

SafeCritic: Collision-Aware Trajectory Prediction

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Abstract

Navigating complex urban environments safely is a key to realize fully autonomous systems. Predicting future locations of vulnerable road users, such as pedestrians and cyclists, thus, has received a lot of attention in the recent years. While previous works have addressed modeling interactions with the static (obstacles) and dynamic (humans) environment agents, we address an important gap in trajectory prediction. We propose SafeCritic, a model that synergizes generative adversarial networks for generating multiple “real” trajectories with reinforcement learning to generate “safe” trajectories. The Discriminator evaluates the generated candidates on whether they are consistent with the observed inputs. The Critic network is environmentally aware to prune trajectories that are in collision or are in violation with the environment. The auto-encoding loss stabilizes training and prevents mode-collapse. We demonstrate results on two large scale data sets with a considerable improvement over state-of-the-art. We also show that the Critic is able to classify the safety of trajectories.

1 Introduction

Forecasting future locations of humans is an essential task to develop safe autonomous agents that interact with people. Autonomous systems such as household and factory robots, security systems and self driving cars need

to know where people will be given their previous movement to plan safe paths.

Predicting people’s future movement is challenging as the target location of a person cannot be known. The static and dynamic layout of the environment, be it a road network or an indoors map complicates the forecasting. Static obstacles place restrictions beyond their narrow definition of spatial extent (pedestrians will tend not to walk between closely situated parked cars). Considering dynamic obstacles like other pedestrians, bicycles or moving cars, one must not only minimize direct future collisions but also take into account hidden social rules (keeping to the right, respecting personal space). This becomes more complex since there are multiple unknown target locations each of the dynamic obstacles might be heading to. Consequently, predicting all the possible and plausible future trajectories is a multi-modal problem. Respecting the hidden rules and addressing the challenges is key for systems that are not just accurate but also safe.

Computationally tractable generative models has led to a great number of methods [Gupta et al., 2018, Sadeghian et al., 2018b, Lee et al., 2017] that model the multi-modality of future trajectory prediction. While these models focus on producing accurate future trajectories, they do not take into account the safety of the trajectories explicitly in terms of collisions. As a result, the generated paths might be **unsafe**, wherein they collide with other road users, or even **infeasible**, i.e., they go through static scene elements like buildings, cars or trees.

Consequently, these trajectories cannot easily be trusted in practice.

In this work we argue that one should take into account safety, when designing a model to predict future trajectories. The problem is that future trajectories are generated online and cannot be predetermined. Thus, applying standard and differentiable supervised learning is not straightforward. Even if one could minimize collisions with static elements and the ground truth trajectories, the model must learn to minimize collisions with the generated, and therefore unseen, future trajectories. Thus, in the absence of a clear learning objective, we rely on Generative Adversarial Networks (GAN) [Goodfellow et al., 2014] for the generative modelling and cast the learning within the Inverse Reinforcement Learning framework [Ng and Russell, 2000]. Inverse Reinforcement Learning guides the model towards optimizing an unknown reward function and shares many similarities with GANs. Here, our unknown reward function accounts for learning safe and “collision-free” future trajectories that have not even been generated yet.

This work has three contributions: (a) to the best of our knowledge, we are the first to propose generating “safe” future trajectories, minimizing collisions with static and dynamic elements in the scene, (b) the generated trajectories are not only safer but also more accurate. The reason is that the model learns to prune out unlikely trajectories and generalize better. In fact, we show that the remaining few collisions proposed strongly correlate with ground truth collisions, thus showing that the model learns to also anticipate collisions. and (c), we rely on attention mechanism for spatial relations in the scene to propose a compact representation for modelling interaction among all agents. The representation, which we refer to as attentive scene representation, is invariant to the number of people in the scene and thus is scalable.

