Pedestrian Trajectory Prediction

Overview

- What is pedestrian trajectory prediction good for?
- What is the task of pedestrian trajectory prediction?
- What makes trajectory prediction challenging?
- What kind models are used for trajectory prediction?
  - Deterministic models
  - Stochastic Models
- How to model social interactions?
- How to model agent-scene interactions?

Introduction

- Autonomous vehicles must predict the future movements of pedestrians in order to avoid fatal collisions

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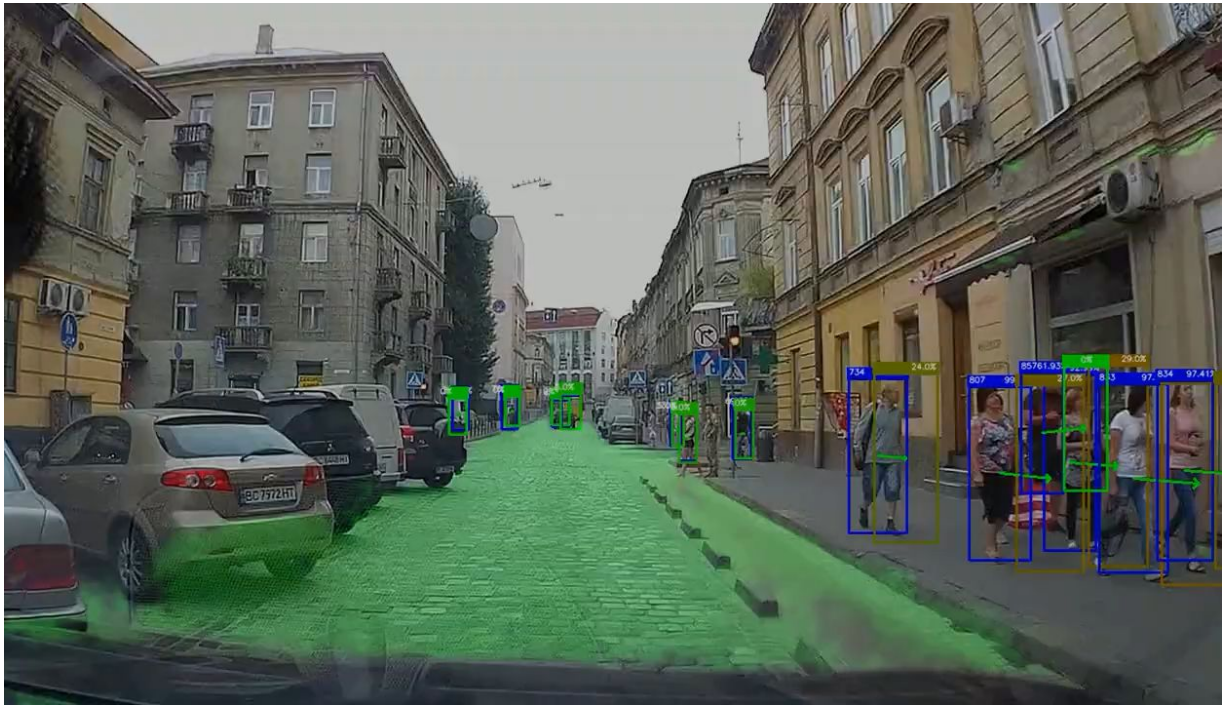
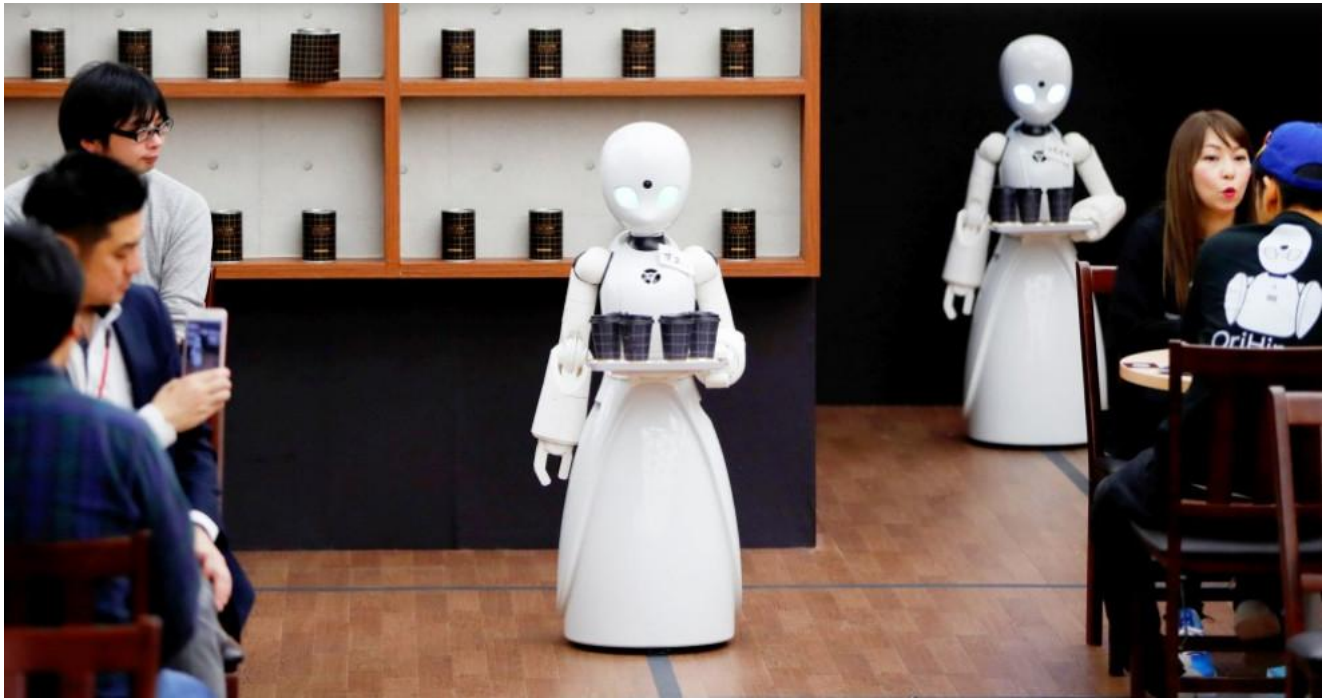


Introduction

- Social robots that move autonomously through crowded scenes and interact with moving humans



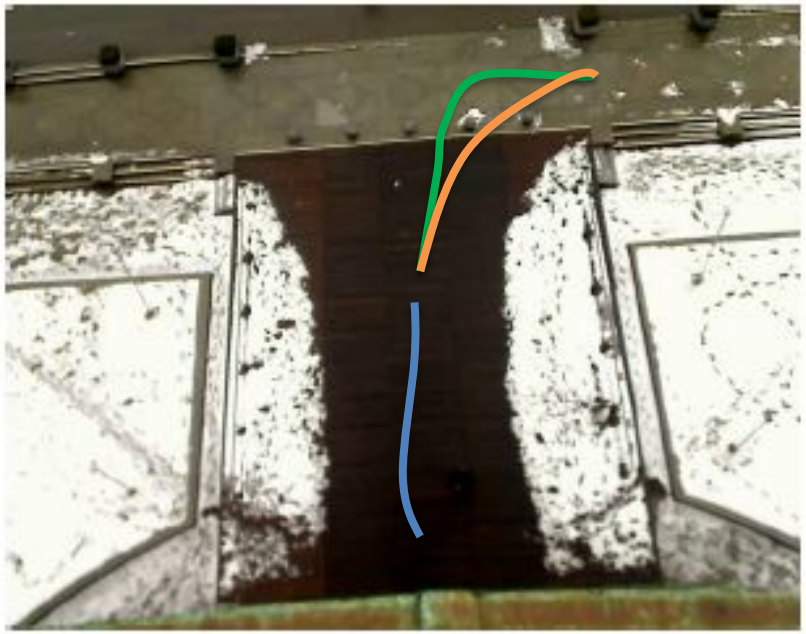
Introduction

- Motion models improve the performance of Multi-Object Trackers

www.motchallenge.net

Task of pedestrian trajectory prediction

Scene



- Sequence of observations:

$X_i^t = (x_i^t, y_i^t)$ for $t = 1, \dots, T^{Obs}$

- Ground Truth:

$Y_i^t = (x_i^t, y_i^t)$

for $t = T^{Obs+1}, \dots, T^{Pred}$

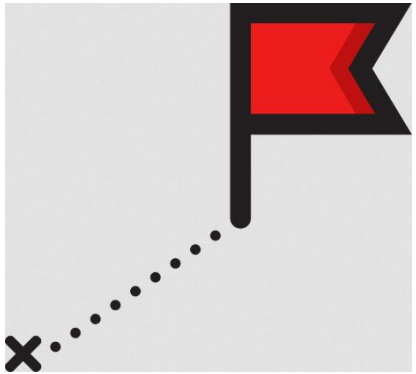
- Prediction:

$\hat{Y}_i^t = f_W(X_i) = (x_i^t, y_i^t)$

for $t = T^{Obs+1}, \dots, T^{Pred}$

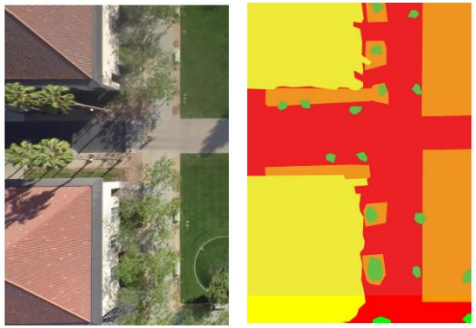
Introduction

- Human motion behavior is influenced by a variety of different factors:

