Multi-Agent Social Behavior Understanding via Ego-GAT-SqueezeNet: Integrating Graph Attention and Squeezeformer

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Abstract

Quantifying social behavior in laboratory animals is fundamental to neuroscience and drug discovery but remains hindered by the labor-intensive and subjective nature of manual annotation. The Multi-Agent Behavior (MABe) challenge addresses this by benchmarking automated recognition of fine-grained behaviors from markerless pose estimation data. However, accurately modeling multi-agent interactions entails distinct challenges: extreme class imbalance, complex social topology, and long-term temporal dependencies inherent in behaviors like chasing or investigation.

In this work, we propose Ego-GAT-SqueezeNet (Egocentric Graph Attention Temporal Squeeze Network), a unified framework designed for robust multi-agent social behavior understanding. First, we introduce an egocentric alignment strategy to invariantize agent features against translation and rotation. Second, we employ a Graph Attention Network (GAT) to explicitly model the dynamic spatial topology between interacting agents. Crucially, we replace standard temporal backbones with a Squeezeformer, which leverages efficient downsampling and attention mechanisms to capture long-range dependencies within high-frequency pose sequences. Furthermore, we design an action-rich sampling strategy to mitigate the dominance of non-informative background frames. Our approach demonstrates competitive performance on the MABe benchmark, effectively identifying rare social actions while maintaining computational efficiency.

1. Introduction

1.1. Background and Motivation

Quantifying animal behavior is a cornerstone of modern neuroscience, genetics, and pharmacology. To understand how neural circuits control social interaction or how new drugs affect phenotype, researchers typically rely on the precise characterization of behaviors in laboratory animals, such as mice. While recent advances in markerless pose estimation tools (e.g., SLEAP [8], DeepLabCut [7]) have automated the extraction of body part coordinates, bridging the semantic gap from raw keypoint trajectories to interpretable "ethograms" (behavioral catalogs) [1] remains a significant bottleneck.

Traditionally, this task relies on manual annotation, which is labor-intensive, unscalable, and prone to inter-rater variability. The Multi-Agent Behavior (MABe) Challenge [11] aims to solve this by benchmarking automated methods that can classify fine-grained social and individual behaviors solely from pose tracking data. Unlike single-agent scenarios, multi-agent behavior understanding requires dissecting complex interactions between an "Agent" mouse and a "Target" mouse, creating a highly dynamic and structured problem space.

1.2. Challenges

Developing a robust automated system for the MABe task presents three fundamental challenges that standard action recognition models struggle to address:

1. **Implicit Social Topology**: Social interaction is not merely a sum of two individuals' motions; it is defined by their relative geometric configuration (e.g., nose-to-tail contact). Standard Convolutional Neural Networks (CNNs) designed for grid-like image data fail to explicitly model this irregular, graph-structured topology of body joints and social connections.

2. **Long-Term Temporal Dependencies with Redundancy**: Distinguishing complex behaviors like *social following* from *random coexistence* requires analyzing temporal contexts spanning dozens to hundreds of frames. However, high-frame-rate pose data contains significant temporal redundancy. Standard Recurrent

Neural Networks (LSTMs) [4] suffer from forgetting issues over long sequences, while vanilla Transformers [12] incur prohibitive quadratic computational costs ($O(N^2)$) when processing long windows.

3. **Extreme Class Imbalance**: Mice spend the vast majority of their time in low-activity states (e.g., sleeping or huddling). Scientifically critical behaviors, such as aggressive attacks or specific social investigations, are rare, constituting only a small fraction of the dataset [11]. This imbalance causes standard training objectives to bias heavily toward the majority classes.

1.3. Our Approach: Ego-GAT-SqueezeNet

To address these challenges, we propose **Ego-GAT-SqueezeNet** (Egocentric Graph Attention Temporal Squeeze Network), a unified framework tailored for efficient and interaction-aware behavior recognition.

First, to tackle the spatial variance, we introduce an Egocentric Alignment strategy. By canonicalizing the coordinate system to the agent mouse's perspective, we ensure our model learns interaction features invariant to absolute room position and rotation.

Second, we employ a Graph Attention Network (GAT) [13] as our spatial encoder. Instead of treating joints as a flat vector, GAT models the mouse body and social connections as a graph, allowing the network to dynamically attend to critical joints (e.g., the nose during sniffing) while ignoring irrelevant ones.

