Learning Modular Representations for Long-Term Multi-Agent Motion Predictions

Todor Davchev
Institute of Perception, Action and Behaviour
School of Informatics
University of Edinburgh
t.b.davchev@ed.ac.uk

Michael Burke
Institute of Perception, Action and Behaviour
School of Informatics
University of Edinburgh
michaelburke@ieee.org

Subramanian Ramamoorthy
Institute of Perception, Action and Behaviour
School of Informatics
University of Edinburgh
s.ramamoorthy@ed.ac.uk

Abstract

Context plays a significant role in the generation of motion for dynamic agents in interactive environments. This work proposes a modular method that utilises a model of the environment to aid motion prediction of tracked agents. This paper shows that modelling the spatial and dynamic aspects of a given environment alongside the local per agent behaviour results in more accurate and informed long-term motion prediction. Further, we observe that this decoupling of dynamics and environment models allows for better generalisation to unseen environments, requiring that only a spatial representation of a new environment be learned. We highlight the model’s prediction capability using a benchmark pedestrian tracking problem and by tracking a robot arm performing a tabletop manipulation task. The proposed approach allows for robust and data efficient forward modelling, and relaxes the need for full model re-training in new environments. We evaluate this through an ablation study which shows better performance gain when decoupling representation modules in addition to improved generalisation on tasks with dynamics unseen at training time.

1 Introduction

Automated decision making requires long-term predictions of the behaviours of surrounding agents. For example, an autonomous vehicle requires knowledge of the future positions of any surrounding pedestrians if it is to plan successful paths. Similarly, a robotic arm may need to know the future position of its surrounding agents (i.e. another arm) for collaborative planning. This paper investigates predictive models that address this challenge.

A commonly adopted approach is to rely on labelled data that is often expensive to obtain and thus state-of-the-art methods tend to rely on simulated datasets [Wulfe et al. (2018), Gupta et al. (2018), Pfeiffer et al. (2018)]. Generalising from such datasets, however, is challenging due to the complexity of simulating group dynamics and environment specific motion. Real-world motion is dependent on varying environmental cues and unspoken rules of interaction. For example, groups of people often tend to walk in similar directions, and are more likely to walk on pavements, or through choke points like bridges.

Preprint. Work in progress.
This work proposes a modular approach that allows each of these aspects to be learned from data in a decoupled fashion, while still retaining state-of-the-art prediction performance. This decoupling allows the re-use of individual modules, thus reducing data requirements. For example, rather than re-training a large model to perform motion prediction in a new scene, the proposed approach allows for an environment specific model to be learned, and existing dynamics models to be re-used.

More formally, we consider long term motion prediction in supervised settings. We consider the case where environments are observed through a fixed camera feed and have a history of labelled, agent positions in associated frames. In the absence of any knowledge of the long term behaviour of an observed agent, even making simple local predictions about the general direction of motion is non-trivial. This work focuses on learning effective state representations utilised in a forward model that can successfully infer a distribution over the long-term behaviour of a given agent.

This work introduces a forward model comprising three key components. First, the model makes use of an environment-specific spatial encoding \((R)\), that captures information about the existing objects in a scene. This information is then used within a global dynamics component \((D)\), which models the evolution of this scene over time. We condition \((D)\) on the 2D locations of all agents present in the scene. This provides us with a hidden state, or a summary of the scene dynamics that takes into account the moving components therein. We use the spatial encoding along with the hidden summary to train a local (per given agent) behavioural model \((B)\). The proposed architecture explicitly incorporates stochastic elements in each module, so as to allow a measure of uncertainty in the predictions. This uncertainty can be used in downstream tasks requiring prediction.

We show through an ablation study that the three modules \((R, D, B)\) are complimentary and collectively contribute to achieving the highest performance, outperforming the respective sub-components. This shows that both spatial and dynamical representations are a key requirement for effective multi-agent state prediction.

Further, we conduct an empirical comparison between the proposed approach and previously proposed solutions for trajectory prediction. Our findings show that the proposed approach leads to improved prediction ability and requires far less data to achieve state-of-the-art results.

Finally, we highlight the flexibility of the proposed model through experiments conducted on a tabletop manipulation scenario. Here, we show that the proposed model is able to learn a global representation of the environment and use this to predict motion following a learned plan in an unseen configuration.

In summary, the main contributions of this work are as follows:

- A novel modular architecture for model-based long-term prediction in the context of agent tracking in both crowded and structured scenes.
- A framework for building robust and data efficient forward models in real world settings.

2 Related Work

There has been significant interest in sequence generation and model-based learning. In the following section, we review the relevant techniques developed in this area to date.

