Scene Gated Social Graph: Pedestrian Trajectory Prediction Based on Dynamic Social Graphs and Scene Constraints

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Abstract

Pedestrian trajectory prediction is valuable for understanding human motion behaviors and it is challenging because of the social influence from other pedestrians, the scene constraints and the multimodal possibilities of predicted trajectories. Most existing methods only focus on two of the above three key elements. In order to jointly consider all these elements, we propose a novel trajectory prediction method named Scene Gated Social Graph (SGSG). In the proposed SGSG, dynamic graphs are used to describe the social relationship among pedestrians. The social and scene influences are taken into account through the scene gated social graph features which combine the encoded social graph features and semantic scene features. In addition, a VAE module is incorporated to learn the scene gated social feature and sample latent variables for generating multiple trajectories that are socially and environmentally acceptable. We compare our SGSG against twenty state-of-the-art pedestrian trajectory prediction methods and the results show that the proposed method achieves superior performance on two widely used trajectory prediction benchmarks.

1. Introduction

The forecasting of pedestrian trajectories is essential for numerous applications ranging from autonomous robots for delivery and driverless vehicles for collision avoidance to crowd management from a security aspect. From the pioneering Social Force Model based approaches [17] [35] [54] to data-driven Long Short Term Memory (LSTM) based methods [1] [49] [27] [13] [5] [50] [15] [16] [45] [48] [6] [28] [52] [20] [36] [53] [44] or Convolutional Neural Network (CNN) based methods [55] [34] [12] [31], many models have been designed for the prediction of pedestrians trajectories. However, it is still a challenging task because of three key elements that need to be addressed in trajectory prediction:

(i) Social Influence. One of the most significant current discussions in pedestrian trajectory prediction is person-person interaction, also known as social influence. When people move in public areas, they exhibit different social behaviors: keeping the same pace when they walk in a group, turning slightly to avoid collision with incoming pedestrians, etc. Such person-person interaction plays a major role in the pedestrians’ trajectories in a scene.

(ii) Multimodal Nature of Trajectory Prediction. There are several plausible future paths for a pedestrian to move around in a scene. For example, a person can choose to turn right or turn left to bypass an obstacle.

(iii) Scene Constraints. The physical environment surrounding pedestrians is another key element that should not be ignored. There are static obstacles and building structure that constrain the trajectories of pedestrians. So trajectory prediction methods that consider only social influence may end up generating trajectories that are not environmentally acceptable.

The importance of these three key elements is not unrecognized in the literature. Indeed, many existing studies have given very thorough treatment to social influence in pedestrian trajectory prediction. The social LSTM model [1] is one of the early papers that uses a neighborhood region around each person of interest (POI) to capture social influence information. Other methods such as [47] [45] use complete graphs to model social influence. While these papers and other related studies [61] [13] [16] [58] [52] analyze social influence in depth, they have not integrated scene constraints and multimodal predictions into their models.

For the scene constraint element, several existing studies such as [51] [46] [30] have incorporated it as well as the social influence into their work. For example, a hierarchical LSTM network called SS-LSTM [51] that integrates scene context extracted by a CNN and social influence has been used in trajectory prediction. In addition to the social pooling for capturing social influence, a semantic pooling based on pre-defined pixel-level semantic maps has been designed to capture scene influence [30]. However, these methods have not been designed to capture the multimodal nature of pedestrian trajectories.
In the trajectory prediction task, multimodality is commonly tackled by designing a suitable latent variable $z$ through which random samples are drawn, often from the normal distribution $\mathcal{N}(0, 1)$. Representative work includes the Social GAN [15] which extends the Social LSTM model [11] by adding multimodal predictions and the STGAT method [19] which uses the $\mathcal{N}(0, 1)$ sampling with their spatial-temporal graph attention network. Instead of the normal distribution, the mean $\mu$ and standard deviation $\sigma$ of an appropriate dimension have also been learned for the latent variable $z$. Typical examples that use the $\mathcal{N}(\mu, \text{diag}^2(\sigma^2))$ distribution for multimodality include the IDL [28] and Trajectron [20]. While the above methods handle multimodal predictions, they have not included both social influence and scene constraints.