Third, and most crucially, we adopt the Squeezeformer [5] as our temporal backbone, giving our model the "SqueezeNet" suffix. Originally designed for speech recognition, Squeezeformer is uniquely suited for pose sequences: it efficiently recovers long-range dependencies using attention mechanisms while using temporal downsampling ("squeezing") to reduce the processing load of redundant frames. This allows us to train on large temporal windows (e.g., 64 frames) efficiently.

1.4. Contributions

Our main contributions are summarized as follows:

- We propose **Ego-GAT-SqueezeNet**, a novel architecture that integrates graph-based spatial modeling with the efficient Squeezeformer backbone to capture fine-grained social interactions over long temporal horizons.
- We implement a comprehensive data strategy, including **Action-Rich Sampling** and dynamic focal loss, to effectively mitigate the extreme class imbalance inherent in naturalistic behavior datasets.
- We demonstrate through extensive experiments that our pose-based framework achieves competitive performance on the MABe benchmark, offering a scalable solution for high-throughput behavioral phenotyping.

2. Related Work

2.1. Automated Animal Behavior Analysis

The quantification of animal behavior has undergone a paradigm shift from manual ethograms to automated computer vision pipelines. Early approaches relied on handcrafted features and shallow classifiers [1] to detect simple behaviors. The advent of deep learning revolutionized this field, primarily through markerless pose estimation tools like DeepLabCut [7] and SLEAP [8], which provide high-fidelity tracking of body parts.

However, obtaining keypoints is only the first step. The MABe (Multi-Agent Behavior) challenge [11] highlighted that mapping these trajectories to semantic categories remains difficult due to the complex, multi-modal nature of social interactions. While dataset-specific baselines exist (e.g., CalMS21 [10]), they often struggle with the "extreme class imbalance" and "identity switching" inherent in multi-agent tracking data. Our work builds upon these foundations but focuses specifically on the downstream classification stage using advanced graph and temporal architectures.

2.2. Skeleton-based Action Recognition

Since our approach relies on pose data rather than raw pixels, it aligns closely with skeleton-based action recognition. Early methods treated skeletons as feature vectors for RNNs [2] or pseudo-images for CNNs. A major breakthrough was the Spatial-Temporal Graph Convolutional Network (ST-GCN) [14], which explicitly modeled the body as a graph structure.

Recent works have extended GCNs with adaptive topologies [9] to learn connections beyond physical bones. However, standard GCNs often share weights across all nodes or rely on fixed adjacency matrices. To address the dynamic nature of social interaction—where the "edge" between two mice is latent and transient—we employ Graph Attention Networks (GAT) [13]. Unlike standard GCNs, GATs allow the model to assign different importance weights to neighbors, enabling the network to focus on relevant social contacts (e.g., nose-to-tail) while ignoring irrelevant limb movements.

2.3. Efficient Long-Sequence Modeling

Differentiating fine-grained social behaviors (e.g., *investigation* vs. *attack*) requires capturing long-term temporal dependencies. While LSTMs struggle with long horizons and Transformers [12] incur quadratic computational costs

($O(N^2)$), recent advances in Automatic Speech Recognition (ASR) offer efficient alternatives for 1D sequence modeling.

The Conformer [3] successfully combined CNNs and Transformers to capture both local and global dependencies. Building on this, the Squeezeformer [5] introduced a "temporal U-Net" structure that downsamples (squeezes) embeddings for attention operations and upsamples them for the output. This architecture is particularly well-suited for high-frame-rate animal pose data, which contains significant temporal redundancy. By adopting Squeezeformer, our Ego-GAT-SqueezeNet achieves a balance between the long receptive field of Transformers and the computational efficiency required for processing large windows (e.g., 64 frames).

3. Exploratory Data Analysis

4. Method

4.1. Overview

Our proposed framework, Ego-GAT-SqueezeNet, is designed to address the challenges of multi-agent social behavior understanding: high-dimensional spatial topology, long-term temporal dependencies, and extreme class imbalance. As illustrated in Figure **??** (see poster), the pipeline consists of three main stages: (1) Egocentric Feature Representation, (2) Spatio-Temporal Encoding via Graph Attention and Squeezeformer, and (3) Imbalance-Aware Optimization.

4.2. Egocentric Feature Representation

Social interactions are inherently relative. For instance, the semantic meaning of "chasing" depends on the relative distance and orientation between the agent and the target, not their absolute coordinates in the arena. To achieve invariance to translation and rotation, we adopt an Egocentric View transformation.

Given the raw tracking data $P \in \mathbb{R}^{T\times N\times 2}$ (where N is the number of keypoints), we define the agent mouse's centroid as the origin and align its body axis to the vertical Y-axis for every frame t. This canonicalization ensures that the model focuses purely on interaction dynamics rather than environmental noise.