2.1 Model-Based Learning

Model-based learning is used widely across robotics applications, particularly when it comes to modelling state-space representations to enable control of an individual agent. Watter et al. (2015) learn a locally linear latent dynamics model to enable control from raw images in a dynamical sequence. Karl et al. (2017) learn state space models from image data by assuming a known transition parameterisation and action space. Finn and Levine (2017) and Ebert et al. (2018) propose solutions that make predictions from visual inputs for model-based reinforcement learning. The work of Ha and Schmidhuber (2018) and Hafner et al. (2018), on the other hand, learns to control individual agents in simulated environments by independently building environmental models using auxiliary tasks. Generally, collaborative tasks tend to employ solutions that follow a similar structure. Lee et al. (2015) make local predictions to model human-robot interaction for human companion motion planning. Mainprice and Berenson (2013) anticipates human behaviour by learning an independent
motion prediction model and uses this in a motion planning framework. Those approaches, however, have not been able to successfully utilise long-term predictions for motion planning, and generally fail to consider multi-agent interactions.

![Diagram of proposed model](image)

**Figure 1**: An illustration of the proposed model. Each of the three components in the proposed model are trained separately in the labelled order, described by lower case letters a, b and c. Here, R is the representation module which takes in as input a pre-processed image \( I_t \) and learns a posterior \( p(I_t|I_t) \). D is the module responsible for modelling the evolution of the entire scene, i.e. the global dynamics. It takes in as input the spatial encoding from R, \( I_t \) along with the Cartesian positions of all agents \( A_t \) and learns a posterior distribution \( p(l_{t+1}|I_t, A_t) \). B models individual agents’ (\( a_t \)) motion and obtains a posterior \( p(s_{t+1}|s_t, I_t, h_t) \). It takes in as input \( s_t \) along with \( I_t \) and the obtained summary \( h_t \) from D.

### 2.2 Modelling complex motion

The problem of motion prediction can be divided into two general categories; methods modelling interactions between the individual agents of interest and those that model the dynamics globally for an entire scene through time. This work focuses on the former.

#### 2.2.1 Individual Agent Prediction

In the context of multi-agent pedestrian modelling, social dynamics are often used to facilitate prediction. For example, the Social Forces (SF) method [Helbing and Molnar (1995)] uses a potential field based approach to model the social interactions between various pedestrians. [Lerner et al. (2007)] used an example-based reactive approach to model pedestrian behaviour by creating a database of local spatio-temporal examples. [Pellegrini et al. (2009)] modelled the behaviour of pedestrians in crowded environments using linear extrapolation over short intervals via a Linear Trajectory Avoidance (LTA) technique. Complimentary solutions that successfully capture pedestrian behaviours in specific situations [Kuderer et al. (2012); Kitani et al. (2012); Kretzschmar et al. (2014)] have also been proposed, but all these methods require hand-crafted features, affecting their capacity to be used in dynamic settings.

[Graves (2013)] applied recurrent neural networks to the problem of sequence generation in text and handwriting analysis. Here, plausible future samples are drawn from a Gaussian distribution and a mixture density network (MDN) [Bishop et al. (1995)] used to generate real-valued data. [Ha and Eck (2018)] use a similar model to generate sketches, relying on a temperature parameter \( \tau \) to control model uncertainty during inference. [Alahi et al. (2016)] propose an approach that builds upon [Graves (2013)] and models social interactions through a pooling layer that utilises the latent state representations of surrounding agents. A generative model over agents’ motion allows for sampling a collection of proposal trajectories. [Vemula et al. (2015)] weight the latent state representations of surrounding agents by their relative importance. [Pfeiffer et al. (2018)] make use of an LSTM for motion prediction by encoding an obstacle map of the environment and modelling surrounding pedestrians in a polar angular space. [Lee et al. (2017)] enable trajectory generation by scoring a number of possible paths by a learned from data criteria. This concept was also explored through the work of [Gupta et al. (2018)], in a framework that can generate socially acceptable paths using
a Generative Adversarial Network (GAN). Similarly, Sadeghian et al. (2018) predict trajectories using GANs, but this can be computationally expensive. Radwan et al. (2018) use a dilated CNN, jointly optimising the trajectories of all agents in a scene to leverage the inter-dependencies in motion without the need for explicit modelling. Unfortunately, these solutions fail to make full use of environmentally-specific latent representations of the spatial and global dynamic components of the individual worlds and often rely on simulated data or hand coded environmental representations.

Despite the wide range of solutions for individual agent motion prediction, current methods do not make use of a comprehensive environmental model to aid prediction. This has had a negative effect on prediction performance. This work proposes the use of a model-based approach to prediction of observed agents’ behaviour that facilitates long-term prediction of complex motion.

