LAGNet: Logic-Aware Graph Network for Human Interaction Understanding

Zhenhua Wang †, Jiajun Meng †, Jin Zhou †, Dongyan Guo †, Guosheng Lin ♯, Jianhua Zhang †, Javen Qinfeng Shi ♭, Shengyong Chen ‡
† Zhejiang University of Technology, China; ♯ Nanyang Technological University, Singapore
‡ Tianjin University of Technology, China; ♭ The University of Adelaide, Australia
zhhwang@zjut.edu.cn

Abstract

Compared with the progress made on human activity classification, much less success has been achieved on human interaction understanding (HIU). Apart from the latter task is much more challenging, the main cause is that recent approaches learn human interactive relations via shallow graphical representations, which is inadequate to model complicated human interactions. In this paper, we propose a deep logic-aware graph network, which combines the representational ability of graph attention and the rigorousness of logical reasoning to facilitate human interaction understanding. Our network consists of three components, a backbone CNN to extract image features, a graph network to learn interactive relations among participants, and a logic-aware reasoning module. Our key observation is that the first-order logic for HIU can be embedded into higher-order energy functions, minimizing which delivers logic-aware predictions. An efficient mean-field inference algorithm is proposed, such that all modules of our network could be trained jointly in an end-to-end way. Experimental results show that our approach achieves leading performance on three existing benchmarks and a new challenging dataset crafted by ourselves. Code is available at: https://git.io/LAGNet.

1. Introduction

Analyzing human activities in natural scenes is a fundamental task to many potential applications like video surveillance [33], key-event retrieval [10], social behavior interpretation [2] and sports analysis [26]. Abundant techniques have been developed for human activity recognition (HAR, where the goal is to assign an activity label to each image or video) [7, 23, 14, 31, 19, 42, 42, 25], which have gained impressive progress on recognition accuracy. However, the task of human interaction understanding (HIU) is much less successful mainly because current methods learn human interactive relations via shallow graphical representations [41, 40, 39, 23, 7, 44], which is inadequate to model complicated human activities.

Serving as an effective way of integrating CNN for local feature extraction and graphical representation for relational-inductive-bias learning [4], graph networks have recently achieved impressive success on multiple vision tasks like collective activity recognition (CAR) [25, 42], skeleton-based human action recognition [28], gaze-communication understanding [9], feature matching [47] and one-shot semantic segmentation [45]. Unfortunately, we find that a straightforward implementation of such graph networks for HIU can yield inconsistent predictions. Taking the prediction “$1 \leftrightarrow 2$ & $(2 \leftrightarrow 3) & (1 \leftrightarrow 3)$” of the scene...
depicted by Figure 1 as an example, clearly ‘‘(1 ↔ 3)’’ contradicts ‘‘(1 ↔ 2) & (2 ↔ 3)’’. Another issue is that the predicted action labels for two interacting people can be incompatible, e.g., `handshake` versus `kick`. Our key observation is that these graph networks are designed to enhance local representations by a soft-aggregation of non-local features (i.e., the graph attention mechanism), while they are unaware of the underlying logic which is essential to achieve consistent HIU predictions.

As commonly done in literature [41, 39, 40], we decompose HIU into two sub-tasks: 1) The individual action prediction task which assigns each participant an action label; 2) The pairwise interactive prediction task which determines if any pair of participants are interacting or not. Figure 1 gives an example of HIU, where targets (1, 2, 3) and (4, 5) naturally form two groups of concurrent human activities. Solving the two sub-tasks provides a way to disentangle concurrent human activities with multiple participants, as well as a comprehensive understanding of surveillance scenes. Then we present a logic-aware graph network (LAGNet) for HIU. As shown by Figure 1, LAGNet consists of a backbone CNN to extract image features, a graph network to learn relations among participants, and a logic aware module to make consistent action and interaction predictions. All components of LAGNet could be trained jointly and efficiently with GPU acceleration. We empirically validate that these three components complement each other, and the combination of them always delivers best results.