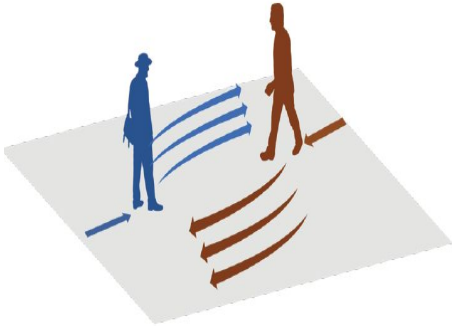


1. Destination

2. Personal Preferences



3. Human – Space Interactions



4. Human – Human Interactions

Social Force Model

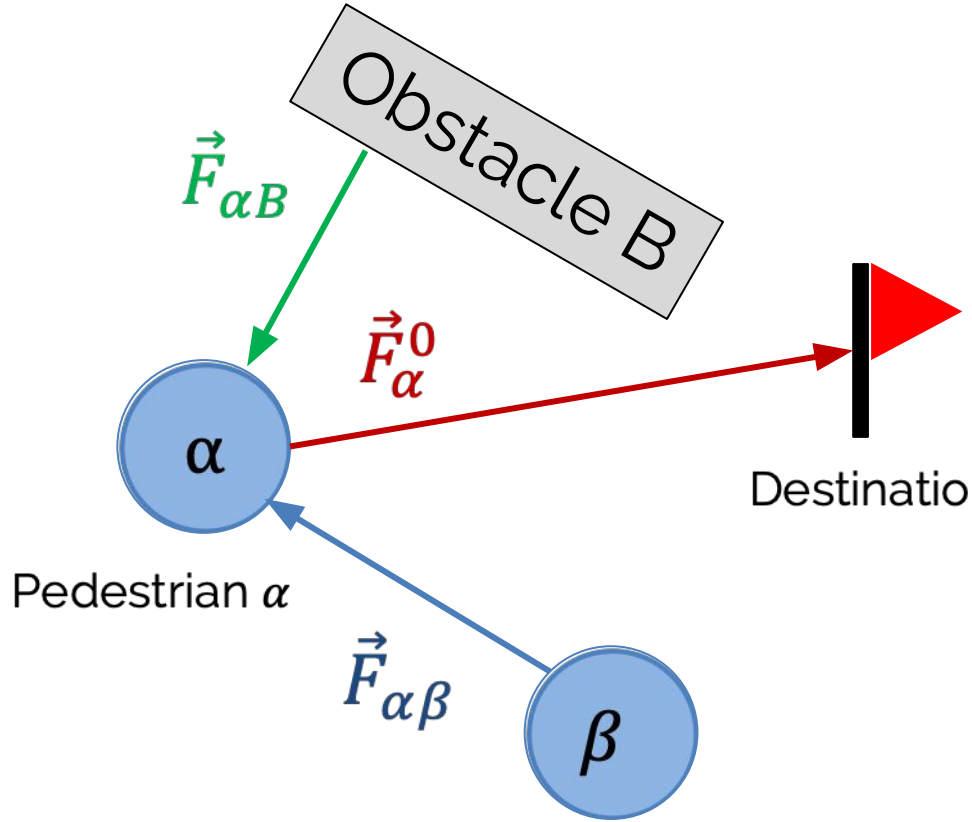
- Contribution: Mathematical model of dynamics

- **Idea**: Pedestrian act in force field $\boldsymbol{F}$ like particles e.g. in an electric field
- Second Newton's law: $\ddot{\boldsymbol{x}} = \frac{d\boldsymbol{x}^2}{d\boldsymbol{t}^2} = \frac{\boldsymbol{F}(\boldsymbol{t})}{\boldsymbol{m}}$

- Trajectory $\mathbf{x}(\boldsymbol{t})$ is solution of differential equation

[Helbing et al. 98] *Social Force Model*

Social Force Model



Destination and personal

desired velocity

direction of destination

$$\vec{F}_{\alpha}^{0} = \vec{F}_{\alpha}^{0}(\vec{v}_{\alpha}(t), v_{\alpha}^{0}\ \vec{e}_{\alpha})$$

Human – Human interactions

distance betw. peds

$$\sum_{\beta} \vec{F}_{\alpha\beta}(\vec{e}_{\alpha}, \vec{r}_{\alpha\beta})$$

Human – Space interactions

$$\sum_{B} \vec{F}_{\alpha B}(\vec{e}_{\alpha}, \vec{r}_{B}^{\alpha})$$

Social Force Model

- Force resultant determines motion of pedestrian $\boldsymbol{\alpha}$

$$\vec{F}_\alpha(t) := \underbrace{\vec{F}_\alpha^{\,0}(\vec{v}_\alpha, v_\alpha^0 \vec{e}_\alpha)}_{\substack{\text{acceleration term} \\ \text{towards dest.}}} + \underbrace{\sum_\beta \vec{F}_{\alpha\beta}(\vec{e}_\alpha, \vec{r}_{\alpha\beta})}_{\substack{\text{force} \\ \text{between pedestrians}}} + \underbrace{\sum_B \vec{F}_{\alpha B}(\vec{e}_\alpha, \vec{r}_B^{\,\alpha})}_{\substack{\text{force} \\ \text{between ped. and obstacles}}}$$

- The respective trajectory $\boldsymbol{x(t)}$ is the solution of a differential equation:

$$\ddot{\boldsymbol{x}}(t) = \frac{d\boldsymbol{x}^2}{dt^2} = F_\alpha\,(t)$$

Social Force Model

- The force between pedestrians is described by the gradient of a repulsive potential $\boldsymbol{V_{\alpha\beta}}$:

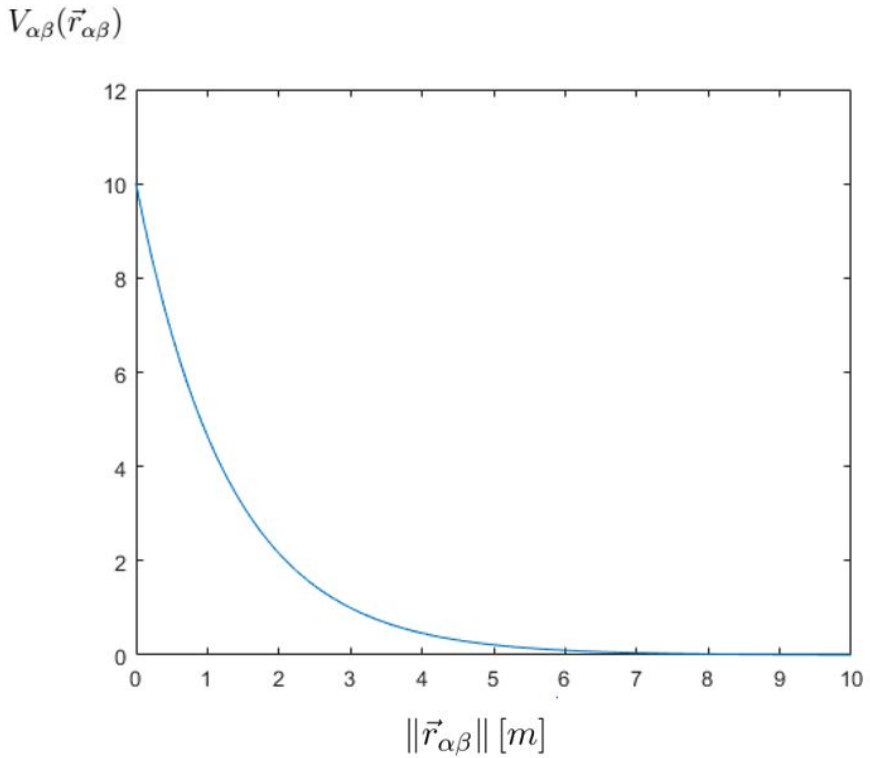
$$\vec{F}_{\alpha\beta}(\vec{r}_{\alpha\beta}) = -\nabla_{\vec{r}_{\alpha\beta}} V_{\alpha\beta}(\vec{r}_{\alpha\beta}) \text{ with } V_{\alpha\beta}(\vec{r}_{\alpha\beta}) = V^0 \, e^{-\frac{\|\vec{r}_{\alpha\beta}\|}{\sigma}}$$

- Parameters $\boldsymbol{V^0}$ and $\boldsymbol{\sigma}$ determine the shape of this potential
- Parameters effect strength of interaction between pedestrians

Social Force Model

- Exponential potential shaped by V^0 and σ:

- Interaction Potential:
  - $V_{\alpha\beta}(\vec{r}_{\alpha\beta}) = V^0 \, e^{-\frac{\|\vec{r}_{\alpha\beta}\|}{\sigma}}$



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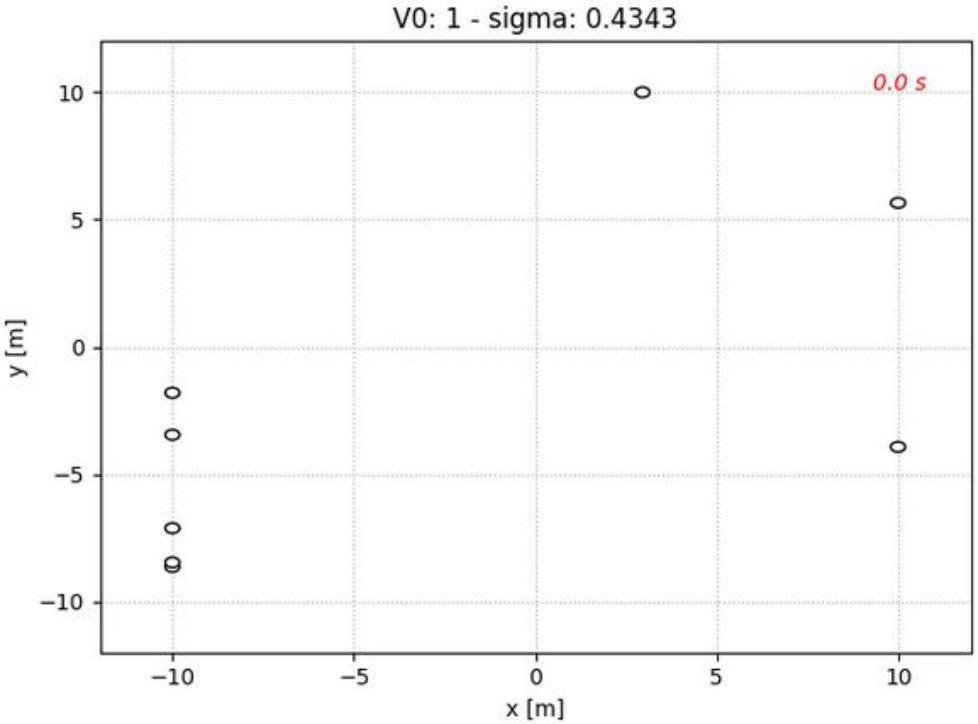

