Understanding Dynamic Scenes using Graph Convolution Networks

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Abstract—We present a novel Multi Relational Graph Convolutional Network (MRGCN) to model on-road vehicle behaviours from a sequence of temporally ordered frames as grabbed by a moving monocular camera. The input to MRGCN is a Multi Relational Graph (MRG) where the nodes of the graph represent the active and passive participants/agents in the scene while the bidirectional edges that connect every pair of nodes are encodings of the spatio-temporal relations. The bidirectional edges of the graph encode the temporal interactions between the agents that constitute the two nodes of the edge. The proposed method of obtaining this encoding is shown to be specifically suited for the problem at hand as it outperforms more complex end to end learning methods that do not use such intermediate representations of evolved spatio-temporal relations between agent pairs. We show significant performance gain in the form of behaviour classification accuracy on a variety of datasets from different parts of the globe over prior methods as well as show seamless transfer without any resort to fine tuning across multiple datasets. Such behaviour prediction methods find immediate relevance in a variety of navigation tasks such as behaviour planning, state estimation as well as in applications relating to detection of traffic violations over videos.

1. INTRODUCTION

We consider a traffic scene such as in Fig. 1 consisting of potentially active participants/agents/objects such as cars and other vehicles that constitute the traffic and passive entities/agents/objects such as lane markings and poles. The paper proposes a framework to classify the behaviour of each such active agent/object in the scene by analyzing the spatio-temporal evolution of their relations with other active and passive agents/objects. Henceforth we use the term object or agent interchangeably. By relation we indicate the spatial relations an agent possesses and enjoys with other agents, for example between the vehicle and lane marking as shown in Fig. (c). The evolution of this spatial relation for an agent $O_i$ with respect to another agent $O_j$ is encoded by a vector of dimension $d$ and vice versa. This results in a connected graph of bidirectional asymmetric relational encoding between every pair of objects in the Interaction graph (Fig. 1(c)). We call this graph as the Spatio Interaction Graph $G$ as the encoder of all bidirectional relations between every pair of objects in the scene. The Graph $G$ is input to a Multi Relational Graph Convolutional Network (MRGCN) which outputs the overall behaviour exhibited by each agent/object in the scene. While the MRGCN maps the input graph to an output behaviour for every graph node we are only interested in the behaviour of active and not the passive objects. Hitherto by behaviour we denote the overall behaviour of an active agent in the scene. For example in Figure 1 the behaviour of Car on the left is Overtaking and the car on the right is moving ahead. The choice of Graph Convolutional Networks (GCN) and the use of its Multi Relational Variant as a choice for this problem stems from recent success of such networks in learning over data that does not present itself in a regular grid like structure and yet can be modeled as a graph such as in social and biological networks. Since a road scene can also be represented as a graph with nodes sharing multiple relations with other nodes, MRGCN is an apt framework for inferring overall node behaviour from a graph of interconnected relations.

The decomposition of an on-road dynamic scene into its associated interaction graph $G$ and the classification of the agent behaviour by the MRGCN supervised over labels that are human understandable (Lane Change, Overtake etc) forms the main thesis of this effort. Such behaviour classification of agents in the scene finds immediate utility in downstream modules and applications. Recent research showcase results to the effect that understanding on road vehicle behavior leads to better behaviour planner for the ego vehicle [1]. In [1] belief states over driver intents of the other vehicles, where the intents take the labels "Left Lane Change", "Right Lane Change", "Lane Keep" is used for a high level POMDP based behavior planner for the ego vehicle. For example the understanding that a car on the ego vehicle’s right lane is executing a lane change behaviour...
into the current lane of the ego vehicle can activate “Change to Right Lane” behaviour in the ego vehicle for the right lane is becoming free. Similarly understanding an active object such as a car is parked can make the ego vehicle to make use of feature descriptors of the parked car to estimate its state, which would not be possible if the active object was engaging in any other behaviour. Understanding on-road vehicle behaviours also lends itself to very pertinent applications such as detecting and classifying traffic scene violations such as "Overtaking Prohibited", "Lane Change Prohibited".