Our contributions include four aspects. First, we propose a logic-aware graph network for HIU to overcome the inconsistent predictions made by recent graph networks. Second, we present an efficient mean-field inference algorithm to solve the logic-aware reasoning problem. Third, we create a new challenging benchmark (will be publicly available to the community) for HIU. Finally, our proposed LAGNet outperforms the state-of-the-art results by salient margins on four evaluated benchmarks.

2. Related Work

**Action/Activity Recognition** Since the invention of the two-stream network [31], numerous works on HAR (predicting each image or video an action class) have been proposed [14, 37, 15, 38, 5, 21, 43]. These methods take the video as a whole and focus on extracting powerful features to represent human motions. Though they could be taken to recognize the collective activity (CAR) of multiple participants, an increasing number of works justify the importance of modeling the spatio-temporal correlations among action variables of different people [7, 20, 6, 8, 2, 29, 13, 26, 42, 25]. Early works in this vein explore conditional random fields (CRFs) [7, 20, 6], while recent efforts contribute most on the joint learning of image features and human relations with RNN [8, 2, 29, 26, 30] or deep graphical models [13, 42, 25]. These approaches are designed to predict each input an activity category, leaving the HIU task rather unsolved.

**Human Interaction Understanding** In order to understand human interactions, abundant conditional random field (CRF)-based models have been proposed [44, 18, 19, 24, 23, 40, 39, 41] to model the interactive relations in both spatial and temporal domains. The main drawback is that these CRFs are of shallow graphical-representations, which is neither effective in terms of learning complicated human interactions nor efficient to solve the associated maximum a posteriori inference [41]. Moreover, they perform deep feature learning and relational reasoning separately, which typically results in sub-optimal HIU results. Our LAGNet addresses these issues by incorporating a graph network, which can benefit from both the representative power of deep architectures and the attentive capability of graph convolution.

**Graph Networks** have become a popular choice to many vision tasks which involve modeling and reasoning relations among components within a system [4, 16, 48, 46, 9, 49]. Graph networks share the computational efficiency of deep architectures while are more powerful and flexible in terms of modeling relations in non-grid structures, for instance, the correspondences between two sets of points in a matching problem [48], the correlations between query and support pixels in one-shot semantic segmentation [46], human gaze communication [9], and the inter-person relations for CAR [42]. Essentially, these works implement the graph attention which enhances the feature representation of a node by aggregating features from other relevant nodes. We improve such graphical representations by incorporating a logic-aware reasoning module, which helps to reduce the chance of obtaining inconsistent HIU predictions.

**Logical Reasoning** As a way to high-level intelligence, logical reasoning has seen a renaissance in very recent years. Since traditional logical reasoning has relied on methods and tools which are very different from deep learning models, such as Prolog language, SMT solvers and discrete algorithms, a key problem is how to bridge logic and deep models effectively and efficiently. Recent works viewed graph networks as a general tool to make such a connection. For example, [3, 4] take graph networks to incorporate explicitly logic reasoning bias, [22] builds a neuro-symbolic reasoning module to connect scene representation and symbolic programs, and [1] introduces a differentiable first-order logic formalism for visual question answering. In contrast, we take the well-established oracles to formalize the logic system, and fuse logic and graphical representations with an optimization system, solving which delivers logic-compatible predictions for HIU.
3. Our Approach

Task Description and Notations Given an input image I and the bounding boxes (RoIs) of n detected human bodies, the HIU task decomposes into two sub-tasks: 1) predicting the action category \( y = (y_i)_{i=1}^n \) for every individual where \( y \in \mathcal{Y} \), and 2) predicting all pairwise interactive relations \( z = (z_{j,k})_{j=1,...,n; k=1,...,n} \) for each pair of people. Here the binary variable \( z_{j,k} \in \{0,1\} \) represents if the \( j \)-th participant and the \( k \)-th participant are interacting \( (z_{s,t} = 1) \) or not \( (z_{s,t} = 0) \). All vectors in this paper will be column vectors unless otherwise stated.