There are only a few existing pedestrian trajectory predictors that consider all the three elements. DESIRE [24] adopts a conditional variational auto-encoder (CVAE) and an RNN to learn $\mu$ and $\sigma$ for the latent variable. It has a scene context fusion module to capture scene features and social interactions of pedestrians. SoPhie [38], on the other hand, uses a VGGNet-19 [42] and two attention modules to encode the scene and social influences. For multimodal predictions, it adopts a GAN based model. Based on BicycleGAN [60], Social-BiGAT [22] develops a bijection between the output trajectories and the latent space input to the trajectory generator. It utilizes a graph attention network and VGG to encode social and scene influences.

To tackle all the three key elements described above, we propose a novel architecture which we call SGSG (Scene Gated Social Graph). Our SGSG differs, in two respects, from the aforementioned pedestrian trajectory predictors that also implement all the three elements. First, although both DESIRE [24] and our method use VAE to generate multiple trajectories, they are different in the way scene and social influences are incorporated. DESIRE [24] uses the encoded hidden states of the POI’s own trajectory as input to the VAE, so $\mu$ and $\sigma$ are learned from the POI only, whereas SGSG directly passes social graph and scene features to the VAE, so the learned $\mu$ and $\sigma$ capture these influences. As a result, DESIRE [24] requires an extra refinement stage to incorporate social and scene influences. Our proposed way of learning $\mu$ and $\sigma$ also differs from Social-BiGAT [22] in that their estimates of these parameters do not include scene context information. Second, for the social influence element, we propose to use dynamic star graphs to encode other pedestrians for each POI. In contrast to existing studies [47][35][19][33] which commonly use the complete graph structure, our star graph structure is memory efficient. Our social encoder using dynamic star graphs also has an advantage over SoPhie [38] in that it does not impose a limit to the maximum number of pedestrians in the scene.

In summary, the contributions of this paper are: (i) We propose a novel scene gated social feature to incorporate scene and social cues to trajectory prediction. Through our ablation studies which evaluate the proposed gating operation against other feature merging methods, such as concatenation and addition, the superiority of our method is validated. (ii) We design a dynamic star graph data structure to model the social graph features around pedestrians. Our experimental evaluation demonstrates that these star graphs are not only memory efficient but also effective in producing state-of-the-art prediction results. (iii) Through exhaustive experiments, we show that SGSG achieves state-of-the-art performances in predicting both single and multimodal future trajectories.

2. Related Work

Many methods in the literature of pedestrian trajectory prediction focus on forecasting trajectories that can better cope with the effect of social influence [54][11][58][58][20] (person-person interactions), surrounding physical environment [4][49][32][37][36] (person-scene interaction), or both types of interactions [24][51][29][38]. With the generative models such as the Generative Adversarial Network (GAN) [14] demonstrating their successes in other applications [56][10][23], a few methods [15][38][28][23][19] start to incorporate multimodality into trajectory prediction.

Person-Person Interaction A classical paper that models person-person interaction is the Social Force Model (SFM) [17] which uses the attractive and repulsive forces to capture the social influence among pedestrians. Following the SFM, Pellegrini et al. [35] propose the Linear Trajectory Avoidance (LTA) algorithm to minimize collisions among pedestrians and to also improve pedestrian tracking: Yamaguchi et al. [54], on the other hand, include more behavior factors such as damping and collision to model social interactions. In addition to the Social LSTM described in the previous section, the Social Attention method [47] and the Attention LSTM method [13] take advantages of the attention mechanism and imposed different degrees of attention to different neighbors in the trajectory prediction network. While the MX-LSTM method [16] takes the head pose information into account during trajectory forecasting, SR-LSTM [58] uses a social-aware information selection mechanism for message passing between neighboring pedestrians. Another recent method involves using a social pyramid [52] to differentiate the influences from pedestrians in nearby neighborhoods and those in remote areas. All the methods above do not model scene influence and can not generate multiple trajectory predictions.