2 Related work

Future trajectory prediction. Predicting future trajectories of road users has recently gained an increased attention in the literature. In their pioneering work Alahi *et al* [Alahi et al., 2016] define future trajectory prediction as a time series modelling problem and proposed SocialLSTM, which aggregates information of multiple in

a single recurrent model. While SocialLSTM is a deterministic model, [Gupta et al., 2018] proposes SocialGAN to learn to generate multi-modal future trajectories. To make sure that novel future trajectories are sampled, the encoder and decoder were trained using a Conditional Generative Adversarial Network [Gauthier, 2014, Mirza and Osindero, 2014] learning framework, leading to impressive results.

Extending on SocialGAN, SoPhie [Sadeghian et al., 2018b] incorporate semantic visual features extracted by deep networks, combined with an attention mechanism. Inspired by [Sadeghian et al., 2018b], DESIRE [Lee et al., 2017] also relies on semantic scene context and introduces a ranking and refinement module to order the randomly sampled trajectories by their likelihood. Further, [Rhinehart et al., 2018] develop R2P2, which is a non-deterministic model trained by modified cross-entropy objective to balance between the distribution and demonstrations. SocialAttention [Vemula et al., 2018] connects multiple RNNs in a graph structure to efficiently deal with the varying amount of people in a scene.

Future trajectory prediction models beyond the deep learning have also been explored. The Social Force [Helbing and Molnar, 1995] is one of the first models of pedestrian trajectory prediction that was successfully applied in the real-world [Sud et al., 2008]. Interacting Gaussian Process (GP) based methods [Trautman and Krause, 2010] model the trajectory of each person as a GP with interaction potential terms that couples each person’s GP. An extensive array of comparisons is available in [Becker et al., 2018], based on the TrajNet [Sadeghian et al., 2018a] benchmark.

Here, we adopt a modified Conditional Generative Adversarial Network framework [Gauthier, 2014, Mirza and Osindero, 2014] to generate novel future trajectories from observed past ones. Compared to [Gupta et al., 2018, Sadeghian et al., 2018b, Sadeghian et al., 2018b, Lee et al., 2017] our focus is to generate trajectories that are not just accurate but also lead to minimum collisions and thus are safe. Safe trajectories are different from trajectories that try to imitate the ground truth [Rhinehart et al., 2018], as the latter may lead to implausible paths, *e.g.*, pedestrians going through walls.

Generative Adversarial Networks + Reinforcement Learning. To model safe trajectories we propose a model that combines Generative Adversarial Networks Generative Adversarial Networks [Goodfellow et al., 2014] and Inverse Reinforcement Learning [Ng and Russell, 2000]. [Goodfellow et al., 2014] are generative models that rely on the min-max optimization of two competing sub-models, the generator and the discriminator. As standard GANs do not have an encoder, Conditional GANs [Gauthier, 2014, Mirza and Osindero, 2014] include an encoder, which can be used to generate novel samples given observations. [Finn et al., 2016] show that GANs resemble Inverse Reinforcement Learning [Ng and Russell, 2000] in that the discriminator learns the cost function and the generator represents the policy. Inspired by [De Cao and Kipf, 2018, Guimaraes et al., 2017] who showed the potentials of using external simulators as critic objectives [Konda and Tsitsiklis, 2000], we propose to use a critic network to model collision minimization by Inverse Reinforcement Learning. To prevent mode collapse, an additional autoencoding loss is considered.

3 SafeCritic

3.1 Overview

Our goal is a model that predicts accurate, diverse and safe, *i.e.* collision-free, future trajectories for all relevant road users in a driving scene. We denote the past trajectories of all n road users participating in the scene with $\mathbf{X} = \{X_1, X_2, \dots, X_n\}$. Each trajectory is a sequence of vectors $X_i = [\bar{x}_i^t]_{t=-T_{obs}}^0$ for T_{obs} past consecutive time steps. Each element is a $\bar{x}_i^t = (\delta x_i^t, \delta y_i^t)$ is a 2D coordinate displacement vector for agent i , with $\delta x_i^t = x_i^{t+1} - x_i^t$. We also denote the ground truth future trajectories also containing 2D displacement vectors as elements with $\mathbf{Y} = \{Y_1, Y_2, \dots, Y_n\}$ and the predicted trajectories with $\hat{\mathbf{Y}}$. The time span of the prediction is $[T_0, \dots, T_{pred}]$. To reduce notation clutter, we drop the subscript and superscripts i and t when they can be inferred from the context.