3.1. Model Overview

Figure 2 shows an overview of the proposed LAGNet, which consists of three key components including a base-model, a graph network and a logic-aware reasoning module. Given an input image and the detected human bodies, the base-model takes a backbone CNN to extract features from the input, which are then processed by a RoIAlign module [11] to generate local features for each individual. The local features are then passed to one FC layer to generate the initial node features for our graph network. We also compute a matrix \( P = (p_{j,k})_{j=1,...,n; k=1,...,n} \) beforehand based on the position of each participant, where \( p_{j,k} \) represents the Euclidean distance between the centers of the associated bounding boxes. Afterwards, taking as inputs the local features and \( P \), we build a graph network in order to capture the attentive relations of people based on their interactive relations. Each node in the graph network represents the action label of the associated person, and each edge takes a weight (learned from data) encoding how likely the associated people are interacting. Next, we implement graph attention for each node by performing a weighted aggregation of features from neighboring nodes to get the node feature updated (Section 3.2). Though the graph attention is able to enhance the feature representation of each node, the labeling consistency among nodes is rather neglected. To alleviate this, next we introduce a logic-aware module, which essentially performs a deductive reasoning leveraging the logical system designed for HIU (Section 3.3). In practice the reasoning is achieved via solving a surrogate mean-field inference with high-order energy functions such that all modules of the proposed LAGNet could be trained in an end-to-end manner with GPU acceleration.

3.2. The Graph Network

The graph network can be seen as an attention mechanism with global receptive field, which augments the feature representation of each variable through a weighted aggregation of features from relevant variables. We closely follow the formulation of the graph network (GN) proposed by [42], and make straightforward modifications to facilitate the subsequent logic-aware reasoning.

Graph Definition Our graph network uses a complete graph \( G = (V, E) \), which takes \( V = \{1, 2, \ldots, n\} \) as its node set and \( E = \{(i, j) | i \in V, j \in V\} \) as the edge set. As stated, each node \( i \in V \) is associated with an action variable \( y_i \) to denote the action category performed by the \( i \)-th individual, and each edge \((s, t) \in E \) takes a binary variable \( z_{s,t} \in \{0,1\} \) to represent whether the related people are interacting \( (z_{s,t} = 1) \) or not \( (z_{s,t} = 0) \).

Relation Reasoning In order to evaluate the existence of interactive relations, we learn a confidence score \( r_{i,j} \in \mathbb{R} \) for each edge \((i,j) \in E \) through

\[
    r_{i,j} = \frac{\exp \left\{ \mathbf{1}(p_{i,j} \leq \rho) \cdot \delta \cdot [\alpha(x_i)^{\top} \beta(x_j)] \right\}}{\sum_{k \in V} \exp \left\{ \mathbf{1}(p_{i,k} < \rho) \cdot \delta \cdot [\alpha(x_i)^{\top} \beta(x_k)] \right\}}, \tag{1}
\]

where \( r_{i,j} \in [0, 1] \), \( x_i \in \mathbb{R}^{1,024} \) and \( x_j \in \mathbb{R}^{1,024} \) are initial node features extracted by the base-model. Here \( \alpha(\cdot) \) and \( \beta(\cdot) \) denote two linear transformations that map local feature vectors to the \( \mathbb{R}^{128} \) space, and \( \delta = \frac{1}{128} \). \( \mathbf{1}(\cdot) \) is an indicator function which outputs 1 if the Euclidean distance \( p_{i,j} \) between the \( i \)-th target and the \( j \)-th target is smaller than a threshold \( \rho \), otherwise it gives 0. With this function,
the graph network is able to filter distant people (the trifling relations) out for later attentive aggregation.

**Interactive Score** For each \((i, j) ∈ E\), we compute a score vector \(\theta_{i,j} ∈ \mathbb{R}^2\) using

\[
\theta_{i,j} = [1 - r_{i,j}; r_{i,j}] \quad ∀(i, j) ∈ E, \tag{2}
\]

where the first entry represents the confidence of assigning 0 to \(z_{i,j}\), while the second entry measures the confidence of assigning 1 to \(z_{i,j}\). This score vector is to be taken as inputs for the subsequent logic-aware reasoning module.