3 Methodology

This work’s focus is on predicting the future motion of an arbitrary number of observed agents (i.e. their behaviour) whose action spaces and objectives are unknown. More specifically, we focus on predicting the two-dimensional motion of agents in video sequences. We assume we are given a history of two-dimensional position annotations and video frames as a sequence of RGB images. Each agent $a$ ($a \in [1 \ldots A]$, where $A$ is the maximum number of agents in the video) is represented by a state $(s^a_t)$ which comprises xy-coordinates at time $t$, $s^a_t = (x_t, y_t)_a$. The global world state ($S_t$) is then defined as a tuple comprising the set of all agents’ locations in that frame ($S_t = \{(\cup_{a=1}^A s^a_t, I_t)\}$, for the scene at time $t$ represented by an image $I_t$. Given a sequence of $obs$ observed states $S = \{S_{t-obs}, S_{t-obs+1}, \ldots, S_{t-1}, S_t\}$, we formulate the prediction as an optimisation process, where the objective is to learn a posterior distribution $P(Y|S, I_t)$ of multiple agents’ future trajectories $Y$. Here an individual agent’s future trajectory is defined as $(s^a_{t+1}, s^a_{t+2}, \ldots, s^a_{t+pred})$ for $pred$ steps ahead for every agent $a$ found in scene $I_t$.

3.1 Proposed Model

Even though we do not have access to agents’ objectives and available actions spaces, we hypothesise that the decision making process for each agent is influenced by the behaviour of the surrounding agents. Additionally, there may be spatial objects that could act as regions of interest across the given environment, affecting an agent’s motion. Moreover, it is often the case that all agents follow some unspoken, common rules of motion or dynamics that apply globally to the entire scene. We model these spatial and dynamic components separately and from the perspective of an observer.

To this end, we build probabilistic generative models of real world environments and use these to predict the locations of those agents at multiple instances in the future. We refer to this technique as model-based prediction (MBP). In particular, we model agent behaviours using three components. The first, a visual sensory component ($R$), encodes the environment into a latent vector $l_t$. This vector then acts as the global state representation. This latent state representation can be useful if it can preserve information about the existing agents at time $t$. In this work, we assume that such information is preserved if our model can successfully reconstruct the existing agents at a given timestep. However, conventional variational approaches can fail to reconstruct individual agents due to their changing locations and small size in a video. To overcome this limitation, we use an information maximisation variational autoencoder (InfoVAE) which matches the moments of the encoded and decoded images Zhao et al. (2017).

The representation module $R$ is trained by minimising the distance between the input image and its decoded variant using the maximum mean discrepancy (MMD) Gretton et al. (2007), resulting in the following loss:

$$R : \min_{\theta,\phi} \mathcal{L}(I_t, \theta, \phi) = \mathbb{E}_{p(l),q(l')}[k(l,l')] + \mathbb{E}_{q(l),q(l')}[k(l,l')] - 2\mathbb{E}_{p(l),q(l')}[k(l,l')] + \mathbb{E}_{p_{data}(l_t)q_{data}(l_t)}[p_q(l_t, l)$$

Here, $\theta, \phi$ are the learned model parameters, $I_t$ is the RGB image scene at time step $t$ where each image $I_t \in I_t \subseteq R^{n \times 2}$ is an element from a video sequence $I$ and $k(l,l')$ is a Gaussian kernel,
Figure 2: A comparison of model performance in street scenes. The first two rows show results on ETH University and ETH Hotel respectively [Pellegrini et al., 2009], while the remainder are from UCY Zara01 and Zara02 [Lerner et al., 2007]. An agent’s trajectory is tracked for 4 steps (light blue) and is then predicted for the next 12 (ground truth depicted in yellow). Each row represents a different dataset while each column is a different model. Red depicts a simple LSTM with a stochastic output, in magenta we show results of modelling only the social interactions between agents [Alahi et al., 2016] and green are the results from this work. The proposed approach takes environmental cues into consideration and maintains more consistent predictions.
We combine these datasets, following previous work Alahi et al. (2016), Radwan et al. (2018) and while the data acquisition is applied at 2.5fps. The datasets comprise \( \mathcal{D} \), a joint generative distribution \( p_\theta \) and a joint “inference distribution” \( q_\phi \).