We explicitly contribute in the following ways:

1) We propose a novel yet simple scheme for spatial behaviour encoding from a sequence of single camera observations making use of straight forward projective geometry techniques. This method of encoding spatial behaviours for agents is shown to be better than previous efforts that have used end to end learning of spatial behaviours [2]

2) We showcase the aptness of the current pipeline that directly encodes spatio-temporal behaviours as an intermediate representation into the scene graph $G$ followed by the MRGCN based behavioural classifier. We do this by comparing with two previous methods [2], [3] that are devoid of such intermediate spatio-temporal representations but activate the behaviour classifier on per frame spatial representations sequenced temporally. Specifically we tabulate significant performance gain of at-least 25% on an average vis a vis [3] and 10% over [2] on a variety of datasets collected in various parts of the world [4], [5], [6] and our own native dataset Ref Table I.

3) We signify through label efficacy the role for an attention model that integrates with the MRGCN and further boosting its performance to nearly perfect accuracy as seen in Tables III and IV.

4) Critically by incorporating the attention function leads to high performance even in the presence of limited training set, which the MRGCN without attention function is unable to replicate.

5) We also show seamless transfer without further need to fine-tune across various combinations of datasets for the train and test split and wherein each such combination has the train and test split from different dataset. Here again we show better transfer capability of the current model vis a vis prior work as shown in Table IV.

In short through qualitative and quantitative performance gain vis a vis previous approaches and through transfer learning across datasets studies the efficacy of the proposed framework is vindicated.

II. RELATED WORK

1) Vehicle Behaviour and Scene Understanding: The problem of Vehicle scene understanding has traditionally has been modeled either through a rule based approach [7] or leverage a probabilistic model [8], [9], [10], [11], [12], [13], [14] for classification of driver behaviour. [10], [13] are concerned with predicting the future behaviour rather than classification.

2) Graph based reasoning: Using graphs for Behaviour/Scene classification by learning over graphs is gaining traction in the computer vision community. [15] uses graphs for the task of situation recognition in an image.

Wang et al [16] encodes the object centric relations in the image space using a Graph Convolution Network [17] to learn object-centric policies for autonomous driving.

[3] takes advantage of evolving spatio temporal graph by feeding the spatio-temporal graph to an RNN, similar approach is used by [2]. Both [3] and [2] create model the scene as a graph and then predict behaviour based on this graph’s temporal evolution.

Temporal context is very important for understanding the scene. In view of this we break this into two steps, first predicting interaction graph based on evolution of their 3d positions over a time period and then infer over this Graph using a Multi relational graph convolution Network for classification of node behaviour. Wu et al [18] and Li et al [19] comes closest to our work. They predict an affinity graph which captures actor objects relations. Then a graph convolution network is used to reason over this learned affinity graph to classify ego car action. But they are only concerned with classifying the behaviour of the ego car in contrast to our approach which is concerned with classifying behaviour of all objects/vehicles present in the scene. To achieve this we need to have information about all objects present in the scene.

III. PROPOSED METHODOLOGY

Dynamic scene understanding requires well modeling of the different Spatio-temporal relations that may exist between different entities (active agents and passive objects) in a scene. Towards this goal, we propose a pipeline that first computes a time-based ordered set of spatial relations for each entity in the video scene. Secondly, it generates a multi-relational interaction graph that represents the temporal evolution of the spatial relations between entities obtained from the previous step. Finally, it leverages a graph-based behavior learning model to predict behaviors of vehicles in the scene. Fig 2 provides an overview of our proposed framework.

Our proposed pipeline leverages and improves the data modeling pipeline introduced in [2] (MRGCN-LSTM). The performance gains of our pipeline primarily stem from two of our contributions: (i) the interaction graph that provides useful and explicit temporal evolution information of spatial relations and (ii) the proposed Multi-Relational Graph Convolutional Network (MRGCN) with our novel multi-head relation attention function which we name Relational-Attentive-GCN (Rel-Att-GCN).
A. Spatial Graph Generation

For dynamic scene understanding, we need to identify different entities in the scene and determine the atomic spatial relationships between them at each time-step. This phase of the pipeline closely follows the spatial scene graph generation step of [2]. For more details, kindly refer to the same.

1) Object Detection and Tracking: Different vehicles in the video frames are detected and tracked through instance segmentation [20] and per-pixel optical flow [21] respectively. Apart from tracking vehicles in the scene, static objects such as textilane markings are also tracked with semantic segmentation [22] to better understand changing relations among static and non-static objects. [2] has shown that performance improvement can be obtained by leveraging a higher number of static objects in the scene.