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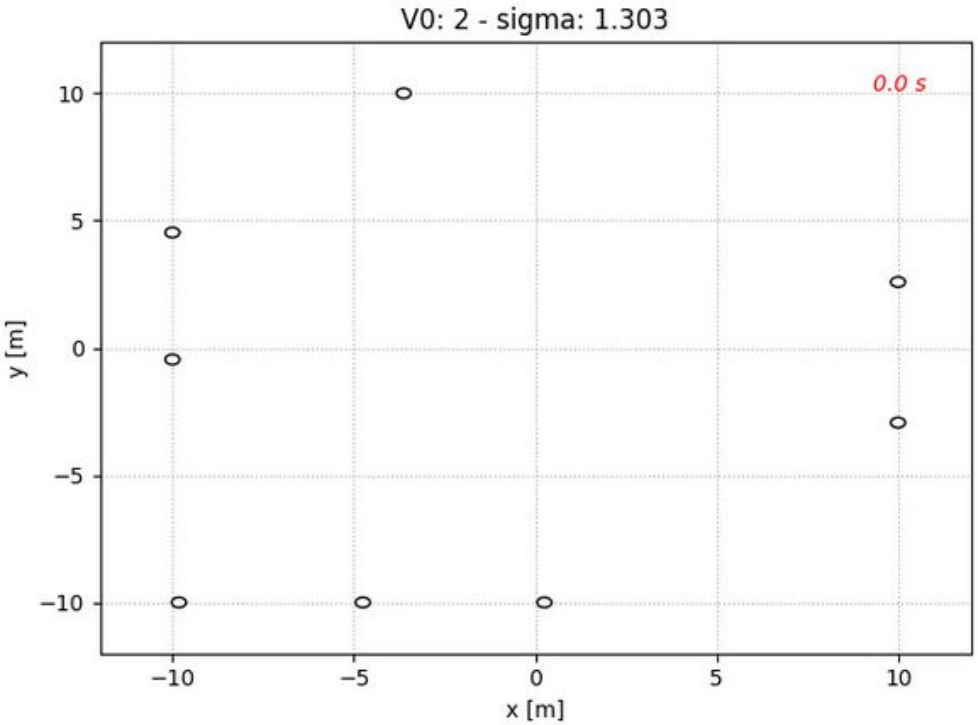

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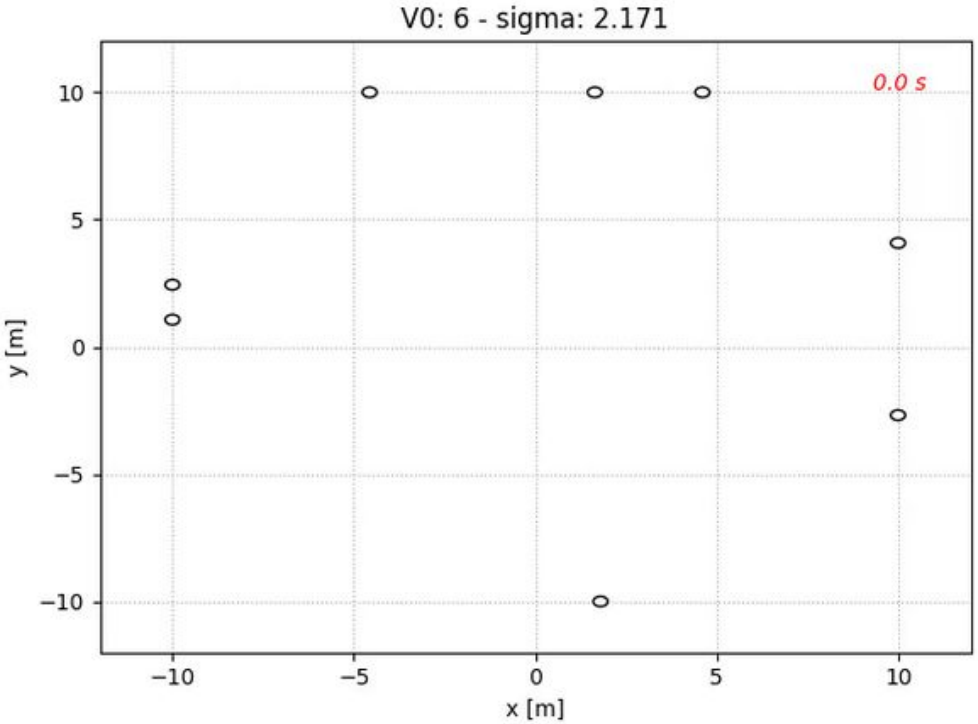
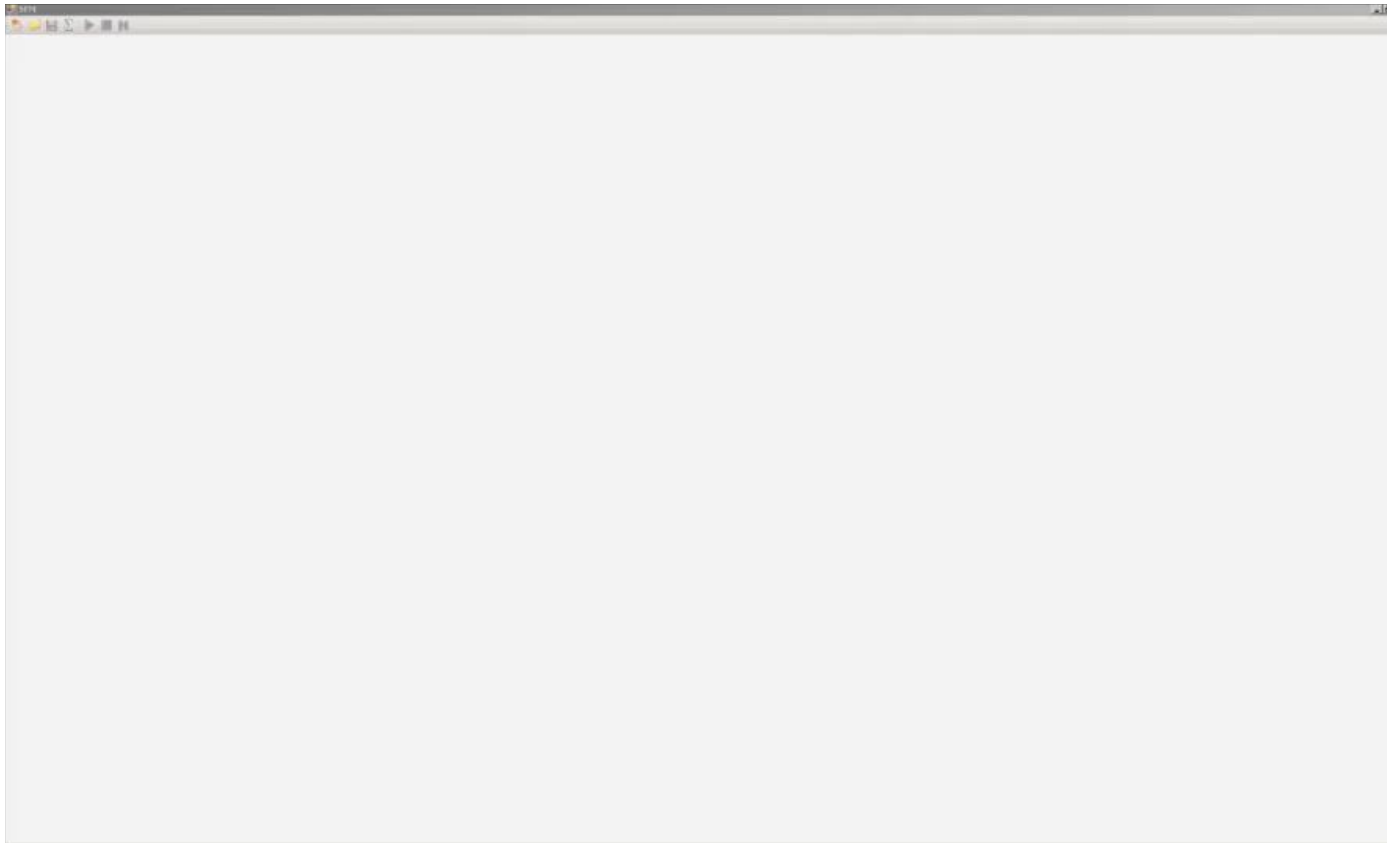


Social Force Model Simulation



Drawback of Social Force Model

- Model requires many parameters for each agent and all agent-agent and agent-environment pairs