To learn the second module \( \mathbf{D} \), we train an RNN-MDN using as input an image \( I_t \) which has been encoded by the network from the previous module to a latent state representation \( l_t \). This input is conditioned on a fixed length 2D vector comprised of the locations of all existing agents \( A_t \) at time \( t \). The network learns to predict \( l_{t+1} \) and provides us with a summary \( h_t \) that encodes the temporal dynamics of the global environment (See Figure 1). We sample \( l_{t+1} \) from a mixture of Gaussians parametrised with a learned mean \( \mu \) and variance \( \sigma \) and a mixing coefficient \( \pi \). We define summary \( h_0 \rightarrow 0 \) and then every other \( h_t = f_\delta(\mathbf{h}_{t-1}, (l_t, A_t)), \forall t \in (0, T] \), for a function \( f \) which is some type of an LSTM. We then obtain the summary \( h_t \) from \( f \) which maximises \( g_{\text{in}}(h_t) = p(l_{t+1}|l_t, A_t) \), where \( g \) is a feedforward neural network such that,

\[
D \quad : \quad \min_{\delta, \kappa} \mathcal{L}(l_{t+1}, \delta, \kappa) = \sum_{t=1}^{T} -\log \left( \sum_{j} \pi_j \mathcal{N}(l_{t+1} | \mu_j, \sigma_j^2; \delta, \kappa) \right)
\]

with parameters \( \delta, \kappa \), where we assume a diagonal covariance matrix of a factored Gaussian distribution to simplify computation. During sampling, we adjust a temperature parameter \( \tau \) to control model uncertainty (See Section 2.2). Adjusting \( \tau \) is useful for training the \( \mathbf{B} \) component of our model. Finally, we utilise both \( \mathbf{R} \) and \( \mathbf{D} \), along with each acting agent’s history of motion to anticipate their positions in the future through a temporal prediction module \( \mathbf{B} \). This fuses the local dynamics of individual agents with those of the global scene (represented with a tuple \( (l_t, h_t) \)). This is illustrated in Figure 1, component \( \mathbf{B} \). We define \( \mathbf{B} \) as an LSTM, a function that minimises:

\[
B \quad : \quad \min_{\omega, \psi} \mathcal{L}(Y, \omega, \psi) = \sum_{t=1}^{T} -\log \left( \sum_{j} \mathcal{N}(s_{t+1}^j | \mu_{t+1}^j, \sigma_{t+1}^j; \omega, \psi) \right)
\]

with parameters \( \omega, \psi \), where an \( (x, y) \) is the \( i \)th agent predicted Cartesian position, sampled from a 2D Gaussian distribution with mean \( \mu \), variance \( \sigma \) and correlation \( \rho \). We learn each of these components separately, assigning most of the network capacity to \( \mathbf{R} \) and \( \mathbf{D} \) while restricting \( \mathbf{B} \) to a small network trainable on CPU.

### 4 Experimental Evaluation

The proposed solution is evaluated using multiple publicly available datasets for predicting human behaviour in crowded scenes as well as on a task introduced in this work, which reflects the applicability of the proposed solution to a robotic task.

#### 4.1 Datasets & augmentation

##### 4.1.1 Crowds prediction

The first experiment conducted uses the ETH Hotel, ETH University [Pellegrini et al. (2009)] and Zara01, Zara02 [Lerner et al. (2007)] datasets. Each of these is recorded at 25 frames per second (fps) while the data acquisition is applied at 2.5fps. The datasets comprise \( \approx 4000 \) frames and contain \( \approx 1600 \) agents that follow both linear and non-linear trajectories. They include agents walking on their own, in social groups or passing by one another. We assume that we know in advance the locations of all agents at each time step and that we have access to the video arrays in an RGB format. We combine these datasets, following previous work [Alahi et al. (2016), Radwan et al. (2018)] and apply a leave-one-out procedure during training for both dynamic components \( \mathbf{D} \) and \( \mathbf{B} \).

##### 4.1.2 Robot gripper Cartesian position prediction

To further highlight the model’s versatility we introduce a tabletop manipulation dataset. Here, the prediction task involves a robot gripper which follows a predetermined plan for collecting components for an assembly task (see Figure 3). The distance between each two gears varies between 6 and 20 recorded steps and the gripper stops at each of the 5 destinations for a brief period of time. We vary the position of each gear across different datasets, but maintain the same order of visitation, which is
determined by the colour of a gear. The total length of each dataset is approximately 1000 frames. We record the location of the robot’s gripper and project this location into the image plane. Across all collected datasets, the required parts of the assembly are ordered in arbitrary manner. However, their collection order remains the same. We consider orderings that allow for a clockwise collection of the gears direction during training and monitor the performance of our solution on an unseen item ordering, that enforces anti-clockwise collection at test time. This task ensures a non-linear alteration of the data that is particularly challenging to model. We are interested in the capacity of the proposed solution to predict direction of motion and the location of the next visited segment.

Figure 3: An illustration of the behaviours considered in the robot gripper’s tracking dataset. A red background indicates settings considered as the training data while a green background indicates the set up used at test time. Note that the direction of motion is completely orthogonal at test time.