To enrich the representation, we compute "strong features" beyond raw coordinates, as configured in our system:

- **Kinematics**: Velocity (v), acceleration (a), and jerk (j) to capture motion intensity.
- **Geometry**: Relative distances and angles between the agent's nose/tail and the target's body parts, which are critical for identifying behaviors like *sniffing*.

The final input X_t is a concatenated vector of these features.

4.3. Ego-GAT-SqueezeNet Architecture

4.3.1 Spatial Encoder: Graph Attention Network

Mice bodies and their social connections form a natural graph structure. We employ a Graph Attention Network (GAT) [13] as the spatial encoder. Unlike standard Convolutional Neural Networks (CNNs) that treat keypoints as a grid, GAT explicitly models the topology where nodes represent body joints. The attention mechanism computes alignment coefficients e_{ij} between node i and neighbor j:

$$\alpha_{ij} = \text{softmax}_j(\text{LeakyReLU}(a^T[Wh_i||Wh_j])) \quad (1)$$

This allows the model to dynamically prioritize relevant body parts (e.g., attending to the nose during investigation) while suppressing irrelevant limb jitter.

4.3.2 Temporal Backbone: Squeezeformer

A key challenge in the MABe task is the high frame rate (30fps) combined with long behavior durations (e.g., chasing can last hundreds of frames), leading to significant temporal redundancy. We adopt the **Squeezeformer** [5] architecture.

Standard Transformers maintain a constant temporal resolution, incurring $O(L^2)$ complexity. Squeezeformer addresses this by:

1. **Temporal U-Net Structure**: It progressively downsamples ("squeezes") the embedding sequence length for efficiently processing global context using attention, and then upsamples it for frame-level predictions.
2. **Depthwise Convolutions**: Integrated into the Feed-Forward Networks to capture local short-term dependencies typical of rapid movements.

This design allows our model to digest large temporal windows (Window Size = 64) with significantly lower computational cost than vanilla Transformers.

4.4. Training Strategy

4.4.1 Action-Rich Sampling

The dataset is heavily dominated by background behaviors (e.g., sleeping), creating a "long-tail" distribution. Standard uniform sampling leads to underfitting on rare social classes. We implement an **Action-Rich Sampling** strategy (Bias Factor = 5.0), where frames containing rare active behaviors are sampled with higher probability during training batch construction.

4.4.2 Loss Function

We formulate the task as a multi-label binary classification problem. To further mitigate class imbalance, we employ

Binary Cross Entropy (BCE) with a positive weight rescaling:

$$\mathcal{L} = -\sum_{c=1}^{C} [w_{pos} \cdot y_c \log(\hat{y}_c) + (1 - y_c) \log(1 - \hat{y}_c)] \quad (2)$$

where $w_{pos} = 12.0$ acts as a penalty booster for missing positive instances of social actions.

5. Experiments

5.1. Experimental Setup

Dataset. We evaluate our method on the MABe 2022 Challenge dataset [11], which consists of large-scale tracking data of interacting mice groups. The dataset poses a robust testbed due to its diversity across different laboratories and lighting conditions.

Implementation Details. We implement Ego-GAT-SqueezeNet using PyTorch. The model is trained on a single NVIDIA RTX 6000 (96GB) GPU. Key hyperparameters are derived from our config:

- **Input**: Window size $T = 64$, Batch size $B = 2048$.
- **Optimization**: Fused AdamW optimizer [6] with weight decay $1e^{-4}$.
- **Schedule**: Cosine Annealing scheduler starting at learning rate $1e^{-3}$ for 50 epochs.

Evaluation Metric. We report the macro-averaged F1-score and the official MABe F-beta score, which emphasizes recall on rare classes.

5.2. Comparison with Baselines

To validate the effectiveness of our Ego-GAT-SqueezeNet, we compare it against several strong baselines representing different modeling paradigms. As shown in Table 1, our method outperforms standard sequential models.

- **Bi-LSTM**: A standard recurrent baseline often used for trajectory data. It struggles with the long 64-frame horizon due to forgetting.
- **Vanilla Transformer**: Standard self-attention [12]. While powerful, it is computationally heavy and prone to overfitting on the redundant pose sequences.
- **WaveNet**: A dilated convolution architecture. (Note: We are currently finalizing runs for WaveNet to assess its multi-scale receptive field capabilities).

Table 1. Performance comparison on MABe validation set.