- Shape of interaction functions are handcrafted

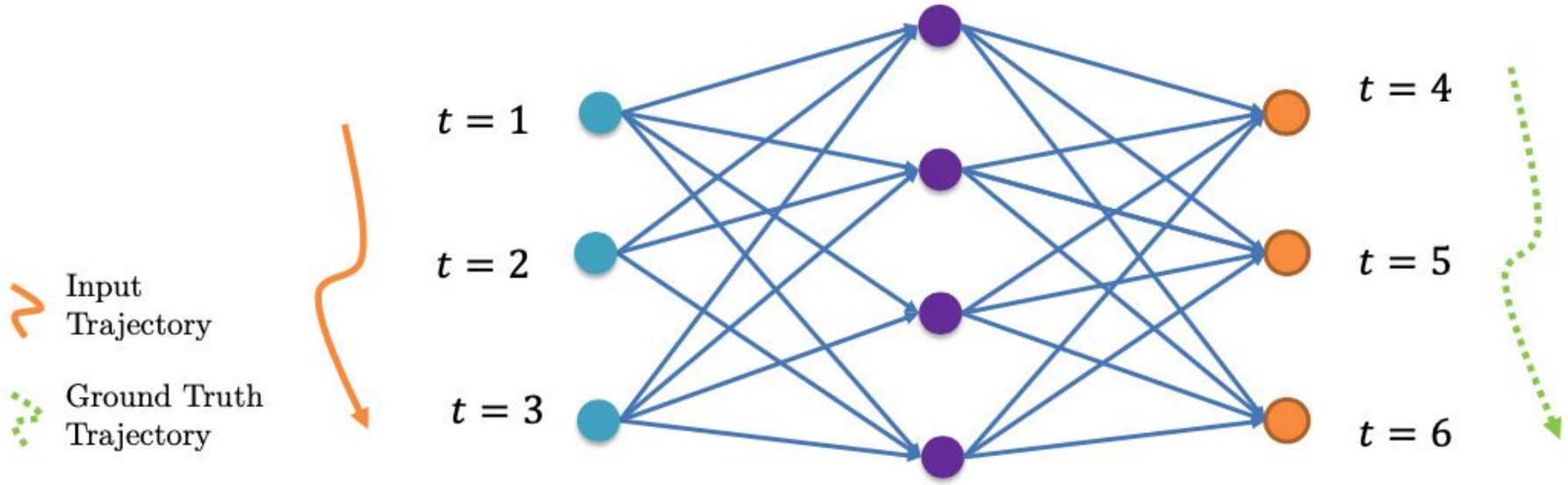
Drawback of Social Force Model

Handcrafted Functions

Learned Functions

Neural Network for Trajectory Prediction

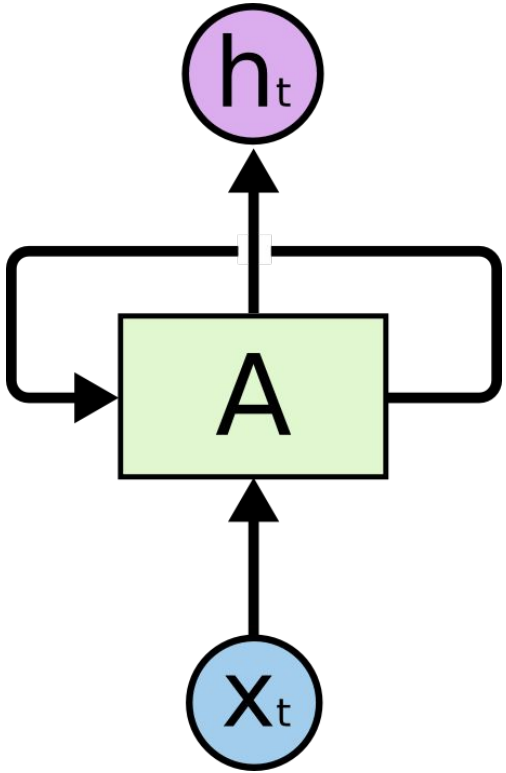
- Building a naïve prediction model with FC layers



- FC Layers do not account for sequential and temporal behavior of trajectories

⇒ Recurrent Neural Networks

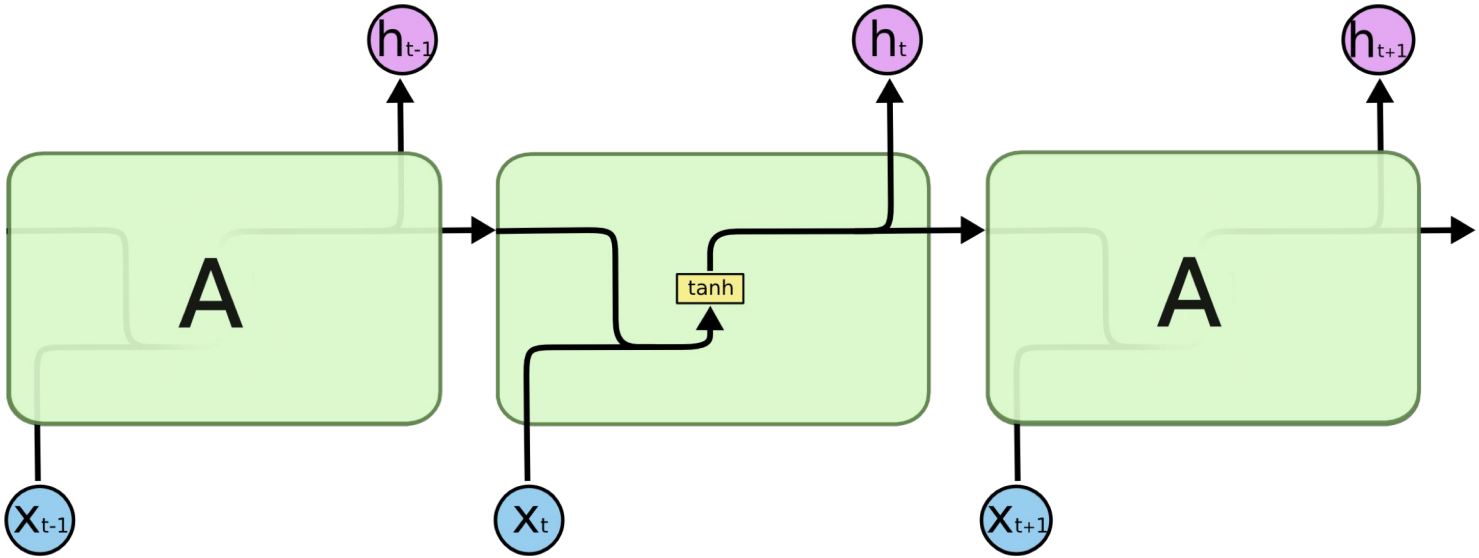
Recurrent Neural Networks



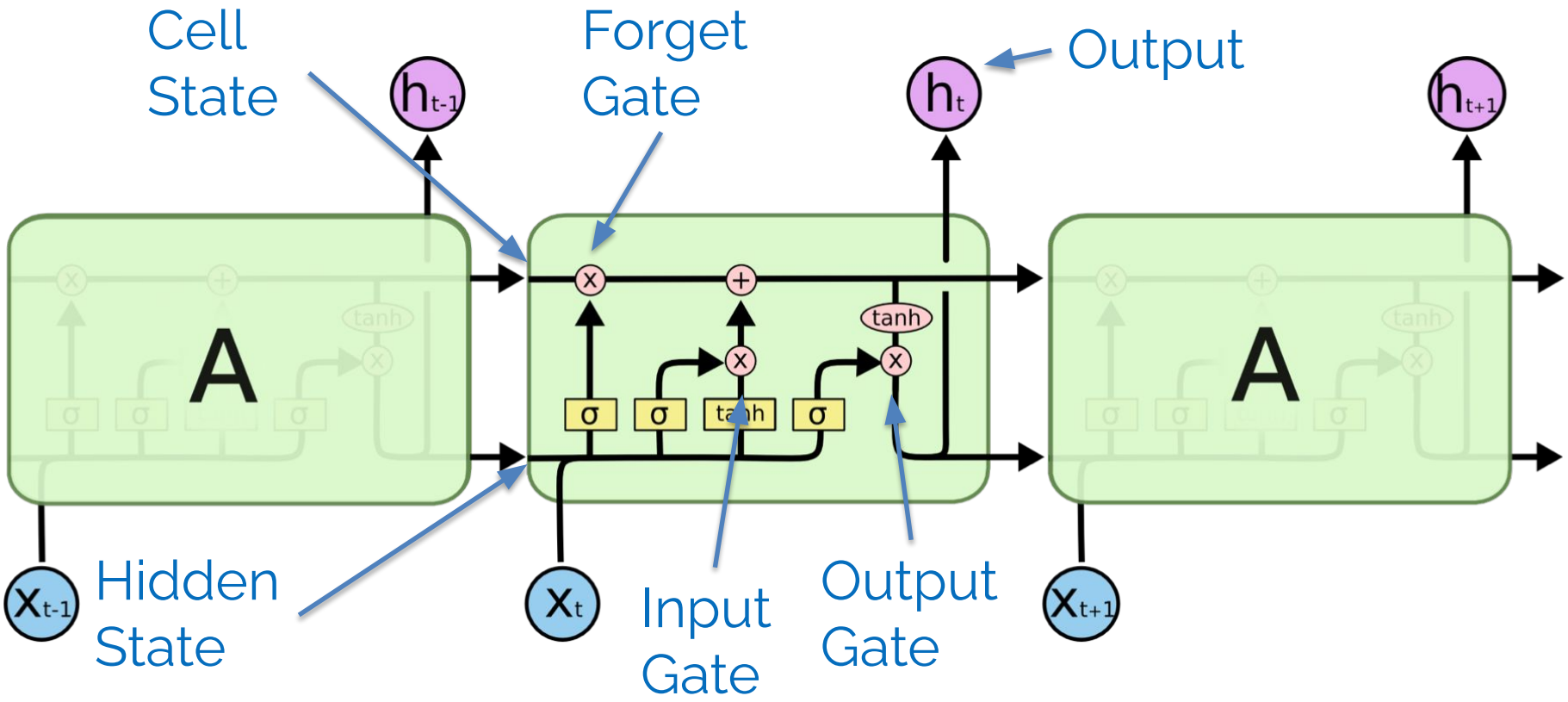
https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Simple RNN