**Graph Attention** Given the initial node features \(x_i \forall i ∈ V\) and the learned relations \(r_{j,k} \forall (j, k) ∈ E\), we now update the node features via graph attention. Specifically, for any node \(i ∈ V\), its new feature \(\tilde{x}_i\) is computed through

\[
\tilde{x}_i = \text{ReLU} \left( \gamma \left( \sum_{j ∈ V} r_{i,j} x_j \right) \right) \quad ∀i ∈ V. \tag{3}
\]

Above, we first aggregate messages (weighted by \(r\)) sent to \(i\) from its neighboring nodes. Afterwards a linear transformation \(\gamma\) is applied, which maps the aggregated feature vector to the same feature space as that of \(x_i\). The resulting feature then undergoes a ReLU operation, which gives the updated node feature \(\tilde{x}_i\).

**Action Score** Finally, we calculate the classification scores (denoted by \(\theta_i\)) for individual actions by applying to the updated node features two linear transformations in succession. Specifically,

\[
\theta_i = \eta \left( \text{ReLU} \left( \mu \left( \tilde{x}_i + x_i \right) \right) \right) \quad ∀i ∈ V, \tag{4}
\]

where \(\eta(\cdot)\) and \(\mu(\cdot)\) are linear transformations which project their inputs to \(\mathbb{R}^{128}\) and \(\mathbb{R}^{31}\) spaces respectively. These scores are taken as inputs (together with the interactive scores) to the subsequent logic-aware reasoning module.

**Parallel Computation** For implementation, all linear transformations, i.e. \(\alpha(\cdot), \beta(\cdot)\), and \(\gamma(\cdot)\) could be performed on all nodes concurrently using matrix multiplication, so does the feature aggregation in Equation (3). For the relation reasoning in Equation (1), all confidence scores could be computed simultaneously again with matrix multiplication, element-wise multiplication and Softmax operation for efficient implementation.

**Comparison with Existing GN** We modified GN differs from the original GN [42] on three aspects. First, the original GN is designed for CAR which aims at assigning a single label to each image to describe the occurring collective activity there, whereas the modified version is designed for HIU. Second, the original GN treats \(r_{i,j} \forall (i, j) ∈ E\) as latent variables which are implicitly supervised by groundtruth labels of individual actions during training, whereas the modified version explicitly supervises learning the parameters of relation reasoning with annotated interactive relations (see Section 3.4). We find that such a straightforward modification offers a boost of performance on HIU compared against the original GN. Third, we add the computation of interactive scores with Equation (2), which prepares inputs for subsequent logic-aware module.

### 3.3. Logic-Aware Reasoning

We first present two deductive oracles for HIU (with logic symbols defined in Figure 1):

- **The compatibility oracle**: For any pair of people \((A, B)\) who are interacting \((\leftrightarrow)\), their action categories must be compatible \((\sqcup)\). In logical words, this rule is represented by \(A \leftrightarrow B \Rightarrow y_A \sqcup y_B\).

- **The transitivity oracle**: Considering the interactive relations among a triplet of people \((A, B, C)\), we have \((A \leftrightarrow B) & (B \leftrightarrow C) \Rightarrow (A \leftrightarrow C)\).

Typical compatible examples include \((\text{handshake, handshake})\), \((\text{pass, receive})\), \((\text{punch, pass})\), \((\text{highfive, handshake})\). Examples obey or violate the transitivity are provided in Figure 3. Though this oracle only considers triplets of people, it is straightforward to prove that the higher-order transitivity for any clique within \(G\) is simply a conclusion of the 3-order transitivity. Intuitively, by enforcing the transitivity across all triplets, participants in the scene are split into different groups, such that individuals in the identical group are interacting with each other, while people in different groups have no interaction.

With such oracles, predictions of the graph network in Section 3.2 could be refined by applying the traditional logical reasoning algorithms. Unfortunately, it is well known that such reasoning algorithms are typically brittle and inefficient. Instead we resort to a work-around which first embeds the knowledge into an energy function defined by

\[
E(y; z; x) = \sum_t -\theta_t(y_t) + \sum_{j,k} \left[ -\theta_{j,k}(z_{j,k}) \right. \\
+ \left. K^C(z_{r,s}, z_{s,t}, z_{r,t}) \right], \tag{5}
\]