Person-Scene Interaction Pedestrians interact with the scene by avoiding static objects lying along their walking paths. Bartoli et al. [4] model the influence of static objects in the scene in their trajectory prediction method through a context-aware pooling strategy. Syed and Mor-
ris replace the scene context part of SS-LSTM by the semantic segmentation architecture from SegNet. Rather than dealing with the whole scene uniformly, the CAR-Net model of Sadeghian et al. uses raw scene images and targets at specific areas when predicting trajectories. RSBG extracts scene features of a POI through a sequence of image patches that contain the POI. To retrieve detailed spatial information of the scene, the Scene-LSTM method divides the scene into small grid-cells which are further divided into sub-grids. Based on the relation reasoning network, Choi and Dariush propose to use a gated relation encoder to discover both person-person interaction and person-scene interaction relations. Liang et al. use a person behavior module and a person interaction module in their LSTM network to capture information on pedestrians’ behaviors and their interaction with the surroundings. While most of the methods reviewed above also incorporate person-person interaction, they simply concatenate scene features and social features together. This is different from our SGSG method where dynamic social graphs are constructed for each POI and then combined with the scene features through a ‘gating’ operation (details in Section 3.3) for the downstream operation.

**Multimodality** Based on the GAN architecture, Gupta et al. propose the Social GAN model (abbreviated as SGAN) for generating multiple trajectory predictions. It uses a pooling module to expand the neighborhood around each POI to the whole scene so that all the pedestrians are covered. Similar to the SGAN, Social Ways, CGNS, MATF, IDL, and Sun et al. also take advantage of the GAN to generate trajectories. SoPhie, proposed by Sadeghian et al., is another GAN based trajectory prediction model. As described in Section 1 SoPhie incorporates social and scene influences and can handle multimodality. Following SoPhie, Social-BiGAT makes use of the BicycleGAN to produce multiple predictions for each observed trajectory. Instead of using GAN, Zhang et al. propose to use a temporal stochastic method to sequentially learn a prior model of uncertainty during prediction. The STGAT method of Huang et al., on the other hand, produces multiple predicted trajectories by randomly sampling a latent variable $z$ from $N(0,1)$. IDL takes it further by learning $\mu$ and $\sigma$ from the motion features constructed from pedestrians’ trajectories.

### 3. Proposed Method

#### 3.1. Problem Formulation and System Overview

In pedestrian trajectory prediction, we assume that the locations of each pedestrian are acquired through a person detection and tracking system in advance. The 2D coordinate $(x_i^t, y_i^t) \in \mathbb{R}^2$ stands for the location of the $i$th POI at time $t$. Depending on the data, coordinates can be in meters (world coordinates) or in pixels (image coordinates). At the time step $t_{obs}$, the history locations of each POI from $t = 1$ to $t = T_{obs}$ are observed. The goal of pedestrian trajectory prediction is to forecast the future locations of the POI from $t = T_{obs} + 1$ to $t = T_{obs} + T_{pred}$. To avoid confusion, in the rest of this paper, $t = 1, \cdots, T_{obs}$ and $t = T_{obs} + 1, \cdots, T_{obs} + T_{pred}$ are referred as the observation period and the prediction period. We denote the $j$th observed trajectory by $X_{i}^{j, obs} = [(x_1^j, y_1^j), \cdots, (x_{T_{obs}}^j, y_{T_{obs}}^j)]$, the ground truth trajectory by $X_{i}^{j, obs} = [(\hat{x}_1^j, \hat{y}_1^j), \cdots, (\hat{x}_{T_{obs}+T_{pred}}^j, \hat{y}_{T_{obs}+T_{pred}}^j)]$, and the predicted trajectory by $\hat{X}_{i}^{j, pred} = [(\hat{x}_{T_{obs}+1}^j, \hat{y}_{T_{obs}+1}^j), \cdots, (\hat{x}_{T_{obs}+T_{pred}}^j, \hat{y}_{T_{obs}+T_{pred}}^j)]$.

Our SGSG model (Fig. 1) consists of: (i) a social graph encoder designed to extract social graph features (Section 3.2); (ii) a scene encoder module to extract scene features to tackle the scene constraints (Section 3.3); (iii) a VAE module to learn the latent variable $z$ and reconstruct the scene gated social graph features (Section 3.4); (iv) a trajectory encoder-decoder architecture for encoding each POI’s own history trajectory and generating future trajectories (Section 3.4).