2) Bird’s Eye View: The tracklets of entities obtained in the image space are re-oriented in the bird’s eye view (Top View) by projecting the image coordinates into 3D coordinates as described in [23]. This reorientation facilitates determining spatial relations between different entities. Each entity is assigned a reference point to account for the difference in heights. For lane markings, the reference is at the center, and for vehicles, it is the point adjacent to the road.

3) Spatial relations: At all $T$ frames of the video, the spatial relations between different entities are determined using their 3D positional information in the Bird’s eye view. Specifically, the spatial relations are the four quadrants, $\{\text{top left, top right, bottom left and bottom right}\}$. For a subject entity, $i$, its spatial relation with an object entity, $j$ at time-step, $t$ is denoted as $S_{i,j}^t$.

B. Temporal Interaction Graph Generation

While modeling entity interactions as a time-based ordered set of spatial graphs is a popular approach in many Spatio-temporal problems. We found that it is harder for models learned with such a data to learn some of the simple temporal-evolution behaviors needed for the end task, specifically in our problem of interest. In our problem of focus, behavior prediction, it is important for the model to learn the nature of some simple temporal evolution of interaction between entities such as $R_d = \{\text{move-forward, move-backward, moved left to right, moved right to left, no-change}\}$. However, we found that modeling such information explicitly was highly beneficial. A simple rule-based model with such interaction information outperformed learned models on the primitive information at the level.
of spatial relations. Having motivated with this insight, we propose a way to define an interaction graph with temporal evolution information, and we also provide a new model that can benefit from such information.

The interaction graph summarizes the temporal evolution of spatial relations from $T$ frames with a single multi-relational graph with temporal relations, $R_d = \{\text{move-forward, move-backward, moved left to the right, moved right to left, no-change}\}$. The edge, $E_{i,j}$, denotes the temporal relation between subject entity, $i$ and object entity, $j$. $E_{i,j}$ is computed by deterministic rule based pipeline, that takes in their spatial relations over $T$ frames, i.e. $\{S^1_{i,j}, S^2_{i,j}, ..., S^T_{i,j}\}$.

For example, an object entity, $j$ that is initially in the bottom-left quadrant with respect to subject entity $i$, changes it's atomic spatial relation to top-left with respect to $i$ at some time $t$, will have the temporal relation $E_{i,j}$ as move-forward. Similarly, an object entity, $j$ that is initially in bottom-left quadrant changes to bottom-right quadrant with respect to subject $i$ at some time $t$, will have temporal relation $E_{i,j}$ as moved left-to-right. Since these temporal relation annotated edges have a proper direction semantics, we can’t treat the graph is undirected. Thus, we also introduce inverse edges for complementary relations suchs as moved forward and backward and moved left-to-right and moved right-to-left. An overview of the temporal interaction graph generation is presented in Fig. 3.

C. Behavior Prediction Model

We propose a Multi-relational Graph Convolution Network (MRGCN) with a relation attention module that conditioned on the scene, automatically learns relevant information from different temporal relations necessary to predict vehicle behaviors.

1) Multi-Relational Graph Convolution Networks: Recently Graph convolution Networks [17] has become the popular choice to model graph-structured data. We model our task of maneuver prediction also by using a variant of Graph Convolutional Networks, Multi-Relational Graph Convolutional Networks (MRGCN) [24] originally proposed for knowledge graphs with multiple relation types. MRGCN is composed of multiple graph convolutional layers, one for each relation between nodes. A Graph Convolution operation for a relation $r$ here is a simple neighborhood-based information aggregation function. In the MRGCN, information obtained from convolving over different relations is combined by summation.

Let us formally define the temporal Interaction Graph as $G = (V, E)$ with vertex set $V$ and Edge set, $E$, where $E_{i,j} \in R_d$ is an edge between node $i$ and $j$. The $i^{th}$ node feature in relation $r$ obtained from a graph convolution over relation, $r$ in $l^{th}$ layer is defined as follows:

$$h^l_{i}[i] = \sum_{j \in N^r_{i}[i]} \frac{1}{c_{i,r}} W^l_{r} h^{l-1}[j]$$

where, $N^r_{i}$ denotes set of neighbour nodes for $v_i$ under relation $r$, $N^r_{i} = \{j \in V \mid e_{j,i} = r\}$ and $c_{i,r} = |N^r_{i}|$ is a normalization factor. Here $W^l_{r} \in R^{d*d}$ is the weights associated with relation $r$ in the $l^{th}$ layer of MR-GCN; $d',d$ are dimensions of $l-1$ th and $l$ th layers of MRGCN.