The proposed SafeCritic uses as a basis a conditional Generative Adversarial Network [Gupta et al., 2018], as well as a Critic Network [Sutton et al., 2000],

[Sutton, 1984],[Barto, 1984], to generate novel and safe future trajectories for the road users in the scene, see Figure 1 for an overview. Next, we describe the particular design of SafeCritic.

3.2 Generating Trajectories with Safe-Critic

The conditional GAN of SafeCritic comprises of two modules, a *Generator*, and a *Discriminator*, as seen in the left of Figure 1. The generator of the conditional GAN is composed of two sub-networks.

The first sub-network is a θ -parameterized encoder $\mathbf{u} = g^{enc}(\mathbf{X}; \theta)$ that receives as input the past trajectories of all road users and maps them to a common embedding space \mathbf{u} . The purpose of the encoder is to aggregate the current state of all road users jointly. The aggregated state of all road users is then passed to the second sub-network, which is a ω -parameterized decoder $\hat{\mathbf{Y}} = g^{dec}(\mathbf{u}, F_d, F_s, z; \omega)$, where F_d, F_s are the dynamic and static aggregated features that will be detailed in 3.4, and $z \sim N(0, 1)$ is the random noise vector for sampling novel trajectories. The purpose of the decoder is to generate novel future coordinates $\hat{\mathbf{Y}}$ for all n road users simultaneously.

The generator is followed by the discriminator, which is implemented as a third ϕ -parameterized sub-network $D = d(\mathbf{X}, \mathbf{Y}, \hat{\mathbf{Y}} | \phi)$. The discriminator receives as inputs the past trajectories \mathbf{X} , as well as the ground truth future trajectories \mathbf{Y} and the predicted trajectories $\hat{\mathbf{Y}}$. Being adversaries, the generator and the discriminator are trained in an alternative manner [Goodfellow et al., 2014]: the generator generates gradually more and more realistic trajectories, while the discriminator classifies which trajectories are fake thus pushing the generator to become better.

3.3 Critic for Obtaining Safe Future Trajectories

While the generator and the discriminator modules are trained to generate plausible future trajectories, the proposed trajectories there are no provisions to avoid possible collisions in the predicted future trajectories. To this end, we incorporate a Critic module responsible for mini-