#### 3.2. Social Graph Encoder

The Graph Neural Network was introduced in and can be defined as an ordered pair $G = (V, E)$, where $V$ and $E$ are the sets of nodes and edges that link the nodes. For the trajectory prediction task, it is natural to consider the pedestrians in a scene as nodes of the graph at each time step. In this paper we model pedestrians as the only dynamic entities in the scene. For more complicated scenarios where the location coordinates of other moving objects, such as vehicles, are also available, they can be included in the model. More specifically, we use a dynamic graph $G^t = (V^t, E^t)$ to describe the social influence of the $i$th POI at time $t$. The set of nodes $V_i^t$ consists of the POI and a set of all other pedestrians, denoted by $N_i^t$ in the scene at the same time $t$. An edge is then assigned between the $i$th POI and each neighbor $j$, for $j \in N_i^t$, to form $E_i^t$. As the number of neighbours for each POI at each time instant is variable, the social graph does not have a fixed architecture. This constructed star graph is different from the complete graph used in STGAT (see Fig. 2). With fewer edges, our star graph is shown to be more efficient computationally yet equally effective for modeling the social interaction of the POI with other pedestrians.

A graph convolutional network (GCN in Fig. 1) is applied to encode each constructed social graph $G_i^t$. Mathematically, the graph convolutional operation can be described as follows. The initial embedding social graph feature $a_i^{l, 0}$ at layer 0 can be set to the location coordinates of the POI, i.e., $a_i^{l, 0} = (x_i^l, y_i^l)$. Given $a_i^{l, l}$ at layer $l$, the
Figure 1. The architecture of SGSG. Two LSTM based encoders are used to encode social graphs and the POI’s own history trajectory separately. The scene image is processed through the scene encoder module. SGSG also includes a VAE to sample the latent variable \( z \) which is used to reconstruct the scene gated social graph feature for multimodal trajectory prediction through the trajectory decoder. To simplify the visualization, the embedding vectors \( e_t \) for all \( t \) are not shown.

Figure 2. Two types of pedestrian graphs: complete graph (left) and star graph (right). The star graph is used in the proposed social graph encoder as it focuses on the influence from other pedestrians (gray) to the POI (red).

The embedding feature at layer \( l + 1 \) is defined as
\[
a^{t}_{i,l+1} = \text{ReLU} \left( b^t + \frac{1}{|\mathcal{N}^t(i)|} \sum_{j \in \mathcal{N}^t(i)} W^t a^t_{i,j,l} \right),
\]
where \( W^t \) and \( b^t \) are the trainable weight matrix and bias term in the \( l \)th graph convolutional layer.

To further capture the temporal social information during the observation period, our SGSG network uses an LSTM layer, denoted by \( \text{LSTM}_{SG}(\cdot) \) in Eq. (2) below, to encode the embedding social graph features \( a^t_i \) (the subscript \( l \) has been dropped to simplify the explanation) across the time steps of the observation period:
\[
g^t_i = \text{LSTM}_{SG}(g^{t-1}_i, a^t_i; W_{SG}).
\]
Here, \( W_{SG} \) represents the trainable parameters in this LSTM layer.

3.3. Scene Encoder

The scene encoder of SGSG takes a scene image \( I^{T_{obs}}_t \) as input and passes it through a CNN to yield the visual feature \( s^{T_{obs}}_t \):
\[
s^{T_{obs}}_t = \text{CNN}(I^{T_{obs}}_t; W_{CNN}).
\]

Unlike SoPhie [38] and Social-BiGAT [22] that used a VGG [42] as the CNN feature extractor to extract scene features, we use the encoder module of the semantic segmentation architecture DeepLabv3+ [11] to extract semantic features. The encoded semantic features are then passed through a convolutional layer and a single fully connected layer to form the scene features \( s^{T_{obs}}_i \), \( \forall i \). The encoder module of DeepLabv3+ used in our scene encoder is initialized with the weight matrix that has been pre-trained on Cityscapes [11]. Our scene encoder (the yellow box in Fig. 1) is then trained together with other parts of SGSG.

For each POI, only the frame at \( t = T_{obs} \) is used to extract the semantic scene feature \( s^{T_{obs}}_i \). This is due to the following two observations: (i) The scene at \( t = T_{obs} \) is more important and contains more up-to-date scene information than the history frames where \( t < T_{obs} \); (ii) Since pedestrians (the only dynamic objects currently modeled by SGSG) are already handled by the Social Graph Encoder and since static objects in the scene, like trash bins, water fountains, etc, have fixed location coordinates for all \( t \), it is not necessary to pass all video frames to the scene encoder. In terms of training SGSG to learn the scene constraints, as different pedestrians’ trajectories cover different periods of timestamps in the video, there are sufficient scene images passed to the scene encoder for training (around 63% of annotated video frames in the experiments are used in the training phase).