Neighborhood information aggregated from all the relations are then combined by a simple summation to obtain the node representation as follows:

$$h^l_{i} = ReLU(W^l_{d} h^{l-1}[i] + \sum_{r \in R_d} h^l_{i}[i])$$  

where the first terms correspond to the node information (self-loop) and $W_{d}$ is the weight associated with self-loop.

To account for the nature of the entity (static or non-static), we learn entity embeddings, $E_i \in \mathbb{R}^{(O_i*d)}$ for node $v_i$ where $O = \{\text{Vehicles, Lane Markings}\}$. The input to the first layer of the MRGCN $h^0[i]$ is the embedding $E_i$ based on nature of node $i$.

2) Relation-Attention MRGCN: The MRGCN defined in Eqn. 5 treats information from all the relations equally, and this might be a sub-optimal choice to learn discriminative features for certain classes. Motivated by this, here we propose a simple attention mechanism that scores the importance of the node information along with neighborhood information from each relation.

The attention scores, $\alpha$ are computed by concatenating the information from the node ($h^{l-1}$) and its relational neighbors ($h^l_r$) and transforming it with a linear layer to predicts scores for each component. The predicted scores are softmax normalized. The attention scores are computed as defined below.

$$\alpha^l[i] = softmax([h^{l-1}[i] \parallel h^1_{i}[i] \parallel h^2_{i}[i] ... \parallel h^l_{(R_d)}]W^l_{u})$$

where, $\parallel$ represents concatenation and $\alpha^l[i] \in \mathbb{R}^{1*|R_d+1|}$ with $W^l_{u}$ being the linear attention layer weights. These probabilities depict the importance a specific relation conditioned on that node and its neighborhood.

The attention scores are used to scale the node and neighbor information accordingly to obtain the node representation as follows.

$$h^l_{i} = ReLU(\alpha^l_{\text{node}}[i] + \sum_{r \in R_d} \alpha^l_{r}[i] h^l_{r}[i])$$

The node representation obtained at the last layer is used to predict labels and the model is trained by minimizing the cross-entropy loss.

IV. EXPERIMENT AND ANALYSIS

A. Dataset

Various datasets have been released in the interest of solving problems related to autonomous driving. We choose 4 datasets for evaluating our framework, of which 3 are publicly available Namely, Apollo-scapes [5], KITTI [25], Honda Driving Dataset [6] and our Indian dataset which is proprietary. These datasets provide hours of driving data with monocular image feed in various driving conditions.
We make a comparison of our framework between various models along with baselines tested on Apollo Scapes dataset. Columns 2 to 7 denote the classes we predict. Each row in first column denotes the method used. Columns for each method denote the class-wise accuracies in percentage.

### Table I

| Method Used | Moving away from us | Moving towards us | Parked | Lane change L-R | Lane change R-L | Overtake |
|-------------|---------------------|-------------------|--------|-----------------|-----------------|----------|
| St-RNN      | 76                  | 51                | 83     | 52              | 57              | 63       |
| MRGCN-LSTM  | 85                  | 89                | 94     | 84              | 86              | 72       |
| Rule Based  | 90                  | 99                | 98     | 81              | 87              | 90       |
| MRGCN       | 94                  | 95                | 94     | 97              | 93              | 86       |
| Rel-Att-GCN | 95                  | 99                | 98     | 97              | 96              | 89       |

### Table II

| Model          | Rel-Att-GCN                | Rule-Based         |
|----------------|---------------------------|--------------------|
|                | perf. measure             |                   |                    |
|                | precision | recall | F1 | precision | recall | F1 |
| MVA            | 0.97      | 0.95   | 0.96 | 0.97      | 0.91   | 0.94 |
| MTU            | 0.94      | 1      | 0.97 | 1         | 0.99   | 0.99 |
| PRK            | 1         | 0.98   | 0.99 | 1         | 0.99   | 0.99 |
| LCL            | 0.94      | 0.98   | 0.96 | 0.96      | 0.81   | 0.88 |
| LCR            | 0.97      | 0.98   | 0.97 | 0.97      | 0.88   | 0.92 |
| OVT            | 0.72      | 0.88   | 0.79 | 0.36      | 0.90   | 0.52 |
| micro avg      | 0.97      | 0.97   | 0.97 | 0.95      | 0.95   | 0.95 |
| macro avg      | 0.92      | 0.96   | 0.94 | 0.88      | 0.91   | 0.87 |