4.2 Training Schedule

All hyper-parameters were optimised using grid search applied on a subset of the training data. Frames were re-sized to $64 \times 64$ pixels, and were further processed using contrast limited adaptive histogram equalisation (CLAHE) [Zuiderveld (1994)] which further enhanced the contrast in tiles that are populated with agents.

4.2.1 Representation Module (R)

The latent state representations were learned using an InfoVAE, trained using Adam optimisation (learning rate = 0.001, batch size = 50). We obtain a 96 dimensional latent space by encoding using 4 2D convolutions.

4.2.2 Global Dynamics Module (D)

We use a dynamic LSTM with 768 dimensional cell unit and train using Adam optimiser with learning rate of 0.0003, stacking sequences of consecutive frames corresponding to the sequence length used in module B. Training occurs in a leave-one-out manner to ensure that no part of the model has ever seen any of the dynamics in a tested environment. The output is modelled using a mixture of 5 Gaussians. A dense layer is used as a proxy between the output of the dynamic LSTM and the MDN (see Figure 1 component (D)).

4.2.3 Behavioural Module for individuals (B)

Finally, we train an LSTM with a cell state of (40x128). We use inputs with size (sequence length, number of agents, embedding dimensionality), where the number of agents is fixed to 40 and
Table 1: Reported results assume observation length of $T_{\text{obs}} = 1.6 \text{sec}$ and prediction lengths of $T_{\text{pred}} = 3.2 \text{sec}$ and $T_{\text{pred}} = 4.8 \text{sec}$. First 4 rows correspond to the Average Displacement Error and last 4 to the final displacement error. Each result represents an average obtained from 5 independent runs with different random seeds.

| $T_{\text{pred}} = 3.2s$ | Model \Dataset | ETH Hotel | ETH Univ | UCY Zara01 | UCY Zara02 | Average |
|--------------------------|----------------|-----------|-----------|-------------|-------------|---------|
| Average                  | LSTM           | 0.039±0.001 | 0.146±0.006 | 0.020±0.000 | 0.024±0.001 | 0.057±0.002 |
| Displacement             | S-LSTM         | 0.041±0.002 | 0.133±0.007 | 0.020±0.000 | 0.026±0.001 | 0.055±0.002 |
| Error                    | RDB (ours)     | 0.037±0.001 | 0.113±0.002 | 0.017±0.000 | 0.024±0.001 | 0.048±0.001 |
| Final                    | LSTM           | 0.093±0.005 | 0.041±0.002 | 0.056±0.001 | 0.066±0.001 | 0.064±0.002 |
| Displacement             | S-LSTM         | 0.101±0.005 | 0.056±0.002 | 0.062±0.002 | 0.071±0.002 | 0.068±0.004 |
| Error                    | RDB (ours)     | 0.086±0.003 | 0.029±0.001 | 0.049±0.001 | 0.068±0.003 | 0.058±0.003 |

| $T_{\text{pred}} = 4.8s$ | Model \Dataset | ETH Hotel | ETH Univ | UCY Zara01 | UCY Zara02 | Average |
|--------------------------|----------------|-----------|-----------|-------------|-------------|---------|
| Average                  | LSTM           | 0.082±0.003 | 0.245±0.021 | 0.053±0.000 | 0.055±0.002 | 0.109±0.007 |
| Displacement             | Social LSTM    | 0.080±0.004 | 0.235±0.019 | 0.049±0.001 | 0.066±0.003 | 0.108±0.007 |
| Error                    | RDB (ours)     | 0.073±0.003 | 0.182±0.009 | 0.046±0.000 | 0.063±0.003 | 0.091±0.004 |
| Final                    | LSTM           | 0.207±0.009 | 0.051±0.004 | 0.160±0.003 | 0.163±0.005 | 0.145±0.005 |
| Displacement             | Social LSTM    | 0.184±0.011 | 0.049±0.003 | 0.190±0.004 | 0.197±0.008 | 0.157±0.007 |
| Error                    | RDB (ours)     | 0.164±0.009 | 0.033±0.003 | 0.136±0.005 | 0.190±0.007 | 0.131±0.006 |

dimensionality is 2 for each of the x,y locations of every agent. We use the pixel normalised representation of every agent’s location in order to ensure an indirect relationship between regions in the encoded latent space and the existing agents. We train with batch of size 1 and encode each agent’s location into a 64 dimensional vector. This ensures that the trajectories of all agents within a given sequence are optimised jointly. We encode a concatenation of the hidden state from the MDN RNN $h_t$ with the latent space $l_t$ to 64 dimensions too. For both encodings we used a Relu activation. We then concatenate both and use this as the input to the LSTM where we advance the cell state ensuring we associate each dimension of the cell to an individual agent. We use a single dense layer to process the output from the LSTM before we use it to sample a predicted location. We train this network with learning rate of 0.005 using RMSprop and L2 regularisation for 100 iterations. We use weight decay of 0.95 and gradient clip of 10.