The social graph features and scene features capture the dynamic and static aspects of the scene. To combine these features for the downstream operation of SGSG, we propose to use a scene gated social graph feature \( G^{T_{obs}}_t \) defined as:
\[
G^{T_{obs}}_t = \text{sigmoid}(s^{T_{obs}}_i) \otimes G^{T_{obs}}_t,
\]
where the \( \otimes \) represents element-wise product. The sigmoid function applied to the scene feature \( s^{T_{obs}}_i \) non-linearly scales it to the range \((0,1)\) and has the effect as a gate on
the encoded temporal social graph features \( g_{i}^{T_{obs}} \). Motivated by the gating mechanism inside the LSTM architecture, this gating process is designed to use the scene features to control the passing or rejection of social graph features.

### 3.4. Multimodal Predictions

Before making predictions about the future routes, we need the knowledge about the past movement information of the POI. To this end, a trajectory encoder LSTM is used to encode the POI’s own history trajectory in the observation period through:

\[
e_{i} = \phi(x_{i}^{l}, y_{i}^{l}; \mathbf{W}_{\text{emb}}) ,
\]

\[
h_{i}^{r} = \text{LSTM}_{\text{enc}}(h_{i}^{r-1}, e_{i}; \mathbf{W}_{\text{enc}}),
\]

where \( \phi(\cdot) \) is an embedding layer, \( \text{LSTM}_{\text{enc}} \) is the LSTM layer in the trajectory encoder, and \( \mathbf{W}_{\text{emb}} \) and \( \mathbf{W}_{\text{enc}} \) are the associated weight matrices.

To achieve multimodal predictions, we use a VAE as the generative network in the proposed SGS to sample the acceptable trajectories. To be more specific, given one sample \( z_{i} \), both \( h_{i}^{T_{obs}} \) and \( G_{i}^{T_{obs}} \) are 32-dimensional also. For the VAE module, \( \mu_{i}, \gamma_{i} \), and the latent vector \( z_{i} \), for all \( i \), are \( \mathbb{R}^{8} \) vectors.

We use the Adam optimizer by minimizing the loss \( L_{i} \) given below for each \( i \)th POI:

\[
L_{i} = \| X_{i}^{t} - X_{i}^{\text{pred}} \|^{2}_{2} + D_{\text{KL}}(Q(z_{i} | G_{i}^{T_{obs}}) || P(z_{i})) ,
\]

where the \( L_{2} \) loss in the first term represents the trajectory prediction loss and the second term is the regularization loss which measures the Kullback-Leibler divergence (KLD) of the distribution \( Q \) given in Eq. (9) and the prior distribution \( P(z_{i}) := \mathcal{N}(0, I) \). Similar to [24, 28], we adopt the reparameterization trick [21] in our experiments. The learning rate and batch size are 0.001 and 128.

### 4. Experiments

#### 4.1. Datasets, Metrics, and Preprocessing

**Datasets.** As we focus on the prediction of pedestrian trajectories in this paper, we evaluate our method using the two public ETH [35] and UCY [25] datasets that are widely adopted in the literature. There are 5 scenes, commonly referred to as ETH, HOTEL, UNIV, ZARA1 and ZARA2, with a total of 1535 different trajectories. The location coordinates of these trajectories are labeled in meters. Following the previous work of others [1, 15, 38, 58, 19], the leave-one-out experiment approach is used, i.e., 4 scenes are used for training and the remaining scene for testing. The observation period and prediction period are 3.2 seconds \( (T_{obs} = 8 \text{ frames}) \) and 4.8 seconds \( (T_{pred} = 12 \text{ frames}) \).

**Metrics.** Similar to the previous work [1, 15, 16, 50], we use two metrics: the average displacement error (ADE) [35] and the final displacement error (FDE) [1] to quantitatively evaluate the trajectory prediction performance of each method. Smaller values of these metrics indicate better performance.
Trajectory Preprocessing and Augmentation. We normalized all the trajectories so that their location coordinates are in the range $[-1, 1]$. After prediction, the inverse normalization is applied to yield the ADE and FDE values back in meters. Similar to [38, 58], we also performed data augmentation. Specifically, we applied the following operations: (i) a sliding time window of stride 1 is used to convert long trajectories into multiple trajectories of length $T_{\text{obs}} + T_{\text{pred}}$. (ii) extra trajectories are generated by rotating all the trajectories and the corresponding video images by 90°.