where \(-\theta_t(y_t)\) and \(-\theta_{j,k}(z_{j,k})\) are data terms (computed by the graph network) that penalize particular \(y\)-label and
z-label assignments respectively based on the learned deep representations from \( I \). The functions \( K^C \) and \( K^T \) are \( P^n \). Potts models \([17]\) defined by

\[
K^C(y_j, y_k, z_{j,k}) = \begin{cases} 
\lambda^C & \text{if } z_{j,k} = 1 \text{ and } y_j \otimes y_k, \\
0 & \text{otherwise.} 
\end{cases}
\]

\[
K^T(z_{r,s}, z_{s,t}, z_{r,t}) = \begin{cases} 
\lambda^T & \text{if } (z_{r,s}, z_{s,t}, z_{r,t}) \in \Gamma, \\
0 & \text{otherwise.} 
\end{cases}
\]

Here the notation \( y_j \otimes y_k \) represents the action label \( y_j \) is incompatible with the action label \( y_k \), \( \Gamma \) is a set \( \{(1, 1, 0), (1, 0, 1), (0, 1, 1)\} \) that includes all cases violating the transitivity oracle, \( \lambda^C \) and \( \lambda^T \) are penalties incurred by predictions which violate the compatibility and transitivity oracles. It is easy to check that when \( \lambda \) is sufficiently large, minimizing the energy (5) delivers desirable \( y \) and \( z \) predictions which satisfy the compatibility and transitivity oracles. In this paper, instead of redesignating suitable \( \lambda^C \) and \( \lambda^T \) values, we learn them from training data in conjunction with other parameters of LAGNet.

**Mean-Field Inference** Minimizing (5) is NP-complete. We derive an efficient mean-field inference algorithm by first approximating the joint distribution \( P(y, z|x) \propto \exp(-E(y, z|x)) \) with a product of independent marginal distributions: \( \prod_t Q_t(y_t) \prod_{j,k} Q_{j,k}(z_{j,k}) \). Then we derive the mean-field updates of all marginal distributions using the techniques described in [35], which gives

\[
\hat{Q}^t_i(y_i) = \sum_{j \in V \setminus \{i\}} \sum_{y_j} \mathbb{I}(y_i \otimes y_k) \lambda^C Q^{t-1}_j(y_j) Q^{t-1}_i(y_i), \quad (8)
\]

\[
Q^t_i(y_i) = \frac{\exp(\theta_i(y_i) - \hat{Q}^t_i(y_i))}{Z^t_i}, \quad (9)
\]

where \( \mathbb{I}(\cdot) \) is an indicator function and \( Z_i \) is a normalization constant. The marginal distributions on \( z \) variables are

\[
\hat{Q}^{k,l}_t(z_{k,l}) = \sum_{y_k, y_l} z_{k,l} \lambda^C Q^{t-1}_k(y_k) Q^{t-1}_l(y_l) \mathbb{I}(y_k \otimes y_l) + \sum_{m \in V \setminus \{k,l\}} \sum_{z_{k,m}, z_{l,m}} \mathbb{I}((z_{k,m}, z_{m,l}, z_{l,m}) \in \Gamma) \lambda^T Q^{t-1}_{k,m}(z_{k,m}) Q^{t-1}_{m,l}(z_{m,l}), \quad (10)
\]

\[
Q^{k,l}_t(z_{k,l}) = \frac{\exp(\theta_{k,l}(z_{k,l}) - \hat{Q}^{k,l}_t(z_{k,l}))}{Z^{k,l}_t}, \quad (11)
\]

Here \( t \in \{1, 2, \ldots, T\} \), and \( Z_{k,l} \) is a normalization constant. We initialize the marginal distributions \( Q^0_k(y_k), Q^0_{k,l}(z_{k,l}) \) by applying the softmax function to the scores output by the graph network. The inference is summarized by Algorithm 1. Note that we can perform the updates of all expectations (Equation (8) and (10)) and marginal probabilities (Equation (9) and (11)) in parallel, which yields very efficient inference.

