph Attention Network (GAT), to model emotions as interconnected nodes and learn their context-dependent relationships for robust decision making.

Graph-Based Emotion Representation

- Frames decision-making as: $f : (\mathcal{E} = \text{Emotions}, ; \mathcal{C} = \text{Context}) \rightarrow \mathcal{A} = \text{Actions}$
- Emotions (Joy, Fear, Anger, Sadness, Surprise, Trust) are nodes (V) in a graph $(G = (V, E))$.
- Nodes have features for activation, intensity, and valence.
- Multi-head Graph Attention Network (GAT) models context-sensitive relationships between nodes.

Fusion & Regularization

Context Fusion and Emotional Balance:

- Environmental context and emotional embeddings are fused via cross-modal attention.
- A regularization strategy is used to prevent collapse to dominant emotions and promote diversity.
- The total loss function is $\mathcal{L}_{total} = \mathcal{L}_{classification} + \lambda_{reg}\mathcal{L}_{regularization}$

Architecture and Results

Affect2Act Architecture
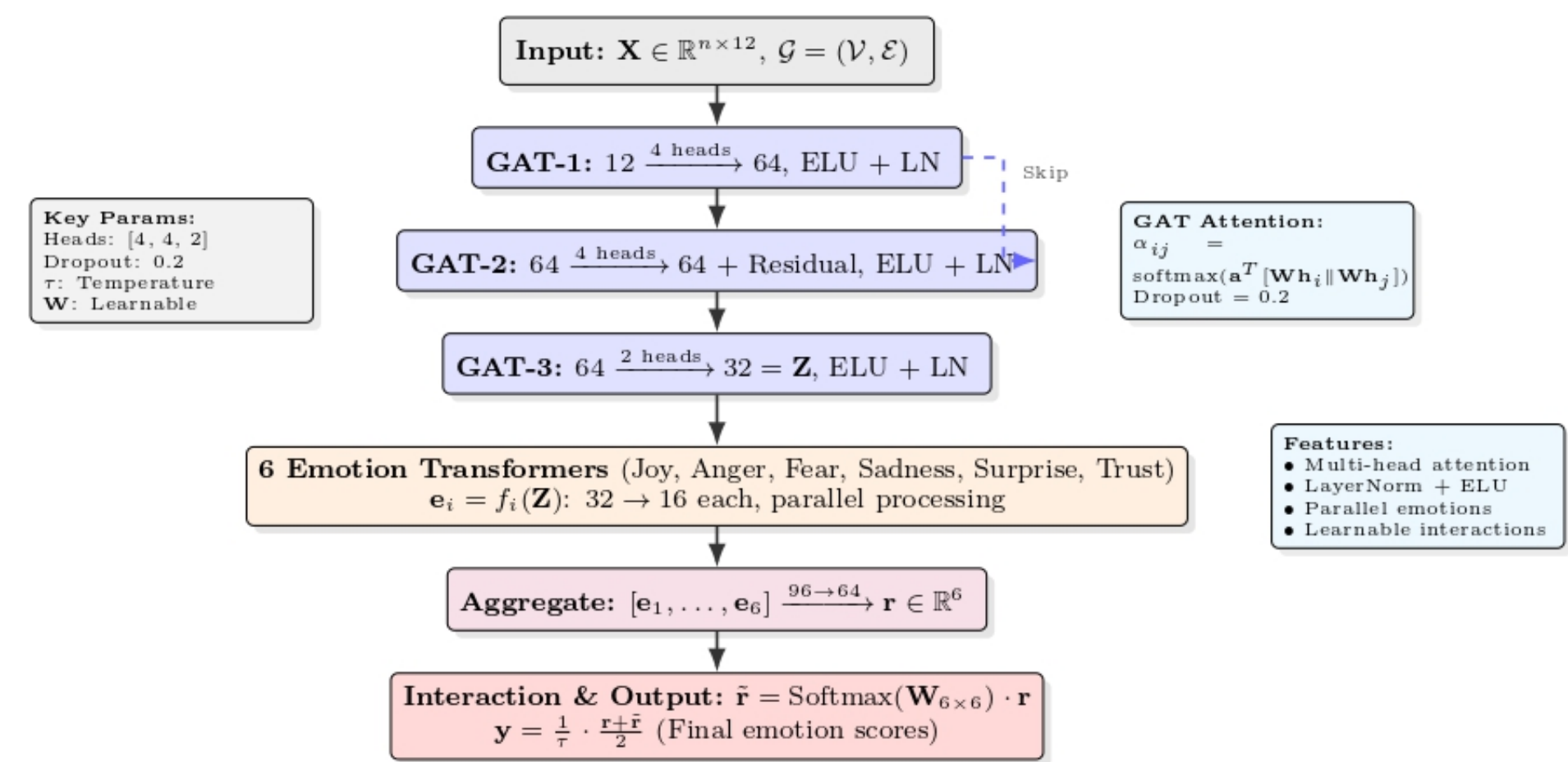
Affect2Act uses three GAT layers with residual connections, followed by emotion-specific transformers and a learnable interaction matrix to derive the final decision.