4.2. Comparison with Existing Methods

We compare the performance of SGSG against 20 existing methods listed below: Social-LSTM [1], CVAE [57], SGAN [15], MX-LSTM [16], Nikhil and Morris [34], Liang et al. [29], SoPhie [38], MATF [59], Social Ways [2], IDL [28], Zhang et al. [57], SAGCN [45], SR-LSTM [58], STGAT [19], Social-BiGAT [22], Trajectron [20], Sun et al. [43], PMP-NMMP [18], Social-STGCNN [33], and RSBG [44]. For the SR-LSTM, two configurations are reported in [38]: SR-LSTM_1 with a 2 meters neighborhood size, and SR-LSTM_2 with a 10 meters neighborhood size. For the MX-LSTM, only evaluation results on the UCY dataset are given in [16]. As the results of DESIRE [24] on the ETH and UCY datasets are not reported in the authors’ paper, we include only the results of CVAE (reported in [57]) in Table 1. It should be noted that, although CVAE was introduced and used to generate multimodal trajectories in DESIRE [24], the implementation in [57] does not include the refinement module of DESIRE.

Table 1 shows the ADEs and FDEs in meters of these pedestrian trajectory prediction methods. We separate these methods and their variants based on whether they generate only one prediction (upper half of the table, # = 1) or multiple predictions (bottom half, # = 20 or # = 100) per observed trajectory. The "#" column indicates how many predictions are generated for each input observed trajectory. As shown in the table, SGSG is able to achieve comparable results with the state-of-the-art methods for the single prediction scenario. Both SGSG and SR-LSTM_2 attain the smallest average ADE of 0.45m. Moreover, SGSG takes the lead for the FDE metric at 0.92m.

When 20 predicted trajectories are generated (the lower half of Table 1), we observe that our SGSG also achieves the second smallest FDE of 0.82m and the smallest average ADE of 0.40m (the latter is on par with IDL). Top performers in the lower half of the table include Social Ways, IDL, MATF GAN, Social-STGCNN, and our SGSG, each of which achieves the smallest ADE/FDE for one or more
Table 2. The ADE / FDE values in meters of the variants of SGSG. The top-performing single prediction and multimodal prediction variants for each scene and on average are marked in boldface.

| Variant | Modules | Merge | #   | Scenes of the ETH & UCY datasets |
|---------|---------|-------|-----|----------------------------------|
|         | SG      | VAE   | Scene | ETH | HOTEL | UNIV | ZARA1 | ZARA2 | Average |
| SGSG-v1 | ✓       |       | ✓    | 1   | 0.67 / 1.29 | 0.35 / 0.65 | 0.67 / 1.36 | 0.43 / 0.90 | 0.38 / 0.77 | 0.50 / 0.99 |
| SGSG-v2 |       | ✓     | ✓    | 1   | 0.76 / 1.58 | 0.40 / 0.75 | 0.73 / 1.40 | 0.45 / 0.95 | 0.42 / 0.90 | 0.55 / 1.12 |
| SGSG-v3 |       | ✓     | ✓    | 20  | 0.79 / 1.61 | 0.42 / 0.79 | 0.70 / 1.41 | 0.46 / 0.98 | 0.41 / 0.87 | 0.56 / 1.13 |
| SGSG-v4 | ✓       | ✓     | ✓    | 20  | 0.73 / 1.48 | 0.39 / 0.76 | 0.66 / 1.36 | 0.42 / 0.92 | 0.36 / 0.79 | 0.51 / 1.06 |
| SGSG-v5 | ✓       |       | gating | 1  | 0.66 / 1.28 | 0.34 / 0.61 | 0.68 / 1.34 | 0.43 / 0.89 | 0.38 / 0.76 | 0.50 / 0.98 |
| SGSG-α  | ✓       | ✓     | ✓    | 20  | 0.62 / 1.13 | 0.30 / 0.56 | 0.61 / 1.28 | 0.41 / 0.85 | 0.34 / 0.69 | 0.46 / 0.90 |
| SGSG-β  | ✓       | ✓     | ✓    | 20  | 0.69 / 1.25 | 0.51 / 0.56 | 0.64 / 1.31 | 0.44 / 0.93 | 0.37 / 0.76 | 0.49 / 0.96 |
|         | ✓       | ✓     | concat | 1  | 0.64 / 1.22 | 0.50 / 0.56 | 0.64 / 1.30 | 0.43 / 0.93 | 0.36 / 0.76 | 0.47 / 0.95 |
|         | ✓       | ✓     | concat | 20 | 0.59 / 1.18 | 0.28 / 0.50 | 0.59 / 1.23 | 0.39 / 0.83 | 0.30 / 0.63 | 0.43 / 0.87 |
| SGSG    | ✓       | ✓     | gating | 1  | 0.62 / 1.23 | 0.29 / 0.54 | 0.62 / 1.27 | 0.41 / 0.87 | 0.33 / 0.70 | 0.45 / 0.92 |
|         | ✓       | ✓     | gating | 20 | 0.54 / 1.07 | 0.24 / 0.45 | 0.57 / 1.19 | 0.35 / 0.79 | 0.28 / 0.59 | 0.40 / 0.82 |