$$h_t = \tanh\left(W \cdot h_{t-1} + V \cdot x_t + b\right)$$

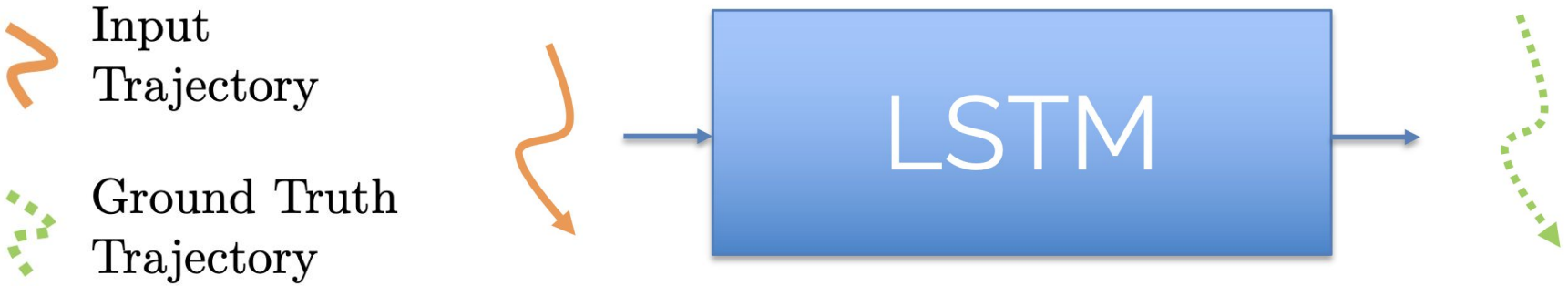


LSTM (Long Short-term Memory)



[Hochreiter et al. 97] *Long Short-term Memory*

LSTM for Trajectory Prediction



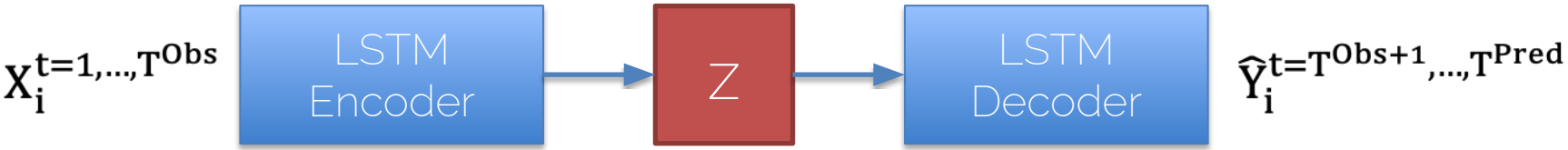
- Using a sinlge LSTM does not work well

Encoder-Decoder Architecture

LSTM Encoder –Decoder Architecture

Input

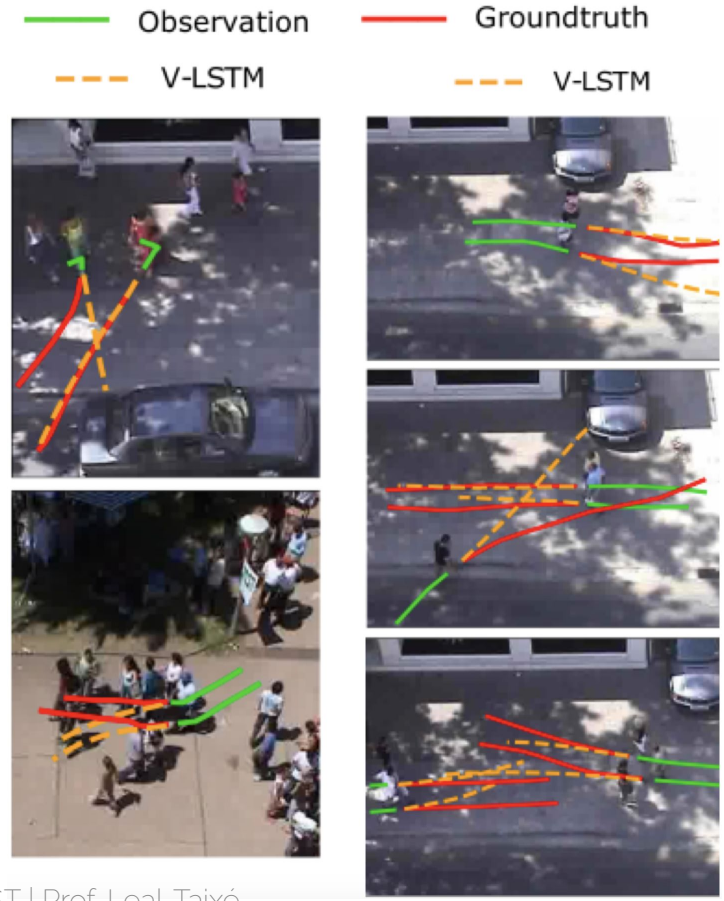
Output



Compressed (latent) representation

Training Objective: $\mathcal{L} = \left\| \hat{\mathbf{Y}} - \mathbf{Y} \right\|_2$

Vanilla LSTM



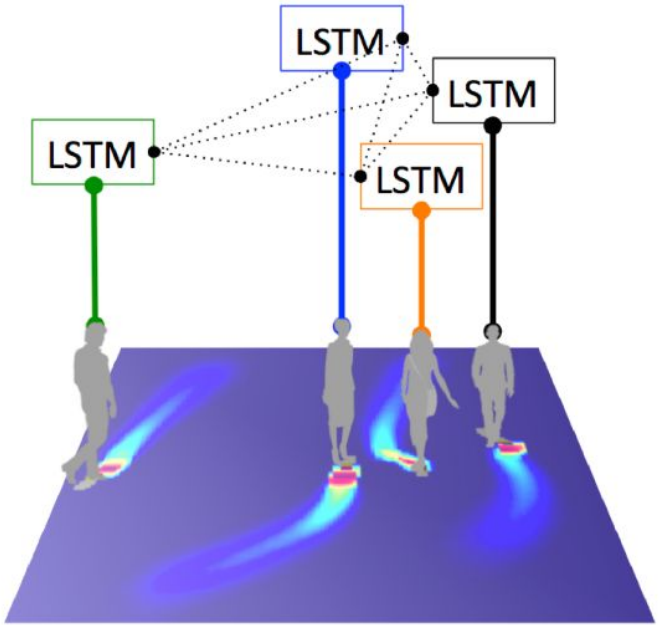
- Vanilla LSTM is not able to predict trajectories of interacting pedestrians

[Zhang et al. 19] SR-LSTM

Social LSTM

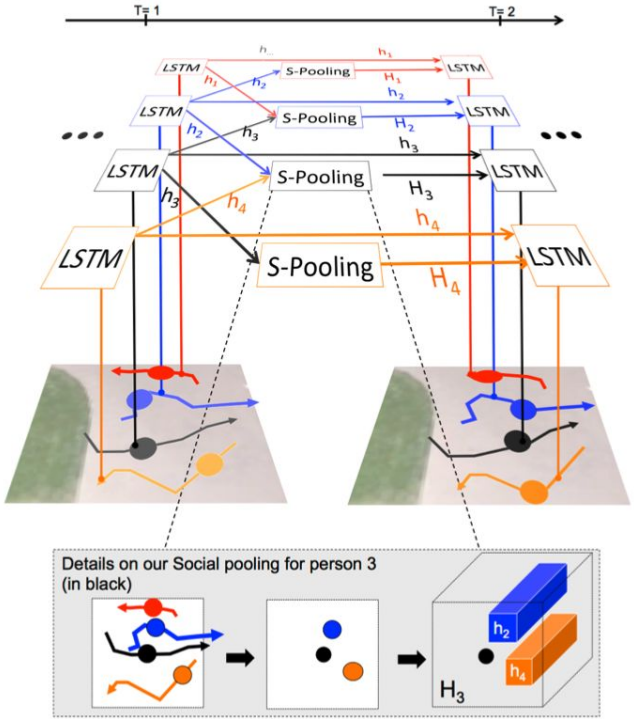
Contribution: Modeling social interactions

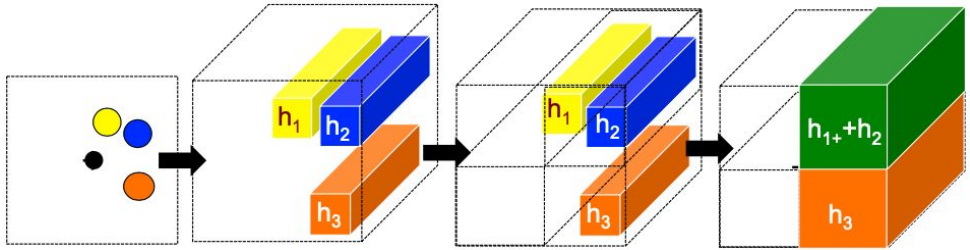
- LSTM encoder-decoder architectures
- Social pooling between neighboring pedestrians in each time step