### Table III

| Train Ratio | 0.05 | 0.1  | 0.2  |
|-------------|------|------|------|
| Method      | MRGCN| Rel-Att-GCN | MRGCN| Rel-Att-GCN | MRGCN| Rel-Att-GCN |
| MVA         | 61   | 94   | 91   | 95   | 89   | 97   |
| MTU         | 47   | 99   | 75   | 99   | 85   | 99   |
| PRK         | 90   | 98   | 86   | 98   | 86   | 98   |
| LCL         | 36   | 98   | 69   | 98   | 89   | 98   |
| LCR         | 54   | 94   | 73   | 95   | 88   | 96   |
| OVT         | 50   | 60   | 58   | 65   | 76   | 77   |

1) Apollo Dataset: We choose Apollo-scapes as our primary dataset as it contains large number of driving scenarios that are of our interest. It includes vehicles depicting overtake and lane-change behaviours. The dataset consists of images feed collected from urban areas and contains various objects such as Cars, Buses etc. We generate a total of 4K frames consisting of multiple behaviours.

2) KITTI Dataset: It consists of images collected majorly from highways and wide open roads unlike Apollo-scapes. We select a total of 700 frames from Tracking Sequences 4, 5 and 10 for our purpose.

3) Honda Driving Dataset: Honda driving dataset consists of multiple datasets in itself. From among them, we choose the H3D dataset for our purpouse due to it’s variety in classes like lane changes. H3d comprises driving in urban city conditions where lane changes are prominent. We do not consider overtake here due to fewer occurrences in the dataset. It consists of a total of 1.5K frames.

4) Indian Dataset: Although above mentioned datasets are widely used, and have wide variation in all aspects, they lack non-standard objects on road such as objects such as trucks, vans etc which are present in Indian driving conditions. We collected a total 600 frames that consists of various type of vehicles.

All datasets are annotated manually and labels are assigned to the particular dataset. We show that our model is scalable and independent of the nature of object by showing quantitative and qualitative results on all the above datasets in section [IV-B].

B. Experimentation details

Each Interaction graph is independently generated for T = 10 time steps. The MRGCN used is identical in both models MRGCN and Rel-Att-GCN. In case of MRGCN, graphs are processed in a similar fashion except that the attention is skipped. Note that the input and output dimensions of attention are equal. We empirically found that using 3 layers of MRGCN with dimensions 64, 32 and 6 (number of classes) respectively works best for our task.

In case of Rel-Att-GCN, simple attention is applied over output of MRGCN for each node individually with 2 heads. Outputs of the heads are concatenated across relations and projected back to output dimension of the MRGCN layer with a linear transformation. We find adding skip connection from every layer l to l + 2 th layer is beneficial. We also observe time of prediction for three models, MRGCN-LSTM, MRGCN and Rel-Att-GCN to be 0.02, 0.03 and 0.04 seconds respectively averaged over 1K graphs. While comparing time of prediction, MRGCN and Rel-Att-GCN include time for creating interaction graph and prediction.
we observe that our method outperforms the traditional temporal based approach by a significant margin, the gap is even more prominent when comparing the complex classes such as lane changing and overtaking, where we observe an average difference of 40% and 26% respectively.

2) Rule Based Baseline: To showcase the effectiveness of an information rich interaction graph over traditional Spatio-temporal modelling with set of spatial graphs, we propose a rule based approach to infer over interaction graph as one of our baselines. We use Interaction Graphs generated by our pipeline and employ an expert set of rules carefully framed to classify between behaviors. The deterministic classification is a simple max function over different relations a vehicle is associated with. We formulate the rule based approach as a two step process. We first predict nodes into only {moving away, moving towards us, lane changes and stationery}, then in a second iteration tackle overtake by differentiating between dynamic behaviour {moving away, moving towards us, and lane changes} and overtaking. All details baselines are available on our project web page: [https://github.com/ma8sa/Understanding-Dynamic-Scenes-using-MR-GCN.git].

C. Baseline Comparisons

In Table I we compare our best models with Spatio-temporal approaches as well as the hard rule based method on interaction graph. Table I shows the evaluation on all five classes in Apollo dataset.