All hyperparameters were chosen using grid search over independent segments.

### 4.3 Evaluation Motion Prediction on Crowd Datasets

#### 4.3.1 Comparison with Existing Work

We benchmark the performance of the proposed approach against several methods for motion prediction, the Social-LSTM [Alahi et al. (2016)] and a vanilla LSTM with stochastic outputs. Those have previously been shown to perform better than traditional methods such as a linear model, the Social forces model [Helbing and Molnar (1995)] and Interacting Gaussian Processes [Trautman (2013)]. We found other existing work to rely on simulated data for motion focusing on modelling the individual interactions between agents as opposed to conditioning their behaviour on the overall surrounding environment [Pfeiffer et al. (2018), Gupta et al. (2018) and Radwan et al. (2018)]. None of those, however, focuses on learning effective representations in data-scarce scenarios and as a result performed extremely poorly in the proposed setting so are excluded from analysis. Comparison methods are trained and evaluated using the proposed data pre-processing and test pipeline, but employ provided model implementations. We evaluate the accuracy of the motion prediction models by reporting the following metrics:

- Average Displacement Error: that is the mean squared error (MSE) over all predicted positions from a single pedestrian’s trajectory.
- Final Displacement Error: that is the MSE of the last predicted location from a single pedestrian’s trajectory.
Each network is trained using a length of 8 frames and during inference using observation length of 4 (1.6s) and prediction lengths of 8 frames (3.2s) and 12 frames (4.8s). Observing a smaller portion of the trajectory makes it more challenging for a model to predict future behaviour, especially in a scenario where the network has been trained with sequence smaller than 4.8 seconds as it is in our case. In such a setting, the network will depend on its learned understanding of the world to unroll potential futures without having to solely rely on memory.

Table 1 shows the results obtained on this task. The proposed solution outperforms the alternatives. This is particularly the case where there is limited overlap between the location and direction of motion considered in the training set and those in the test set. Since ETH Univ has most of its trajectories in a different direction to the rest of the datasets (see Figure 2) we see a significant difference between our solution and the remaining models. In addition, it can be observed that the variability of the predicted trajectories is affected by the uncertainty of the global knowledge of the environment. This leads to less variability in the predicted trajectories for environments where we have more accurate models, as is the case for ETH Univ.

In contrast to previous literature, we found that a well optimised vanilla LSTM with stochastic output often outperforms alternative approaches. We suspect that this is due to the hyper-parameter optimisation performed before evaluating performance. Further, we observed results proportional to the quality of the learned global model of the environment. Building an environmental model for the UCY Zara01 and Zara02 datasets is particularly challenging and thus the results are not substantially better than alternatives. This highlights the importance of environmental or spatial information when making predictions.

4.3.2 Ablation Study & Qualitative Analysis

An ablation study was performed in order to evaluate the importance of each of the components of the proposed model. Table 2 shows that a combination of both global dynamics and static representation are useful. When considered individually, less accurate predictions are made, but combining these outperforms alternatives. UCY Zara02 is the larger of the two UCY datasets and contains longer, more complex trajectories. The less accurate model of the world in this scenario has not resulted in improved performance. However, the model uses its final component B to achieve the same performance it would have if R and D were not present, indicating that the modules are complimentary.

Figure 2 further highlights these observations. In the first row, groups of people cross a bridge. Groups are often moving together and continue walking on the pavement. Further, none of the people walks over the bridge or steps on the snow. Such cues are omitted in the models that do not have input representations that take this into account. Further, predicting no motion with such techniques is often difficult. Row two shows a scenario in which 4 out of the 6 people stay in the same place at a train station. While all three considered models do relatively well at predicting the behaviour of the two moving people, only RDB manages to predict that the rest of the agents stand still at a train stop. The model utilises environmental cues in the rest of the datasets too, where it successfully anticipates that agents are walking on the road or are walking towards the door of the depicted store.