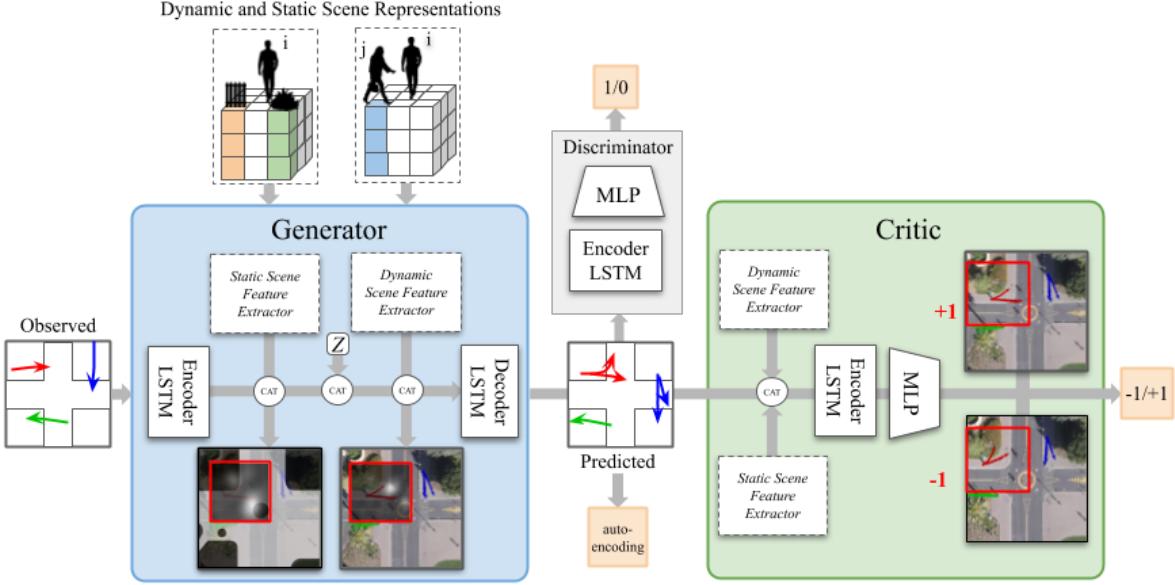


Figure 1: The SafeCritic network consisting of a **Generator** trained by **Discriminator** and **Critic** networks. The Generator observes each trajectory together with the dynamic and static scene and computes a future trajectory. It has an encoder, decoder LSTM’s, and two MLPs for pooling the static and dynamic features. The Critic and discriminator score the predictions. We also show intermediate representations for the person in red: The attention on the dynamic and static scene in the Generator and the reward (+1 and -1) of the Critic. The orange boxes are the three different losses for the Generator. Input to the model are the dynamic and static scene features.

The **Dynamic Scene** Representation are the hidden states of each neighbor j and embedded into a 3D tensor for each target agent i . The **Static Scene** Representation are segmented points around each target. The attention of the person in red is shown on the static and dynamic scene.

mizing the static and dynamic future collisions, as shown in the right of Figure 3.

A natural objective for the Critic module is a supervised loss that minimizes the number of future dynamic and static collisions. Unfortunately, integrating such an objective to the model is not straightforward. The number of non-colliding trajectories in existing datasets is overwhelmingly higher than for colliding trajectories. Moreover, having a generative model means that the generated trajectories will not necessarily imitate the ground truth ones.

To this end, we rely on the off-policy actor-critic framework [Sutton and Barto, 1998] to define the objective of Critic . The actor is the trajectory generator decoder $g^{dec}(\cdot)$, taking a displacement action $\hat{\mathbf{Y}}$. The Critic then is

a ψ -parameterized sub-network $v = o(\hat{\mathbf{Y}}, F_s, F_d; \psi)$ that predicts how likely an eminent collision is or not, given $\hat{\mathbf{Y}}$. The action value v , is the score for the future action causing a collision. Another choice would have been to simply return the reward signal to the generator. However, in that case we would need to rely on high-variance gradients returned by REINFORCE.

Training For training SafeCritic, we must take into account the opposing goals of the generator and the discriminator, as well as the regularizing effect of the critic. Following standard GAN procedure we arrive at a min-max training objective for the generator and the discriminator, $\arg \min \max_{\theta, \phi, \omega} \mathbb{E}_{\mathbf{X}, \mathbf{Y} \sim p_{data}(\mathbf{X}, \mathbf{Y})} [\log(d(\mathbf{X}, \mathbf{Y}))] + \mathbb{E}_{z \sim p_{data}(z)} [\log(1 - d(\mathbf{X}, g(\mathbf{X}, S)))]$, where g is the com-

plete generator with the encoder and the decoder.