[Alahi et al. 16] Social LSTM

Social LSTM – Pooling Module



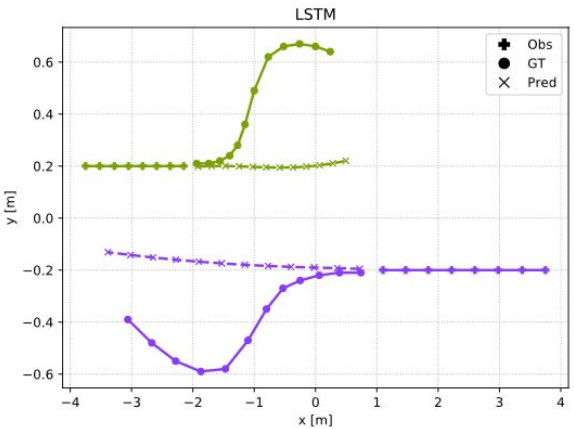


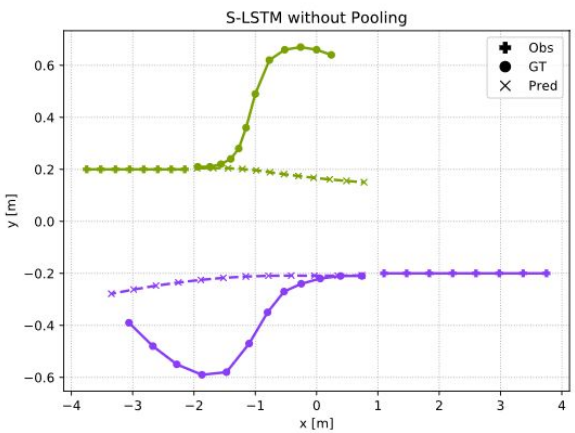
- Interaction Module pools hidden states of LSTM of pedestrian in vicinity
- Pooled hidden states are passed to decoder for next step prediction

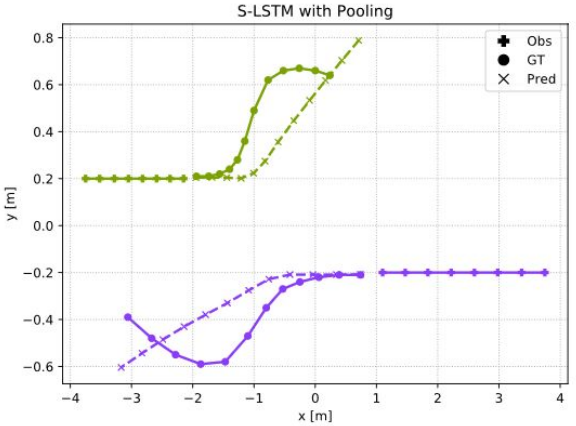
[Alahi et al. 16] Social LSTM

Social LSTM – Result

Comparison of Models with and without social pooling



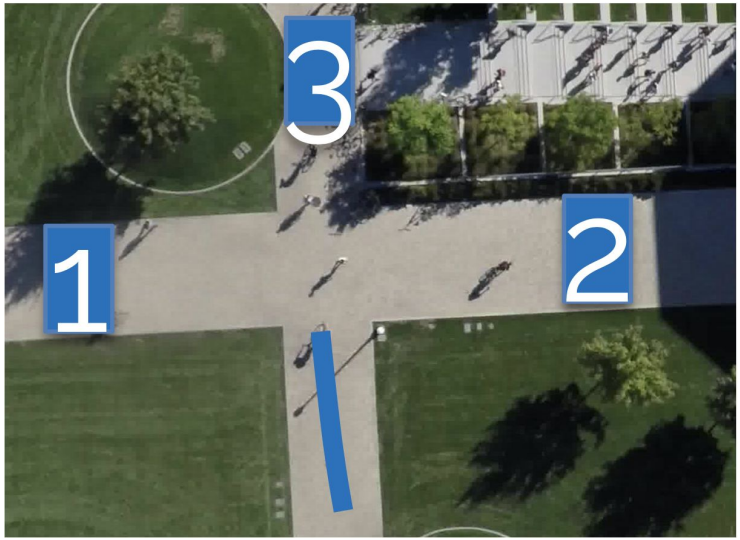




Social Pooling can resolve social interactions

Plots by Philipp Mondorf 20, BA

Pedestrian Trajectories are multimodal

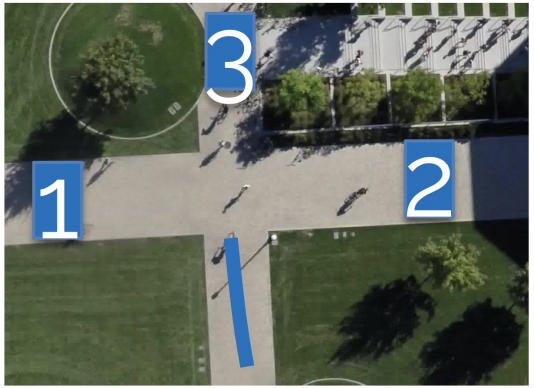


Same past trajectory can have multiple realistic future trajectories

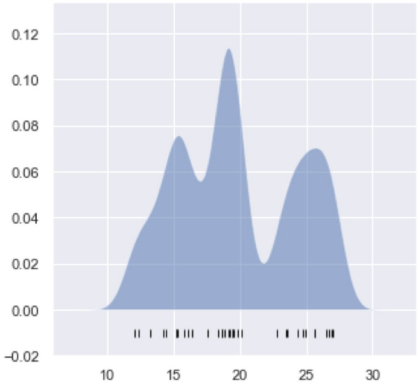
Deterministic vs. Stochastic Models

Deterministic	Stochastic
One-to-one mapping	One-to-many mapping

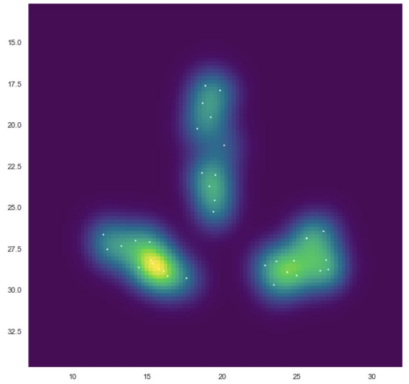
Learning distribution of future trajectories instead of deterministic mapping