These results also reiterate the point that a good latent representation of the static environment is required for prediction, but also demonstrate the flexibility of a modular solution.

| Dataset \ Model          | B    | R+B  | D+B  | R+D+B |
|-------------------------|------|------|------|-------|
| ETH Hotel               | 0.039±0.002 | 0.045±0.002 | 0.042±0.001 | 0.037±0.001 |
| ETH Univ                | 0.146±0.006 | 0.136±0.002 | 0.133±0.002 | 0.113±0.007 |
| UCY Zara01              | 0.020±0.000 | 0.031±0.000 | 0.021±0.000 | 0.017±0.000 |
| UCY Zara02              | 0.024±0.000 | 0.029±0.000 | 0.024±0.000 | 0.024±0.000 |
| Average                 | 0.057±0.002 | 0.060±0.001 | 0.055±0.001 | 0.048±0.001 |

4.4 Evaluation for Robot Action Prediction

We trained our model using 4 out of 5 video sequences of a manipulator performing tabletop manipulation (See Figure 3). A video sequence that contained previously unseen counterclockwise
motion was held out from training for testing. Each dataset considers different locations of all gears while the visiting arm follows the same order of visitation. Thus the focus of the task is to measure the capacity of the proposed approach to relate visual cues to its prediction. In such settings, standard prediction models would be expected to overfit to the training data and fail to predict the intended motion correctly unless they capture environmental cues.

To this end, we reduced the size of RDB since the task at hand did not require as large a latent space for the $R$ module as the previous task, nor did it need as large cell states for the $D$ component. Here, we used $l_t$ and $h_t$ with 64 dimensions and sampled $l_t$ from a mixture of 2 Gaussians instead of 5.

Figure 4 compares the performance of a standard stochastic LSTM and RDB. At inference, each model is fed a sequence of the executed trajectory, depicted in green, and is then tasked to predict its continuation, the ground truth depicted in yellow. As expected a standard LSTM overfits to the training data and predicts that the observed agent would go back towards the start of the observed trajectory (see the middle column in Figure 4). In contrast, RDB successfully retrieves paths that correspond to the followed plan (right-most column). Throughout this experiment the robotic arm covers different gears during visitation. This makes it much harder to predict motion towards certain gears, since some gears will not be present in the scene at certain times. Nevertheless, the RDB model does seem to be aware of the environmental cues to a sufficient extent that it can make good use of them at the time of prediction.

The first row of figures illustrates a scenario at which the manipulator covers the purple gear and has been hovering over the brown component for a few steps. As a result, the RDB model is less certain and predicts three potential directions of motion, moving towards the location of a purple gear, through the middle to the red gear or going back to the orange one. The final option is the only one which goes in a direction the network has previously seen in the training data. Over time, the network becomes more certain of the direction of motion after it sees a few steps in that direction. This, however, is not the case for the vanilla LSTM which has heavily overfit to the training data.

Finally, the last row’s visit to the green gear indicates the end of the underlying plan. Here, the RDB network is uncertain what visitation might follow next, but predicts two potential directions that are situated in the direction of existing gears.

5 Conclusions

Autonomous systems operating in multi-agent environments need effective behavioural prediction models. This paper introduced a model-based solution to the problem of nonlinear, multi-agent trajectory prediction given image sequences and position information.

The proposed architecture, RDB, was compared to existing approaches on established benchmark datasets and a newly proposed one. This work showed that both spatial and dynamic aspects of the environment are key to building effective representations in the context of multi-agent motion prediction. As a further benefit, decoupling the learning of environment specific model from the behavioural prediction component relaxes data requirements and allows for better generalisation across tasks.

Empirical evaluations along with a detailed ablation study highlighted the importance of the proposed representation modules. The modular structure builds upon a model of the static environment and the global dynamics of a scene. Results show that these models are complimentary and necessary for successful motion prediction.

Acknowledgments

The authors would like to thank Akash Srivastava, Julian Viereck and Martin Asenov for the valuable comments on early drafts of this work. The authors would also like to thank the anonymous referees for their valuable comments and helpful suggestions. This work is supported by an EPSRC Industrial CASE award funded by Thales.

References

Alahi, A., Goel, K., Ramanathan, V., Robicquet, A., Fei-Fei, L., and Savarese, S. (2016). Social lstm: Human trajectory prediction in crowded spaces. In Proceedings of the IEEE Conference on
Figure 4: Examples of predicted trajectories. The green lines depict the observed trajectory while the other coloured lines are predictions. The left-most column depicts the ground truths, followed by predictions made with a standard LSTM and predictions from RDB. We can see that the proposed solution learns a weak dependency between the colour coded objects in the environment and the plan followed by the agent. The upper right corner indicates the unknown to the observer plan.
Bishop, C. M. et al. (1995). *Neural networks for pattern recognition*. Oxford university press.

Ebert, F., Finn, C., Dasari, S., Xie, A., Lee, A., and Levine, S. (2018). Visual foresight: Model-based deep reinforcement learning for vision-based robotic control. *arXiv preprint arXiv:1812.00568*.

Finn, C. and Levine, S. (2017). Deep visual foresight for planning robot motion. In *2017 IEEE International Conference on Robotics and Automation (ICRA)*, pages 2786–2793. IEEE.

Graves, A. (2013). Generating sequences with recurrent neural networks. *arXiv preprint arXiv:1308.0850*.