As the discriminator quickly learns to tell the real and generated samples apart, training the generator is harder than training the discriminator, leading to slow convergence or even failure [Salimans et al., 2016]. Inspired from [Gupta et al., 2018], we introduce an additional auto-encoding loss to the ground truth for the best generated sample, $\hat{\mathbf{Y}}, \arg \min_{\theta, \phi, \omega} \sum_i \left\| \mathbf{Y}_i - \hat{\mathbf{Y}}_{i_K} \right\|_2^2$. An additional benefit of the auto-encoding loss is that it encourages the model to avoid trivial solutions and mode collapse, as well as to increase the diversity of future generated trajectories.

Regarding the training objective of the Critic sub-network, we simply opt for minimizing the squared error when a collision was predicted and when it occurred,

$$\arg \min_{\psi} \mathbb{E}_{z \sim p_{data}(z)} \left\| o(\hat{\mathbf{Y}}, F_s, F_d; \psi) - R_{\hat{\mathbf{Y}}} \right\|_2, \quad (1)$$

where $R_{\hat{\mathbf{Y}}}$ indicates the presence or not of a collision and can be computed by any collision checking algorithm, here [Ericson, 2004]. It is important to note that following [Alahi et al., 2016, Sadeghian et al., 2018b, Gupta et al., 2018], all future predictions by the generator and the Critic are performed sequentially, one step at a time. The Critic takes as input the generated trajectory from g^{dec} up to time t , while the collision checker algorithm computes $R_{\hat{\mathbf{Y}}}$ given the generated trajectory at the next time step, $t + 1$.

For the training of the Critic we employ a version of the Deep Deterministic Policy Gradient algorithm [Lillicrap et al., 2015]. Specifically, we rely on the RDPG variant [Heess et al., 2015] that uses a sequence of observations and uses RNNs for both actor and critic networks. The maximum reward is attained when the future trajectories cause minimum number of collisions. In the end, the Critic sub-network acts as a regularizer to the rest of the network, guiding the generator to generate novel trajectories that cause minimal collisions.

3.4 Attentive Scene Representation

To generate novel, accurate, diverse and safe future trajectories, a good representation of the scene as well as the rest of the agents in the scene is required. What is more,

this representation must attend to the relevant elements in the vicinity of every agent.

To this end, we propose the following tensor representations F_d, F_s for capturing possible dynamic interactions between the agents themselves, as well as the static interactions between the agents and the environment, respectively, see Fig. 1. Both representations for dynamic and static interactions follow the same design. We center a grid around the i -th agent $G_i = \{g_{rc}\}$, where r and c run over the height and width of the grid. We then check if a given grid location is occupied by either another agent or a static element. If the rc grid location is occupied by an agent j , we then set the respective entry in $F_{d,i}$ to the hidden state of that agent, namely $F_{d,i}^{rc} = h_j$. Similarly for static features, if the rc grid location is occupied by a static element we set the respective entry in $F_{s,i}$ to the one-hot vector representation of that static element.

Last, we employ an attention mechanism to prioritize certain elements in the latent state representations F_d, F_s of the i -th agent. The attention is applied spatially, such that specific coordinates on the grid receive higher importance than others.

3.5 Architecture

For the encoder we opt for an LSTM network [Gupta et al., 2018]. The observed trajectories are first embedded into an MLP in order to obtain a fixed length vector, $\mathbf{e} = \text{MLP}(\mathbf{X}; W_{emb})$, where \mathbf{X} are the displacement coordinates of the pedestrians in the scene at all time steps $t = [-T_{obs}, \dots, 0]$. The LSTM then updates its hidden states sequentially. The last hidden state of the LSTM is concatenated with the static and dynamic attentive representations F_d, F_s and the noise input z and then passed to the decoder. For the decoder we rely also on a separate LSTM network that *does not* share weights with the encoder. The LSTM decoder generates the hidden states of each person for $t = [0, \dots, T_{pred}]$ predicted time steps. The final hidden state is converted into a displacement vector and added onto the previous prediction $\hat{\mathbf{Y}}^{t-1}$, $\hat{\mathbf{Y}}^t = \hat{\mathbf{Y}}^{t-1} + \text{MLP}(\mathbf{h}_{dec}^t; W_T)$ where W_T is a learnable transformation matrix. The critic takes K predictions $\hat{\mathbf{Y}}_i^t$ of agent i , together with the state in which that agent was F_s^t, F_d^t and assigns a reward for each time-step. In this way, it learns to predict the likelihood of collision at $t + 1$, which is dependant on