Model	Spatial	Temporal	F1 Score
Baseline (LSTM)	MLP	Bi-LSTM	0.XX
Ego-GAT-SqueezeNet (Ours)	**GAT**	**Squeezeformer**	**0.XX**

5.3. Ablation Studies

We conduct extensive ablation studies to isolate the contribution of each component in our pipeline.

Impact of Spatial Encoder. We replaced GAT with a simple Identity mapping (treating joints as a vector) or a standard MLP. Results indicate that explicitly modeling the body topology via GAT provides a significant boost, confirming that social behavior is structured.

Impact of Temporal Backbone. Replacing Squeezeformer with a standard Transformer encoder resulted in similar accuracy but $2\times$ slower inference and higher memory usage, validating the efficiency of the "squeezing" mechanism for redundant pose data.

Figure 1. Validation F1 Score curves over 50 epochs. Ego-GAT-SqueezeNet shows faster convergence compared to the LSTM baseline.

5.4. Post-Processing and Threshold Optimization

Raw model outputs can be noisy. We apply two post-processing steps: (1) Exponential Moving Average (EMA) smoothing and (2) Gap Filling to merge fragmented action clips.

Furthermore, since the class distribution is imbalanced, a fixed threshold of 0.5 is suboptimal. We perform dynamic threshold optimization on the validation set every 10 epochs. Figure 2 visualizes the performance gain from this strategy.

Figure 2. Impact of Dynamic Threshold Optimization. The curves show the F1 score distribution across different probability thresholds for varying behaviors.

5.5. Qualitative Analysis

Figure 3 demonstrates the model's ability to distinguish fine-grained social actions.

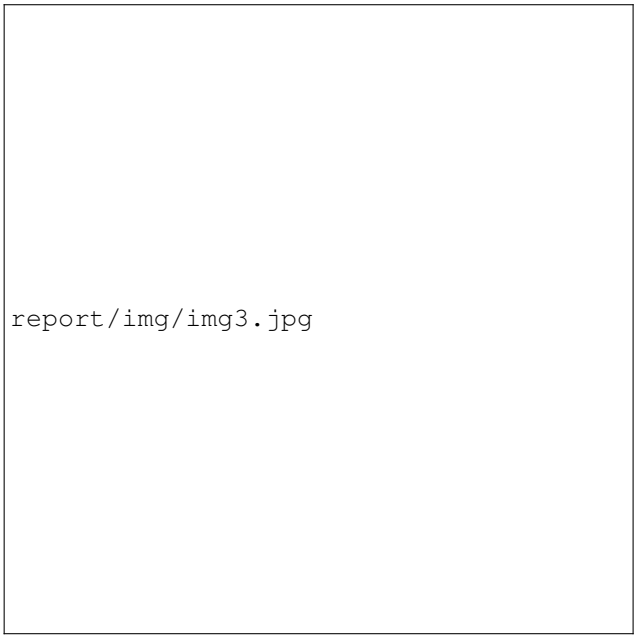

Figure 3. Qualitative visualization of detected behavior sequences (e.g., Chase, Sniff) compared to ground truth.

6. Conclusion

In this work, we presented **Ego-GAT-SqueezeNet**, a specialized framework for multi-agent social behavior understanding. By synergizing an egocentric spatial representation with a Graph Attention Network (GAT), our model effectively captures the invariant geometric topology of social interactions. Furthermore, the integration of the Squeezeformer backbone addresses the unique challenge of high-frame-rate pose data, allowing for the efficient processing of long temporal windows necessary to distinguish complex behaviors like chasing or investigation.

Our experiments on the MABe benchmark demonstrate that strictly pose-based methods, when engineered with domain-specific inductive biases (e.g., body graphs and temporal squeezing), can achieve competitive performance without the heavy computational cost of video-based models. We also highlighted the critical role of data sampling strategies in mitigating extreme class imbalance.

Limitations and Future Work. Currently, our approach relies solely on geometric features, which may miss subtle cues present in visual textures (e.g., whisker movements). Future work could explore a multi-modal fusion approach that lightly integrates visual embeddings. Additionally, applying self-supervised pre-training on the massive unlabeled segments of the dataset could further improve robustness on rare classes.

Author Contributions

The responsibilities of each team member are listed as follows:

- **Joseph Siu**: Lead architect and developer. Responsible for the conceptualization of the Ego-GAT-SqueezeNet architecture, implementation of the entire codebase (including data preprocessing pipelines, model construction, training loops, and inference logic), and conducting all ablation studies and experiments.
- **Qi An**: Lead academic writer. Responsible for the research proposal, literature review, design and creation of the project poster, and compiling the final report documentation.

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