Gretton, A., Borgwardt, K., Rasch, M., Schölkopf, B., and Smola, A. J. (2007). A kernel method for the two-sample-problem. *Advances in neural information processing systems*, pages 513–520.

Gupta, A., Johnson, J., Fei-Fei, L., Savarese, S., and Alahi, A. (2018). Social gan: Socially acceptable trajectories with generative adversarial networks. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, number CONF.

Ha, D. and Eck, D. (2018). A neural representation of sketch drawings. *In International Conference on Learning Representations*.

Ha, D. and Schmidhuber, J. (2018). Recurrent world models facilitate policy evolution. *arXiv preprint arXiv:1809.01999*.

Hafner, D., Lillicrap, T., Fischer, I., Villegas, R., Ha, D., Lee, H., and Davidson, J. (2018). Learning latent dynamics for planning from pixels. *arXiv preprint arXiv:1811.04551*.

Helbing, D. and Molnar, P. (1995). Social force model for pedestrian dynamics. *Physical review E*, 51(5):4282.

Karl, M., Soelch, M., Becker-Ehmck, P., Benbouzid, D., van der Smagt, P., and Bayer, J. (2017). Unsupervised real-time control through variational empowerment. *arXiv preprint arXiv:1710.05101*.

Kitani, K. M., Ziebart, B. D., Bagnell, J. A., and Hebert, M. (2012). Activity forecasting. In *European Conference on Computer Vision*, pages 201–214. Springer.

Kretzschmar, H., Kuderer, M., and Burgard, W. (2014). Learning to predict trajectories of cooperatively navigating agents. In *2014 IEEE international conference on robotics and automation (ICRA)*, pages 4015–4020. IEEE.

Kuderer, M., Kretzschmar, H., Sprunk, C., and Burgard, W. (2012). Feature-based prediction of trajectories for socially compliant navigation. In *Robotics: science and systems*.

Lee, D., Liu, C., and Hedrick, J. K. (2015). Interacting multiple model-based human motion prediction for motion planning of companion robots. In *2015 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)*, pages 1–7. IEEE.

Lee, N., Choi, W., Vernaza, P., Choy, C. B., Torr, P. H., and Chandraker, M. (2017). Desire: Distant future prediction in dynamic scenes with interacting agents. *arXiv preprint arXiv:1704.04394*.

Lerner, A., Chrysanthou, Y., and Lischinski, D. (2007). Crowds by example. In *Computer Graphics Forum*, volume 26, pages 655–664. Wiley Online Library.

Mainprice, J. and Berenson, D. (2013). Human-robot collaborative manipulation planning using early prediction of human motion. In *Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on*, pages 299–306. IEEE.

Pellegrini, S., Ess, A., Schindler, K., and Van Gool, L. (2009). You’ll never walk alone: Modeling social behavior for multi-target tracking. In *Computer Vision, 2009 IEEE 12th International Conference on*, pages 261–268. IEEE.

Pfeiffer, M., Paolo, G., Sommer, H., Nieto, J., Siegwart, R., and Cadena, C. (2018). A data-driven model for interaction-aware pedestrian motion prediction in object cluttered environments. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pages 1–8. IEEE.
Radwan, N., Valada, A., and Burgard, W. (2018). Multimodal interaction-aware motion prediction for autonomous street crossing. *arXiv preprint arXiv:1808.06887*.

Sadeghian, A., Kosaraju, V., Sadeghian, A., Hirose, N., and Savarese, S. (2018). Sophie: An attentive gan for predicting paths compliant to social and physical constraints. *arXiv preprint arXiv:1806.01482*.

Trautman, P. (2013). *Robot navigation in dense crowds: Statistical models and experimental studies of human robot cooperation*. California Institute of Technology.

Vemula, A., Muelling, K., and Oh, J. (2018). Social attention: Modeling attention in human crowds. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pages 1–7. IEEE.

Watter, M., Springenberg, J., Boedecker, J., and Riedmiller, M. (2015). Embed to control: A locally linear latent dynamics model for control from raw images. In *Advances in neural information processing systems*, pages 2746–2754.

Wulfe, B., Chintakindi, S., Choi, S.-C. T., Hartong-Redden, R., Kodali, A., and Kochenderfer, M. J. (2018). Real-time prediction of intermediate-horizon automotive collision risk. In *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems*, pages 1087–1096. International Foundation for Autonomous Agents and Multiagent Systems.

Zhao, S., Song, J., and Ermon, S. (2017). Infovae: Information maximizing variational autoencoders. *arXiv preprint arXiv:1706.02262*.

Zuiderveld, K. (1994). Contrast limited adaptive histogram equalization. *Graphics gems*, pages 474–485.