the motion of agent i , but also of another agent j . If there are multiple approaching neighbors, chances of a collision are higher and since we want to reward avoiding collisions especially in these difficult situations, we do not normalize over the number of agents. We implement the Critic as an LSTM and MLP and train it with Mean Squared Error between the number of collisions.

4 Experiments

We evaluate our method on two state-of-the-art datasets used for future trajectory prediction of pedestrians.

UCY. UCY [Leal-Taixé et al., 2014] has 3 videos, recorded from a bird’s eye point of view in 2 different outdoor locations. It contains annotated positions only for pedestrians with an average of 250 pedestrians per video. The average length of the videos is 361 seconds. Following[Alahi et al., 2016] we use the leave-one-out approach during training.

SDD. Stanford Drone Dataset [Robicquet et al., 2016] contains annotated positions of various types of agents including pedestrians, bicyclists, skateboarders, cars, buses, and golf carts that navigate inside a university campus. On average, there exist 104 agents per video and the average path length is 67,79 meters. We use the standard train and test splits provided by TrajNet [Sadeghian et al., 2018a].

Evaluation metrics We use the standard metrics reported in the literature [Alahi et al., 2016, Gupta et al., 2018, Sadeghian et al., 2018b], namely the minimum Average Displacement Error, $mADE = \min_K \frac{1}{T} \sum_{t=1}^T \|Y_i^t - \hat{Y}_i^t\|_2$, and minimum Final Displacement Error, $mFDE = \min_K \|Y_i^{T_{pred}} - \hat{Y}_i^{T_{pred}}\|_2$ over best sample K .

Last, to evaluate the capacity of the methods to avoid collisions, we measure the number of collisions with dynamic and static elements. The number of collisions is computed as $NC = \sum_{i,j=1}^k \sum_{t=1}^T \delta_{ij} \cdot \mathbf{1}(\hat{Y}_i^t - \hat{Y}_j^t < \epsilon)$ where δ_{ij} is the kronecker delta function, $\mathbf{1}$ is the indicator function, and $\epsilon = 0.10$ (here i and j are two different agents).

Implementation details Following standard protocol [Sadeghian et al., 2018a] we observe trajectories for $T_{obs} = 8$ times steps (3.2 seconds). We then predict the next $T_{pred} = 12$ (4.8 seconds) time steps. The encoder and

DATA	WITHOUT ASR	WITH ASR
	MADE / MFDE	MADE / MFDE
UCY	0.40 / 0.93	0.39 / 0.84
SDD	16.18 / 29.11	15.06 / 28.45

Table 1: Minimum Average Displacement Error (ADE) and Final Displacement Error (FDE) for SafeCritic with and without Attentive Scene Representation (ASR). Following dataset conventions, errors are measured in meters for UCY and pixels for SDD. We conclude that the proposed interaction poolings lead to better modelling of the interactions for predicting future trajectories.

decoder LSTM have an embedding size of 32 each. We use batch normalization [Ioffe and Szegedy, 2015] and Adam optimization [Kingma and Ba, 2014] with learning rates 10^{-3} for the generator and 10^{-4} for the Critic and the discriminator. Like [Alahi et al., 2016] we bound and normalize distances between agents and the boundary points within a neighborhood.

Baselines. We report comparisons with state-of-the-art methods on the UCY and SDD: SocialGAN [Gupta et al., 2018], SocialLSTM [Alahi et al., 2016], Car-Net [Sadeghian et al., 2017], SoPhie [Sadeghian et al., 2018b], DESIRE [Lee et al., 2017], as well as a linear regressor that estimates parameters by minimizing the least square error and Social Force implemented in [Sadeghian et al., 2018b].