As mentioned, Algorithm 1 is a surrogate of the logical reasoning task taking the two oracles as its knowledge-base. This algorithm actually forms the last layer of our network, which outputs updated action scores \( \tilde{\theta}_i \) for \( i \in V \) and updated interactive scores \( \tilde{\theta}_{j,k} \forall (j, k) \in E \). Our experimental results in Section 4 demonstrate that such updated scores indeed deliver much better HIU results.

### 3.4. End-to-End Learning

The mean-field inference algorithm allows the back-propagation of the error signals \( \frac{\partial \text{Loss}}{\partial \theta} \) to all parameters of LAGNet (including that of the base-model, the graph network and the logic-aware reasoning module), which enables the joint training of all parameters from scratch. In practice, we resort to a two-stage training due to the limitation of computational resources. The first stage learns a base-model with the backbone CNN initialized by a model pre-trained on ImageNet. The second stage trains the graph network, \( \lambda^C \) and \( \lambda^T \) jointly with fixed backbone-parameters. Both stages compute losses by summing cross-entropy losses computed on \( y \) and \( z \) predictions.

**Implementation Details** Our implementation is based on PyTorch deep learning toolbox and a workstation with three pieces of NVIDIA GeForce GTX 1080 Ti GPU. We test several backbone CNNs including VGG19 [32], ResNet 50 [12] and Inception V3 [34]. We use the official implementation of RoIAlign by PyTorch, which outputs feature maps with a size of \( 5 \times 5 \times 1056 \) (using Inception V3). We add dropout (the ratio is 0.3) followed by a layer-normalization to every FC layer of LAGNet except for the ones computing final classification scores. We set \( \lambda^C = 0.5 \) and \( \lambda^T = 0.1 \) for initialization. We adopt mini-batch SGD with Adam to learn the network parameters, and train all models in 200 epochs. We augment training data with random combinations of scaling, cropping, horizontal flipping.
Table 1. Ablation study on three datasets. The modified graph network (Modified GN) performs much better than base models as well as the original GN. Our LAGNet further improves the performance of HIU on all datasets by clear margins. Bold texts denote best results.

| Name | # Video | Resolution (w × h) | ANP | ANI |
|------|---------|-------------------|-----|-----|
| UT   | 120     | ≤ 480 × 320       | 2.0 | 1.0 |
| TVHI | 300     | ≤ 640 × 360       | 2.1 | 1.0 |
| BIT  | 400     | 320 × 240         | 2.9 | 1.0 |
| CI   | 340     | 1,920 × 1,080     | 7.8 | 2.5 |

Table 2. Dataset comparison. Columns from left to right list dataset names, numbers of videos, resolutions, average numbers of people per frame and average numbers of interactions per frame.

and color jittering. For the scaling and flipping operations, the bounding boxes are scaled and flipped as well.

4. Dataset, Experiment and Result

Existing Datasets Our experiment uses datasets including UT [27], BIT-Interaction [44] and TVHI [24]. UT contains 120 short videos of 6 action classes: handshake, hug, kick, punch, push and no-action. As done by [39], we extend original action classes by introducing a passive class for each of the three asymmetrical action classes including kick, punch and push (be-kicked, be-punched and be-pushed). As a result, we have 9 action classes in total. Following [39], we split samples of UT into 2 subsets for training and testing. BIT-Interaction covers 9 interaction classes including box, handshake, highfive, hug, kick, pat, bend, push and others, where each class contains 50 short videos. Of each class 34 videos are chosen for training and the rest for testing as that recommended by [44]. TVHI contains 300 short videos of television shows, which covers 5 action classes including handshake, highve, hug, kick and no-action. As suggested by [24], we split samples of TVHI into two parts for training and testing.

4.1. The New Dataset

To our best knowledge, existing datasets for HIU (such as UT, BIT and TVHI) are not challenging enough, mainly because that each frame only contains scanty people and one category of human activity. We address this by proposing a new dataset, namely Campus-Interaction (CI) captured in a campus circumstance, see supplementary for a few examples of this dataset. CI contains 340 short videos and 10 typical action classes including kick, steal, highfive, pass, handshake, hug, support, talk, punch and others. Here others indicates any other action categories beyond the first 9 classes. All interactive classes contain exactly 2 participants except for talk, which might include more people.