For the four methods that appear in both halves of the table, namely SGAN, MATF, STGAT, Liang et al., and our SGSG, we observe that their average percentage reductions of ADEs and FDEs for multimodal predictions are large (or small) when their ADEs and FDEs for single predictions are large (or small). Thus, compared to the other three methods, our SGSG, which already manifests good performance for single predictions, only has a smaller drop (around 11%) in ADEs and FDEs for multimodal predictions. When more predictions are generated (# = 100), our SGSG outperforms the state-of-the-art Trajector. Overall, these results demonstrate the high accuracy of our proposed method in forecasting single and multimodal future trajectories.

4.3. Ablation Study

To fully study the effectiveness of each encoder of our proposed method, five different variants, labeled as SGSG-v1 to SGSG-v5 in Table 2, with one or more of the social graph (SG) encoder, scene encoder, and the VAE module disabled are analyzed on the ETH & UCY datasets. A tick under the Modules column denotes that the module is enabled; a cross denotes that it is disabled. With the VAE encoder/decoder enabled, the SGSG-v3 and SGSG-v4 variants can forecast either one or 20 predictions, as shown under the ‘#’ column. For the variants SGSG-v1, SGSG-v2, and SGSG-v5 that do not include the VAE module, the loss function only contains the L_2 prediction loss term in the training phase. For all of the above five variants, the scene gated social graph feature G_{i | T_{obs}} is given in Eq. 4 reduces to g_{i | T_{obs}} if the scene encoder is disabled, and to s_{i | T_{obs}} if the social graph encoder is disabled.

To further validate the effectiveness of the proposed gating operation on the scene gated social graph features, we design two more variants which implement different methods of merging the social graph and scene features: SGSG-α, which element-wise adds these features; and SGSG-β, which directly concatenates them. As these variants are designed to single out the gating operation for evaluation, they have all the modules enabled like SGSG.

From the results in Table 2, we observe that SGSG outperforms all the variants. This indicates that it is important to include all the three modules in SGSG. What is also noticeable from the table is, while including the scene influence into SGSG helps to improve the prediction performance, it can not work well alone without the social graph encoder. This is evident from the poorer performance of SGSG-v2 and SGSG-v3 when the scene encoder is enabled but the SG encoder is disabled. On the other hand, when the SG encoder is enabled, as in SGSG-v1 and SGSG-v4, lower ADEs and FDEs are achieved. It is interesting that the models with VAE and the same without VAE produce very similar results under the single prediction case. For example, SGSG-v4 (# = 1) and SGSG-v1 have similar performance; so do SGSG-v3 (# = 1) and SGSG-v2; likewise for SGSG(# = 1) and SGSG-v5. These results indicate that the VAE module performs well in the gated feature reconstruction process. Compared to the first four variants which have either the scene feature or the social graph feature removed, both SGSG-α and SGSG-β achieve better performance in most scenes and on average. This further demonstrates the importance of incorporating both social and scene cues. For different merging methods of the social graph and scene features, we observe that the concatenation operation (SGSG-α) performs slightly better than simple addition (SGSG-β). However, comparing with SGSG where the proposed gating operation is implemented, both SGSG-α and SGSG-β clearly have inferior performance. This performance comparison demonstrates the superiority of our scene gated social graph features proposed in SGSG.