**Synthetic Decision-Making Benchmark:**

- Evaluated on a synthetic dataset with six scenario types (e.g., emergency, social, analytical).
- Compared against GCN, Multi-Head Attention, and MLP baselines.
- Metrics: Decision Accuracy ($\uparrow$) and Emotional Balance ($\uparrow$) (normalized entropy of predicted emotion distributions).
- Multi-head Graph Attention Network (GAT) models context-sensitive relationships between nodes.

Superior Accuracy and Emotional Balance:

Model	Decision Accuracy	Emotional Balance
Affect2Act (GAT)	**0.8767**	0.6547
GCN	0.8673	0.4053
Multi-Head Attention	0.7067	**0.6619**
MLP	0.4567	0.4737

Affect2Act achieves the highest accuracy while maintaining high emotional balance, demonstrating a stable equilibrium between performance and diversity.

Progressive Representation Learning.
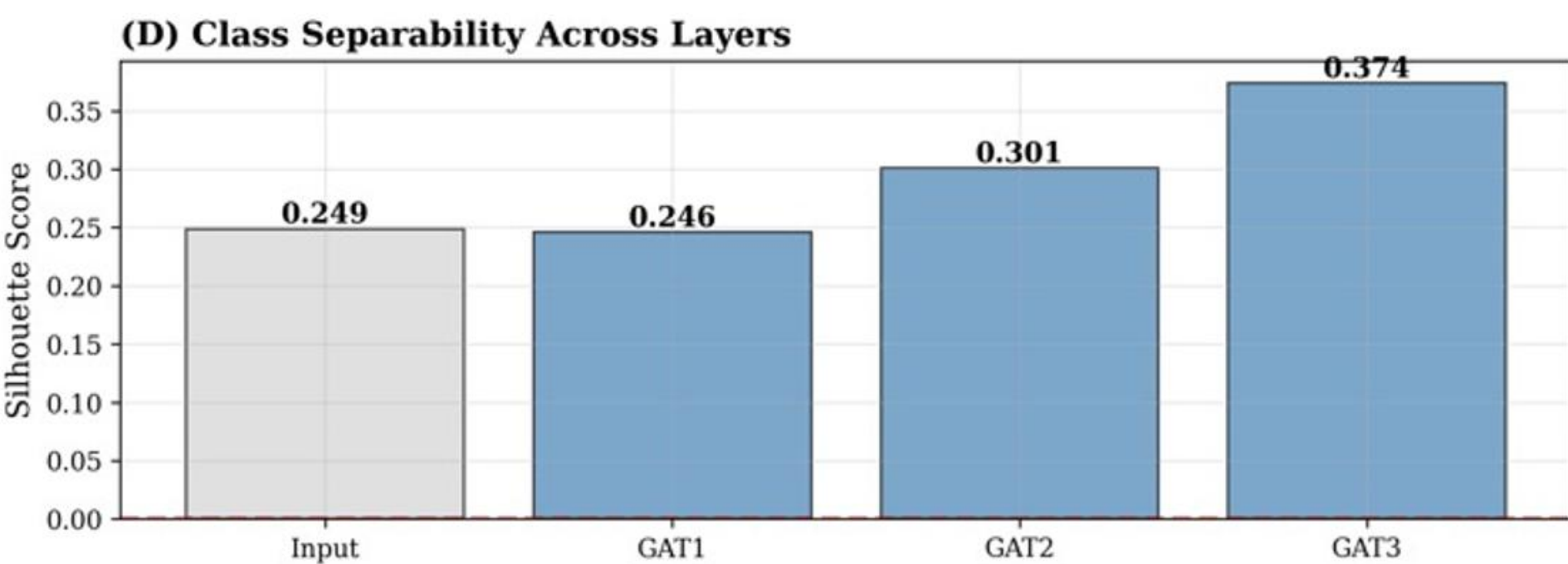
Silhouette score rises from 0.249 to 0.374 across GAT layers, confirming progressive improvement in class separability, demonstrating successful representation refinement

Interpretability and Robustness:

The high emotional balance shows the GAT with attention enhances diversity and stability compared to fixed-structure GCN. Attention analysis reveals interpretable links, such as fear-anger during emergencies. This joint optimization (Accuracy + Balance) is crucial for robust affective reasoning.

Conclusion

- Affect2Act, a Graph Attention Network, models emotions as interconnected nodes with context-dependent attention.
- Achieves strong Decision Accuracy (87.67%) and high Emotional Balance (65.47%).
- Future work: Explore richer emotion taxonomies, multimodal extensions, and real-world evaluations

References

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