Each CI video is captured in either an open square or a sports-ground in campus. The videos may include heavy occlusions, and the appearances, poses and heights of different individuals can vary a lot, which make the dataset more realistic. Moreover, CI contains both symmetric (such as handshake, which involves two participants performing the same action) and asymmetric interactions (such as kick, which involves a person performing kick and the other performing be-kicked).

Table 5 compares CI with existing benchmarks. We can see that each frame of CI videos contains an average of 7.8 people, which significantly surpasses that of UT, BIT and TVHI. More impressively, frames taking any human interaction in CI include 2.5 clusters of concurrent human interactions on average, while the existing benchmarks have at most one group of human interaction per frame.

CI offers frame-by-frame annotations, including the bounding box and the action label of each individual, as well as the pairwise interactive relations among people. Utilizing Vatic [36], we annotate 438,452 bounding boxes in total. The annotation takes around 340 hours, considering each video takes about an hour.

We split CI into training and testing sets with 255 and 85 videos respectively. To avoid overfitting, there is no source-overlap among videos in different sets. In this paper, we sample each video every 10 frames for experiments.

4.2. Ablation Study

Evaluation Metric Since the numbers of instances across different classes are significantly imbalanced, we use F1-score, overall accuracy and mean IoU as the evaluation metrics. Specifically, we calculate the macro-averaged-F1 scores on y and z predictions respectively (using the f1_score function in sklearn package), and present the mean
of the two F1 scores. Likewise, overall accuracy calculates the mean of the action-classification accuracy and the interactive-relation-classification accuracy. To obtain mean IoU, we first compute IoU value on each class, then average all IoU values. Next we validate the capabilities of different components in LAGNet, using results provided by Table 1.

Choice of Backbone CNN. Here we evaluate base models (see Figure 2) taking different backbone CNNs to extract image features. We test three popular backbones: VGG19 [32], Inception V3 [34] and ResNet50 [12], and the results correspond to the first three rows (from top to bottom) in Table 1. Inception V3 performs notably better than other backbones on all benchmarks. The reason might be that Inception V3 is able to learn multi-scale feature representations, which stacks into a feature pyramid to better capture the appearance of human motions. Hence we use Inception V3 as the backbone for all subsequent experiments.

Effect of Graph Attention. Graph network (GN) is typically viewed as an attention mechanism which selectively collects relevant local information from non-local regions to perform inductive inference [4]. For the HIU task, GN is expected to enhance the action representation of each individual by aggregating features from other relevant participants. Somewhat surprisingly, GN [42] (designed for CAR) performs even worse than base model on all evaluated benchmarks. We can see a reverse with the Modified GN, which surpasses base model on all benchmarks (e.g., the improvements on BIT are around 2.1%, 1.7%, 4.4% respectively in terms of F1, accuracy and mean-IoU). The reason probably is that without supervision from annotated human interactive relations, the graph network tends to learn fake attentions, which in turn pollute the original feature representations.

Power of Logic-Aware Reasoning. Here we compare four models: 1) Base model + LAR that consists of a base-model followed by the proposed logic-aware reasoning module; 2) LAGNet-C is the proposed LAGNet without taking the transitivity oracle into consideration; 3) LAGNet-T is the proposed LAGNet without taking the compatibility oracle into consideration; 4) The full LAGNet. We can draw two conclusions based on the results. First, the combination of the modified graph network and both oracles (LAGNet-Full) yields best results, which validates our observation that graph attention and logic-aware reasoning complement each other in terms of modeling human interactions. Second, the proposed LAGNet considerably outperforms the second best (i.e., the Modified GN) by clear margins on all evaluated benchmarks. Specifically, on TVHI it overshoots by 3.4%, 2.4%, 3.8%, on UT it outperforms by 1.0%, 0.7%, 1.0%, and on BIT it surpasses by 0.8, 0.5, 1.4% respectively in terms of F1, accuracy and mean-IoU, which demonstrates the power of the proposed logic-aware reasoning module.