Scenario



Distribution of final end



2d distribution of final end

Towards Generative Models

Deterministic Models

Generative Models

Generative Models

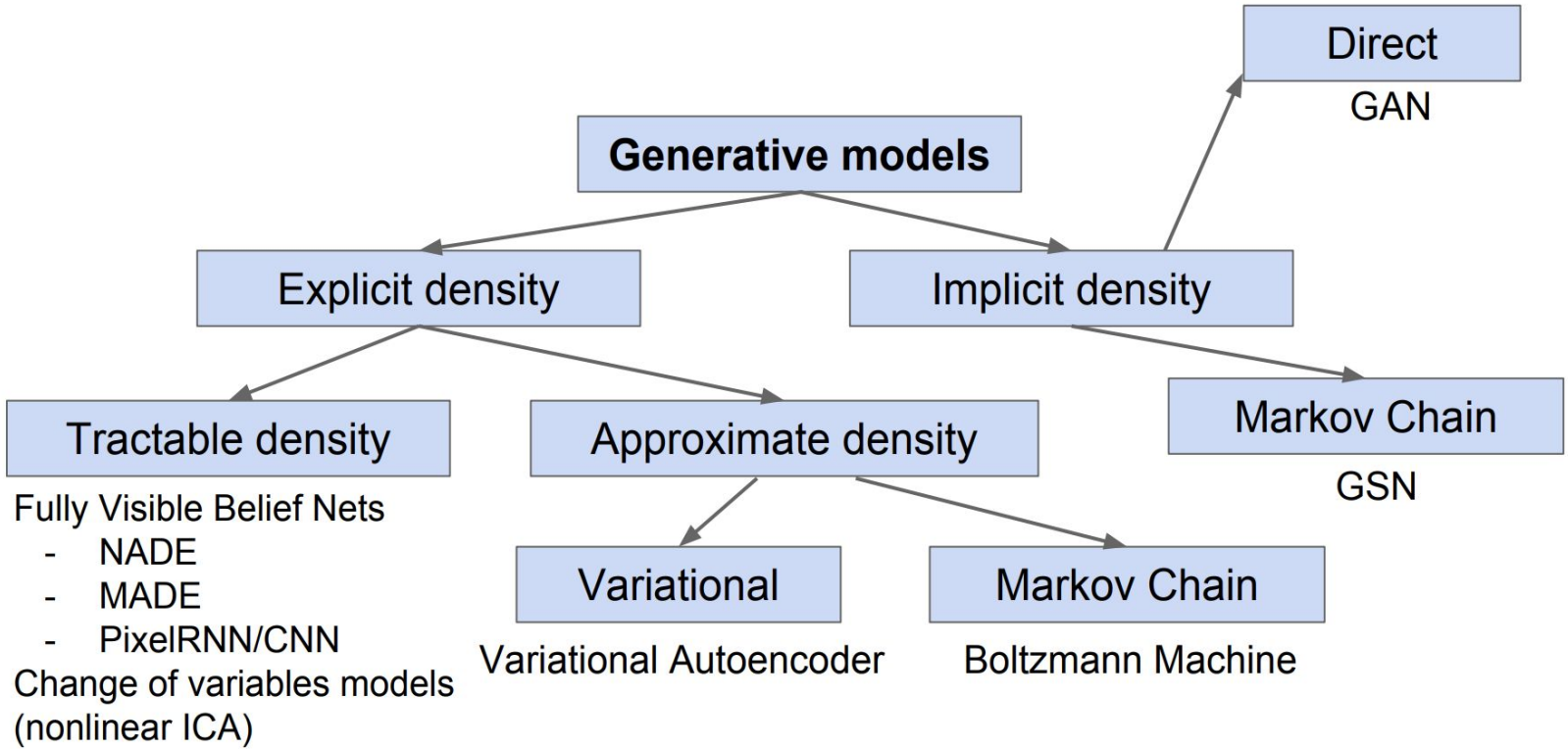


Figure from Ian Goodfellow, Tutorial on Generative Adversarial /networks, 2017

Recap: Generative Models

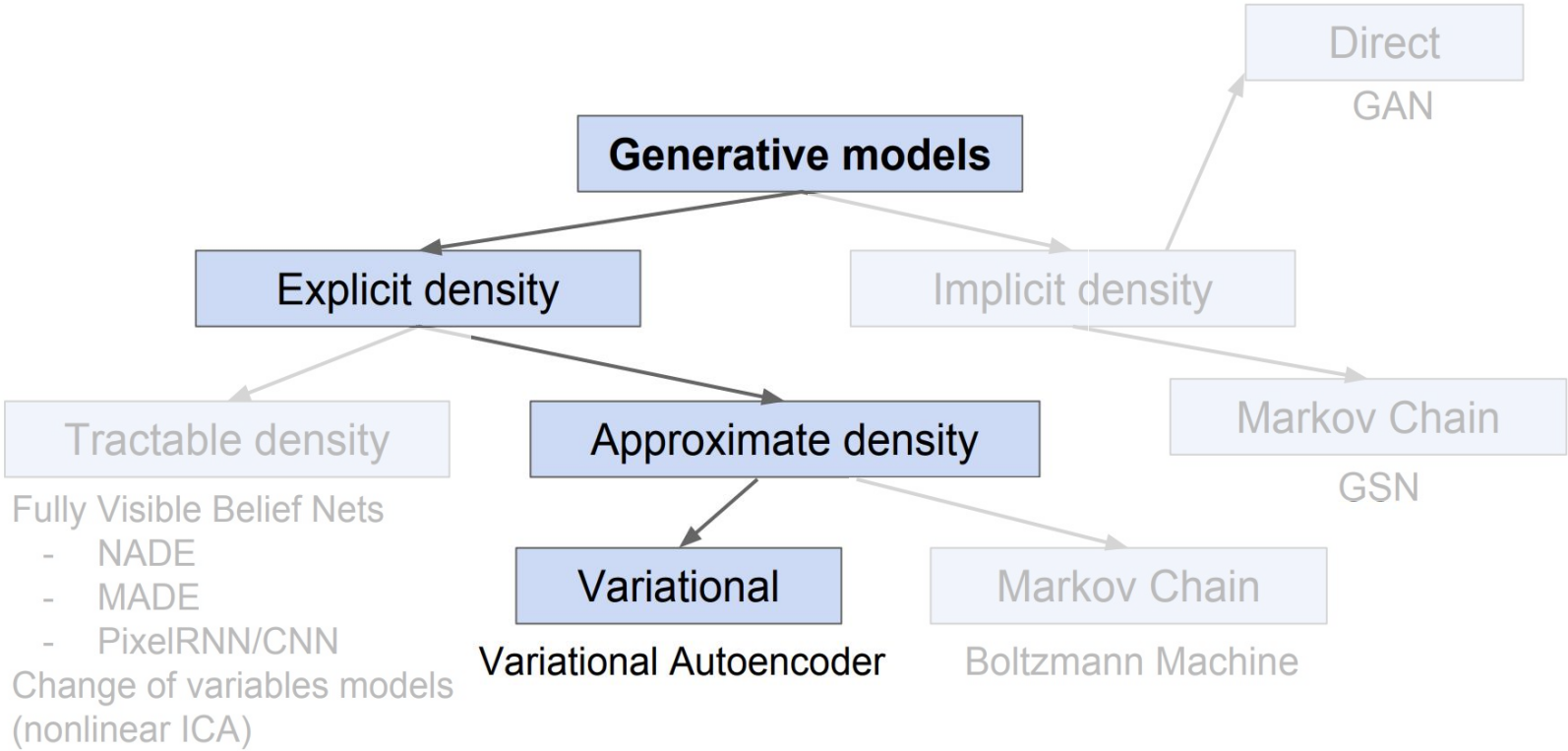
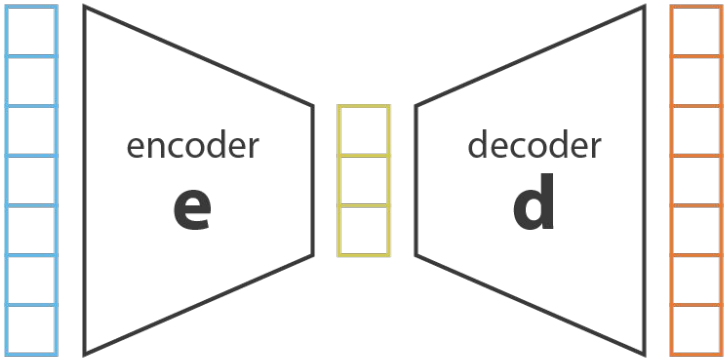


Figure from Ian Goodfellow, Tutorial on Generative Adversarial /networks, 2017

Variational Autoencoder



x — **initial data** in space R^n

$e(x)$ — **encoded data** in latent space R^m (with $m<n$)

$d(e(x))$ — **encoded-decoded data** back in the initial space R^n

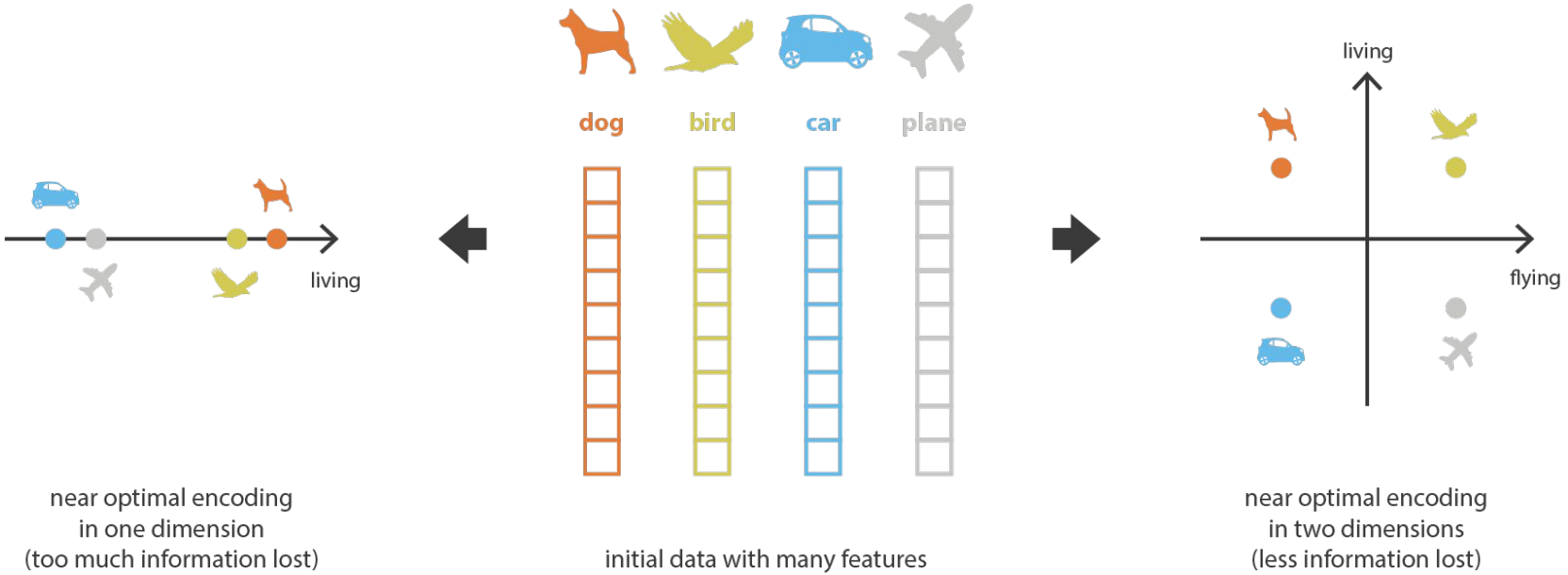
$x = d(e(x))$ ➡ **lossless encoding**
no information is lost when reducing the number of dimensions

$x \neq d(e(x))$ ➡ **lossy encoding**
some information is lost when reducing the number of dimensions and can't be recovered later

https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73

[Kingma et al. 16] Variational Bayes

Variational Autoencoder



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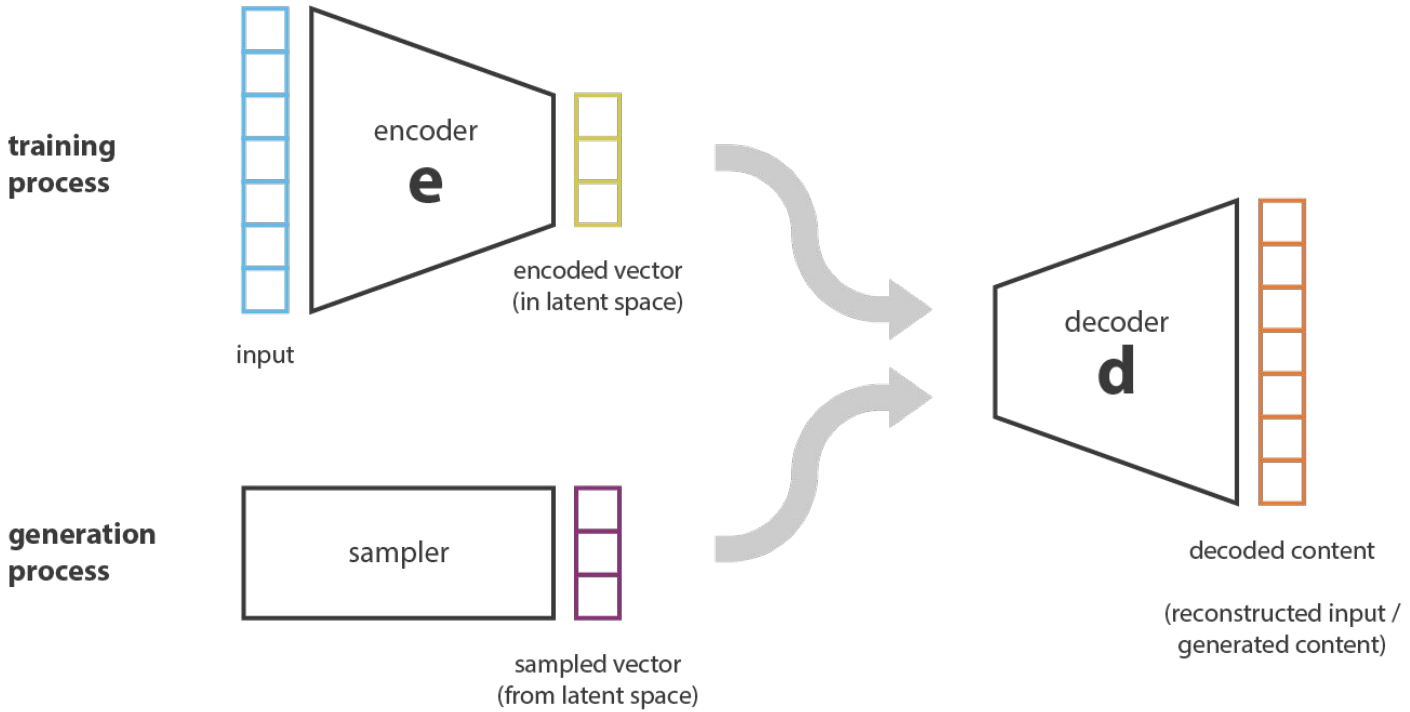