4.4. Memory Usage

In Table 3, we compare the GPU memory usage of the state-of-the-art STGAT [19] against SGSG. The values of STGAT are directly taken from [19] and, for a fair compari-
son, we use the same batch size setting as in [19]. STGAT’s GPU memory usage for the training phase is 4.7 times and for the evaluation phase is 1.17 times of our SGSG’s. The reason for the large memory usage of STGAT is the use of the complete graph structure to represent the social relationship as oppose to the star graph structure used in our SGSG. We also report the GPU memory usage of SGSG-v3 and SGSG-v4 in Table 3. While both variants have the VAE module enabled and can produce multimodal predictions, SGSG-v3 demands much more GPU memory than SGSG-v4 in order to process the semantic segmentation based scene encoder. Its GPU memory usage is almost the same as the full version SGSG. Thus, in the case where the GPU memory is limited, SGSG-v4 can be used instead of SGSG with a small compromise in prediction accuracy.

4.5. Qualitative Results

Some prediction results from our SGSG for different movement scenarios are shown in Fig. 3. More examples are shown in the supplementary materials document. In the first row, the best trajectory of the 20 predictions is shown for each observed trajectory. The background images have been darkened and blurred for better visualization. We can see that SGSG is able to generate realistic predictions for different cases such as stopping (Fig. 3(a)), walking together (Fig. 3(b)), and turning (Fig. 3(c)). Figure 3(c) shows that the predicted trajectories by SGSG are compatible with the scene layouts as SGSG incorporates the scene information through the scene encoder. In addition, when pedestrians are walking together and stopping to chat with each other (Fig. 3(d)), SGSG performs well and the generated trajectories are both socially and environmentally acceptable. In the second row, all 20 prediction of each POI given in the first row are shown as heatmaps. Taken the left POI in Fig. 3(f) as an example, it is a stopping case. In the prediction phase, the pedestrian can remain still or resume walking in any direction. The predicted heatmap shows a good coverage of this situation. Moreover, we can see that the heatmap indicates that the chance of this pedestrian walking towards left is very low as he/she should avoid the obstacle (the bench on the left). These visualizations demonstrate the ability of SGSG to model and predict pedestrians moving in a group (such as Fig. 3(d) and (i)).

The last column of Fig. 3 shows some failure cases that SGSG currently can not handle well. For the top left POI of Fig. 3(e), the POI is moving to the right (yellow trajectory) in the observation period but makes a sudden 180° turn (green) shortly after being in the prediction period. As the multiple predictions shown in the corresponding heatmap in Fig. 3(j) all forecast a right-ward movement, the most reasonable predicted trajectory in this case is the continuation of the observed trajectory (pink). As there are neither scene obstacles nor pedestrians nearby, no social or scene context information is available to help overcome this sudden U-turn scenario. For the two POIs in the bottom of Fig. 3(e), they are walking quite fast together initially but decelerating near the end of the observation period. One of the pedestrians almost comes to a stop in the prediction period. Although SGSG slightly overshoots one of the trajectories, both forecast trajectories are plausible in this scenario. The heatmap in Fig. 3(j) for these POIs shows a well coverage of the ground truth trajectories.

5. Conclusion

In this paper, we have presented a novel method that incorporates all the three key elements in pedestrian trajectory prediction, namely social influence, multimodality, and scene constraints. Our proposed method, SGSG, uses dynamic star graphs to model the social relationship between the POI and all other pedestrians in the scene during the observation period. In addition, the scene features are encoded through a semantic segmentation based scene en-

Table 3. The GPU memory usage in MB.

|          | STGAT | SGSG-v3 | SGSG-v4 | SGSG |
|----------|-------|---------|---------|------|
| Training | 7503  | 1577    | 505     | 1597 |
| Evaluation | 593   | 499     | 457     | 509  |
coder and the encoded scene features are merged with the social graph features to form the scene gated social graph features. To generate multimodal predictions, trajectory samples are drawn through a latent variable whose parameters are learned from the scene gated social graph features. The experimental results demonstrate that, with the two designed encoders and VAE module, SGSG achieves state-of-the-art performance on two widely used trajectory prediction datasets. Finally, we observe that SGSG is simple yet effective as shown by the star graph structure and the memory usage experiments.

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