\begin{table}[h]
\centering
\begin{tabular}{|l|c|c|c|}
\hline
Method & F1 (%) & Accuracy (%) & mean IoU (%) \\
\hline
GN [42] & 80.57 & 82.76 & 66.82 \\
Joint + AS [39] & 83.50 & 87.33 & 71.64 \\
QP + CCCP [41] & 83.42 & 87.25 & 71.61 \\
LAGNet (ours) & \textbf{87.59} & \textbf{90.30} & \textbf{75.07} \\
\hline
\end{tabular}
\caption{Comparison with recent methods on TVHI. Our LAGNet overshoots competitive models under all evaluation metrics.}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{|l|c|c|c|}
\hline
Method & F1 (%) & Accuracy (%) & mean IoU (%) \\
\hline
GN [42] & 89.25 & 91.78 & 78.24 \\
Joint + AS [39] & 92.20 & 95.86 & 80.30 \\
QP + CCCP [41] & 89.71 & 93.23 & 80.35 \\
LAGNet (ours) & \textbf{94.38} & \textbf{97.06} & \textbf{85.27} \\
\hline
\end{tabular}
\caption{Comparison with recent methods on UT.}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{|l|c|c|c|}
\hline
Method & F1 (%) & Accuracy (%) & mean IoU (%) \\
\hline
GN [42] & 70.52 & 78.52 & 65.89 \\
Joint + AS [39] & 86.61 & 91.77 & 72.12 \\
QP + CCCP [41] & 88.80 & 91.92 & 72.46 \\
LAGNet (ours) & \textbf{90.73} & \textbf{93.83} & \textbf{77.86} \\
\hline
\end{tabular}
\caption{Comparison with recent methods on BIT.}
\end{table}

4.3. Comparison with Recent Model

We consider three recent approaches. Joint + AS [39] first extracts motion features of individual actions with backbone CNN. Afterwards the deep and contextual features of human interactions are fused by structured SVM. This method is able to predict \( y \) and \( z \) in a joint manner. QP + CCCP [41] takes a structured model to represent the correlations between \( y \) and \( z \) variables as well. It also developed a new inference algorithm (namely QP + CCCP) to solve the related inference problem. GN [42] is a recent state-of-the-art for recognizing collective human activities. This model is empowered by both the representative ability of deep CNNs and the attention mechanism of graph networks. Note that GN does not yield \( z \) predictions. We fix this by setting \( z_{i,j} = 1 \) if the learned confidence score \( r_{i,j} \geq 0.5 \), and \( z_{i,j} = 0 \) otherwise. For fair comparison, all methods take Inception V3 as the backbone to extract image features. Results on four datasets are provided in Table 3 to Table 6. We can see that LAGNet outperforms GN and shallow structured models (i.e., Joint + AS and QP + CCCP) significantly on all evaluated benchmarks. Compared with LAGNet, GN lacks supervision on interactive relation prediction and a logic-aware reasoning module, consequently
it performs much worse on HIU than LAGNet. Albeit sharing the same feature extractor (Inception V3) with LAGNet, Joint + AS and QP + CCCP learn human interactive relations via shallow structured models without incorporating attentions and logic-aware reasoning, hence their performances are much worse than our LAGNet. Note that the performance on CI is much worse than on existing datasets, which makes CI a new challenge for future HIU study.

To provide a qualitative analysis of different models, we visualize a few predictions in Figure 4. Albeit the predicted action classes are incompatible or the predicted interactive relations violate the transitivity oracle using either the base-model or the modified GN, thanks to the logic-aware reasoning module, our LAGNet is able to make almost perfect predictions. Also note that the last example includes three concurrent human interactions (talk, handshake and steal), which are correctly identified by our LAGNet.

5. Conclusion

We have presented a Logic-Aware Graph Network for human interaction understanding, which requires to predict individual actions as well as interactive relations among people. Compared with previous methods solely based
on reasoning attentive relations, our logic-aware graphical model leverages both attentions and well-established human knowledge which helps to reduce the chance of predicting incompatible action labels as well as inconsistent interactive relations. We further proposed a mean-field-style inference algorithm such that all modules within our network could be trained in an end-to-end manner. We have also presented a challenging dataset for HIU. Experiments on existing benchmarks and the new dataset show that our proposed method significantly outperforms the baseline models and achieves a new state-of-the-art performance.

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