1) Spatio-Temporal approaches: To depict the importance of encoding spatial information as an interaction graph, we compare our model with Structural-RNN [3] and MRCGCN-LSTM [2] that processes a time based ordered set of spatial graphs. Structural-RNN (St-RNN) encodes the spatial representation for each frame in a graph and then reasons over the temporal evolution of these graphs by feeding it to a Recurrent Neural Network. We adapt St-RNN’s pipeline to our problem by replacing humans and objects in their model with vehicles and stationary landmarks, respectively. A similar methodology is employed by [2].

We show a quantitative comparison with all our model variations in Table II. In Table II, we observe that our method using the model. In case of the MRCGCN-LSTM model, it includes only prediction as it is a temporal method and consumes graphs at each time step $t$. All the training and testing is done on a single Nvidia GeForce Gtx 1080 gpu.

Further details about the implementation, training and testing are available on our project web page [https://github.com/ma8sa/Understanding-Dynamic-Scenes-using-MR-GCN.git].

TABLE IV

| Trained on |   | Honda | Apollo | KITTI | Indian |
|------------|---|-------|--------|-------|--------|
| Method     |   | MRCGCN LSTM | MRCGCN | Rel-Att GCN | MRCGCN LSTM | MRCGCN | Rel-Att GCN | MRCGCN LSTM | MRCGCN | Rel-Att GCN |
| Moving away from us | 55 | 92 | 92 | 99 | 99 | 99 | 99 | 99 | 99 |
| Moving towards us | 79 | 60 | 92 | 98 | 98 | 98 | 93 | 94 | 97 |
| Parked | 91 | 65 | 99 | 99 | 98 | 99 | 95 | 99 |
| Lane-Change(L) | 65 | 73 | 94 | - | - | - | - | - | - |
| Lane-Change(R) | 87 | 83 | 92 | - | - | - | - | - | - |

TABLE V

| Trained and Tested on | Apollo | Honda | KITTI | Indian |
|-----------------------|--------|-------|-------|--------|
| Method                | MRCGCN LSTM | MRCGCN | Rel-Att GCN | MRCGCN LSTM | MRCGCN | Rel-Att GCN | MRCGCN LSTM | MRCGCN | Rel-Att GCN |
| Moving away from us | 85 | 94 | 95 | 83 | 97 | 99 | 85 | 92 | 98 |
| Moving towards us | 89 | 95 | 99 | 79 | 86 | 90 | 86 | 91 | 98 |
| Parked | 94 | 94 | 98 | 85 | 88 | 99 | 89 | 95 | 99 |
| Lane-Change(L) | 84 | 97 | 97 | 75 | 91 | 91 | - | - | - |
| Lane-Change(R) | 86 | 93 | 96 | 60 | 81 | 85 | - | - | - |
| Overtake | 72 | 86 | 89 | - | - | - | - | - | - |

We provide results of transfer learning on all datasets. We train on Apollo Scapes dataset and test onHonda, KITTI and Indian datasets. The second row denotes the datasets and third row denotes the method used. Accuracies of each class are depicted from 4th row onwards. All three pre-trained models, MRCGCN-LSTM, MRCGCN and REL-ATT-GCN are tested on all three datasets and all accuracies reported are in percentages.

We provide accuracies for different models trained and tested on multiple datasets. The top row denotes the dataset used for training and testing on the same with a validation split. The second row denotes the method used. 3 Columns under each dataset denote the class wise accuracies for all the three models. MRCGCN-LSTM, MRCGCN, REL-ATT-GCN on that dataset. All the accuracies are in percentage.
over MRGCN and St-RNN respectively.

Though the rule-based model performs well in comparison to the spatio-temporal approaches, it falls short against the learning based models trained on the interaction graph. The rule-based model is not powerful enough especially on lane-change classes. This clearly explains the need of a learnable model to learn complicated patterns.

On a closer look in Table IV it is clear that Rule based methods are not consistently better on precision and recall metrics across classes, especially in Overtake and lane-change classes. The proposed Rel-Att-GCN clear outperforms the rule-based model on aggregate Micro and Macro average scores.

D. Relation-Attention MRGCN (Rel-Att-MRGCN)

Attention takes into account the fact that different relations have different relevancy for predicting different classes. Such importance of the relational-attention in classifying the vehicle behaviors is visualized by analyzing normalized attention scores across relations for each class. This is depicted in the Fig. 4 where rows denote classes and columns denote the temporal interactions. Higher values in each row (class) denotes higher importance given by the attention function to that relation to predict that class. The attention map clearly shows how classes such as overtake and lane changes depend on moving forward and moved left to right or right to left respectively. Despite how both MVA and OVT classes have high probability mass on move-forward relation, they are the ability to distinguish themselves based on the attention score spread over the other relations.