4.1 Evaluating attentive scene representation features

First, we evaluate whether the proposed attentive scene representations allow for better generation of future trajectories. In Table 1 we show results for trajectory generation when we turn on and off the proposed static and dynamic pooling, while also turning off the Critic module to minimize external influences. We observe that when switching on the proposed attentive scene representations we obtain lower errors in terms of $mADE$ and $mFDE$ for both UCY and SDD. We conclude that the attentive scene representations allows for more accurate future trajectory generation.

DATA	GT	LINEAR	SOCIALGAN	SOPHIE	SAFECRITIC
UCY					
STUDENTS3	0.12	1.24	0.55	0.62	0.48
ZARA1	0.00	3.77	1.74	1.02	0.18
ZARA2	0.73	3.63	2.02	1.46	1.22
AVERAGE	0.28	2.88	1.71	<u>1.03</u>	0.45

Table 2: Number of collisions between agents on UCY. A collision is defined with a threshold of 0.10m between two locations. The videos in SDD are less crowded and in less than 0.00 % people are within a proximitz of 0.10 m. Our model scores 0.01 vs 0.06 and 0.05 compared to SocialLSTM and SocialGAN on the SDD.

4.2 Evaluating the safety of SafeCritic

First, we examine how safe the generated trajectories are in terms of the number of collisions caused. We report results in Table 2.

We make two observations. Under all settings and datasets SafeCritic generates three times fewer collisions cpmpared to SocialGAN, Sophie and a linear regressor. What is more, SafeCritic is quite close to the number of the collisions that are actually observed in the ground truth trajectories. This is important because collisions may actually happen in real life and thus a model should also generate collisions when these are likely to occur.

4.3 Evaluating the accuracy of SafeCritic

Next, we examine how accurate the generated future trajectories are. We report results in Table 3 for UCY and Table 4 for SDD. We observe that SafeCritic generates more accurate future trajectories than all other baselines in UCY. Importantly, SafeCritic comfortably outperforms all methods on the much larger and complex SDD dataset.

Last, we evaluate the diversity of the generated trajectories in Fig. 2.

We conclude that SafeCritic predicts future trajectories that are not only accurate, but also cause much fewer collisions and they are more diverse.

4.4 Qualitative results

Last, we present some qualitative results for SafeCritic. In Fig. 2 we plot various generated trajectories at a



Figure 2: As expected SafeCritic generates diverse trajectories. Five trajectories of two persons walking towards a goal (star).

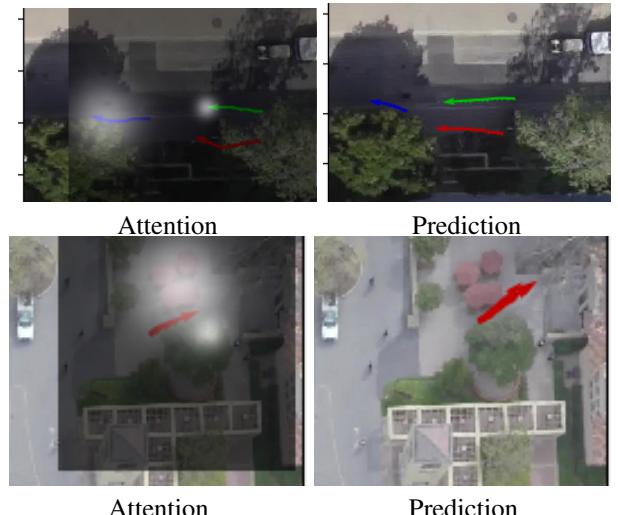


Figure 3: The attention of a person (red) show the importance of other agents (blue and green) (left columns) and of nearby trees and buildings (right columns), resulting in alternating his trajectory.