Such reasoning helps the network to learn effectively under label scarcity, too as given in Table III. Herein, we report results for models trained with 5%, 10% and 20% of training data. Rel-Att-GCN is able to show fidelity even when only 5% percent of data present in contrast to a normal MR-GCN, which finds it difficult to learn from the smaller dataset. A similar trend is observed even as we increase the size of training data to 10% and 20% of the actual dataset. In Table V where the model is learned with 70% data, we observe that Rel-Att-GCN achieves superior performance across all datasets when compared with normal MR-GCN as well as temporal based methods.

E. Transfer Learning

To showcase the generality of our proposed pipeline we trained the model only on Apollo dataset and tested it on validation sets of Honda Driving Dataset, KITTI, and Indian datasets. At the testing phase, we removed the classes which were not present in corresponding datasets. As the proposed pipeline does not rely upon any visually learned features, we are able to achieve fidelity across all datasets; this can be seen in Table V. Evaluation results for the model trained and tested on validation sets of the same dataset can be found in Table V. From a comparison between Table V and Table IV that the transfer learning model though not better than models that are trained and tested on the same dataset, is on par with them. Especially, in the case of Honda dataset, the Rel-Att-MRGCN performs better in transfer for all classes than the model trained and tested on Honda. We attribute this behavior to high variation present in the Apollo dataset, which the other datasets lack.

F. Qualitative

Fig. 5 and 6 show the qualitative results. We follow a consistent convention for color-coding to depict behaviours. Red depicts vehicles Moving forward, Blue denotes Parked ones and Green for Moving towards Us. Yellow and Orange depict Lane Change left to right and Lane Change right to left respectively while Magenta corresponds to overtaking vehicles. Fig. 5(a), (b) shows instances of Vehicles moving ahead and Moving backwards on the Kitti dataset. In Fig. 5(c) and (d), we showcase results on our Indian Dataset, in (c), we see a bus and truck parked and in (d) we see Lane change behavior depicted by the car on the right. In Fig. 6(a) we see a car changing lane and in Fig. 6(b) we observe a car correctly classified as overtaking. Fig. 6(c) and (d) show fidelity of our pipeline in traffic scenarios. In Fig. 6(c) we observe a car changing lane and merging into the road on the right and two cars coming towards us, in (d) we see a car changing a lane (on the right), a car parked on the left and two pickup trucks moving away from us.

To summarize, the qualitative result validates the proposed model’s generalizability across datasets even in the presence of new vehicles such as trucks and cars. We also showcase accurate classification of all behaviors through these results.

V. CONCLUSIONS

This paper proposed a novel pipeline for on-road vehicle behavior understanding and classification. It decomposed an evolving dynamic scene into a Multi-Relational Graph (MRG) whose nodes are the agents/actors in the scene, and edges are Spatio-temporal encodings that signify spatial behaviors exhibited by the agents to form the edge. The MRG was further acted upon by a Muti Relational Graph Convolution Network (MRGCN) to learn and classify the overall behavior exhibited by the vehicle. The key takeaway is this two-stage classification shows much-improved performance over end to end learning frameworks. The improved performance is attributed to edge encodings of MRG being an accurate intermediate representation of spatial behaviors between agents that are difficult to characterize in an end to end learning framework. The MRGCN is integrated with an attention layer that further improves the performance, often nearing complete accuracy. Significant performance gain on a variety of datasets that are consistent across several metrics confirms the efficacy of the proposed framework. Seamless data transfer across datasets further showcases its reliability. Future directions include integrating the proposed framework with a behavior planner.

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Fig. 5. Figure depicts accurate behaviour classification of standard and non-standard vehicles. While (a), (b) show cases from KITTI dataset with standard vehicles, predictions on Petrol Tanker, Bus in (c) show object class agnosticism and (d) denotes complex behaviours like lane changes.

Fig. 6. Figure shows multiple scenarios depicting various behaviours such as overtaking and lane changing. (a), (b) are samples from Apollo scapes dataset while (c) and (d) are from Honda dataset. In (a), (c) and (d) we observe the model accurately classifying lane change, both left to right and right to left. (b) depicts the case of overtaking with the car in magenta overtaking the car moving forward in red.

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