specific moment in time, examining whether mode collapse is happening. Mode collapse is problematic, because the model could learn to generate trajectories that cause a low number of collisions, while failing to predict the whole space of possible future paths. We observe that SafeCritic does not suffer from mode collapse [Salimans et al., 2016], as also quantified earlier. Interestingly, the diversity of the generated trajectories is

DATA	SOCIALSTM	SOCIALGAN	SOPHIE	LINEAR	LSTM	SAFECRITIC
	MADE / MFDE	MADE / MFDE	MADE / MFDE	MADE / MFDE	MADE / MFDE	MADE / MFDE
UCY						
STUDENTS3	0.67 / 1.40	0.76 / 1.52	<u>0.54 / 1.24</u>	0.82 / 1.59	0.61 / 1.31	0.52 / 1.23
ZARA1	0.47 / 1.00	0.35 / 0.68	<u>0.30 / 0.63</u>	0.62 / 1.21	0.41 / 0.88	0.29 / 0.60
ZARA2	0.56 / 1.17	0.42 / 0.84	<u>0.38 / 0.78</u>	0.77 / 1.48	0.52 / 1.11	0.30 / 0.69
AVERAGE	0.56 / 1.19	0.51 / 0.96	<u>0.41 / 0.88</u>	0.74 / 1.43	0.51 / 1.10	0.32 / 0.80

Table 3: Given 8 past time steps the proposed SafeCritic is more accurate in predicting the future 12 timesteps on UCY (3 videos, 2492 frames).

DATA	SOCIALSTM	SOCIALGAN	SOPHIE	DESIRE	LINEAR	SF	CAR-NET	SAFECRITIC
	MADE / MFDE	MADE / MFDE	MADE / MFDE	MADE / MFDE	MADE / MFDE	MADE / MFDE	MADE / MFDE	MADE / MFDE
SDD	31.19 / 56.97	27.25 / 41.44	<u>16.27 / 29.38</u>	19.25 / 34.05	37.11 / 63.51	36.48 / 58.14	25.72 / 51.80	14.39 / 27.39

Table 4: Given 8 past time steps the proposed SafeCritic is more accurate in predicting the future 12 timesteps on SDD (48 videos, 14558 frames).

different for different pedestrians, showcasing the important of the attentive scene representations. Further, in Fig. 3 we visualize the attention to other agents and static scene elements, like nearby trees and buildings. We observe that the generated future trajectories are nicely sampled such that the attended agents and static elements are avoided and no collisions are generated. Last, in Fig. 4 we show how the predicted locations of SafeCritic do not collide. The second row shows how multiple sampled trajectories of SafeCritic move around a lawn.

5 Conclusion

In this work we introduced SafeCritic, a model that is based on training a generator-discriminator along with a reinforcement learning based reward network to predict both accurate and safe trajectories. A novel way of handling static and dynamic features in both the generator and reward network makes it possible to discard unsafe trajectories. Our proposed collision metric enables the evaluation of safety aspect of predicted trajectories. We show that SafeCritic outperforms baseline models both on accuracy as well as on the number of collisions. Furthermore, our experiments show that a convex combination of trajectory’s ‘safe’ and ‘real’ aspects achieves a perfect balance for the final prediction.

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Observed



SocialGAN



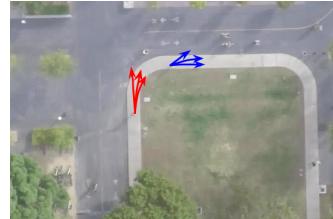
SafeCritic



Observed



SocialGAN



SafeCritic

Figure 4: As expected SafeCritic generates safe trajectories. Trajectories of two walking persons with final ground truth location (star). Collisions between people for Coupa 0 (upper row) with the locations at $t=1s$ and $2s$ (circles) and going onto lawn for Bookstore 2 (lower row).