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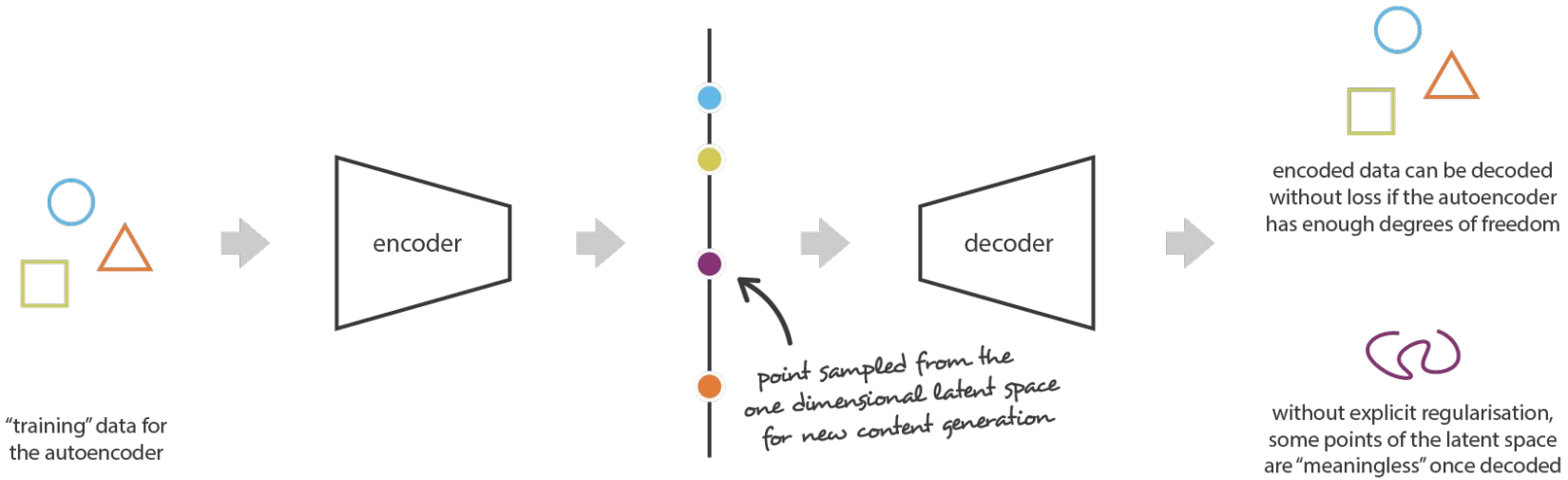

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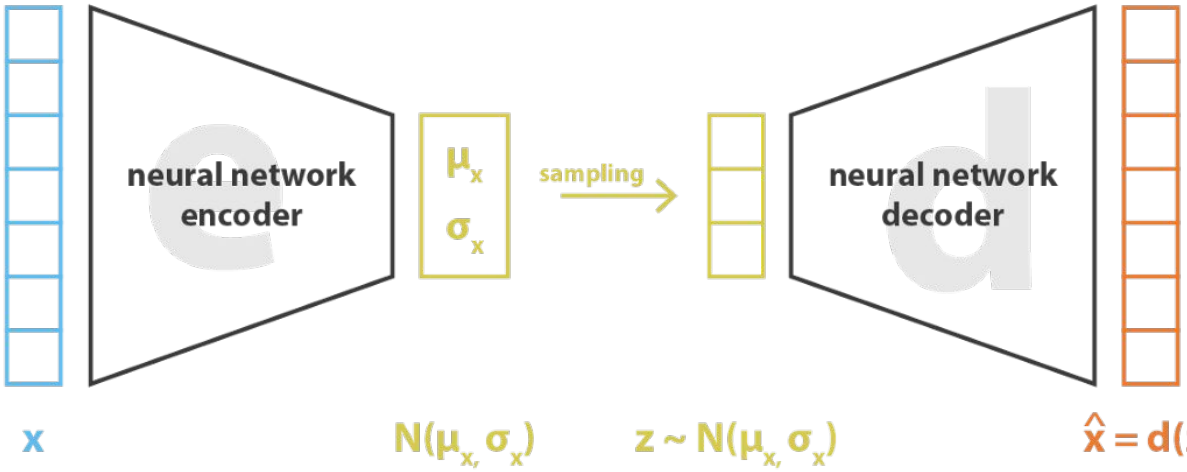

Kulback-Leibler (KL) divergence

$$\text{loss} = ||x - \hat{x}||^2 + KL[N(\mu_x, \sigma_x), N(0, I)] = ||x - d(z)||^2 + KL[N(\mu_x, \sigma_x), N(0, I)]$$

https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73

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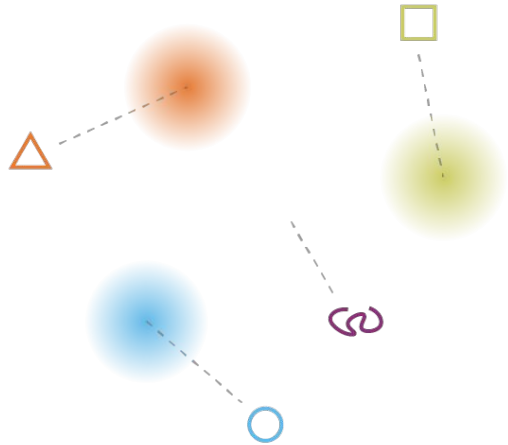
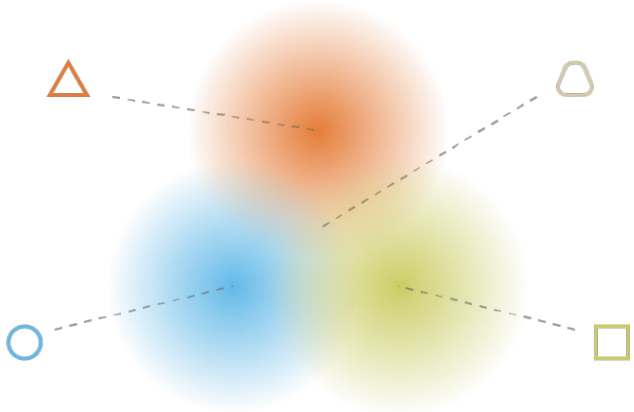
Variational Autoencoder



what can happen without regularisation



what we want to obtain with regularisation

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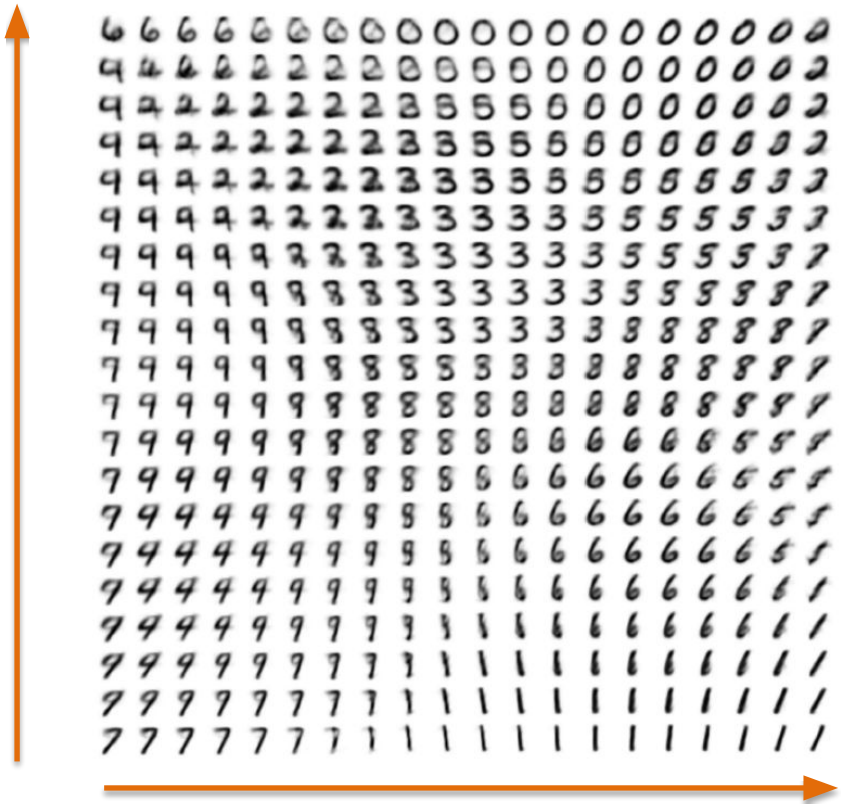
[Kingma et al. 16] Variational Bayes

Variational Autoencoder



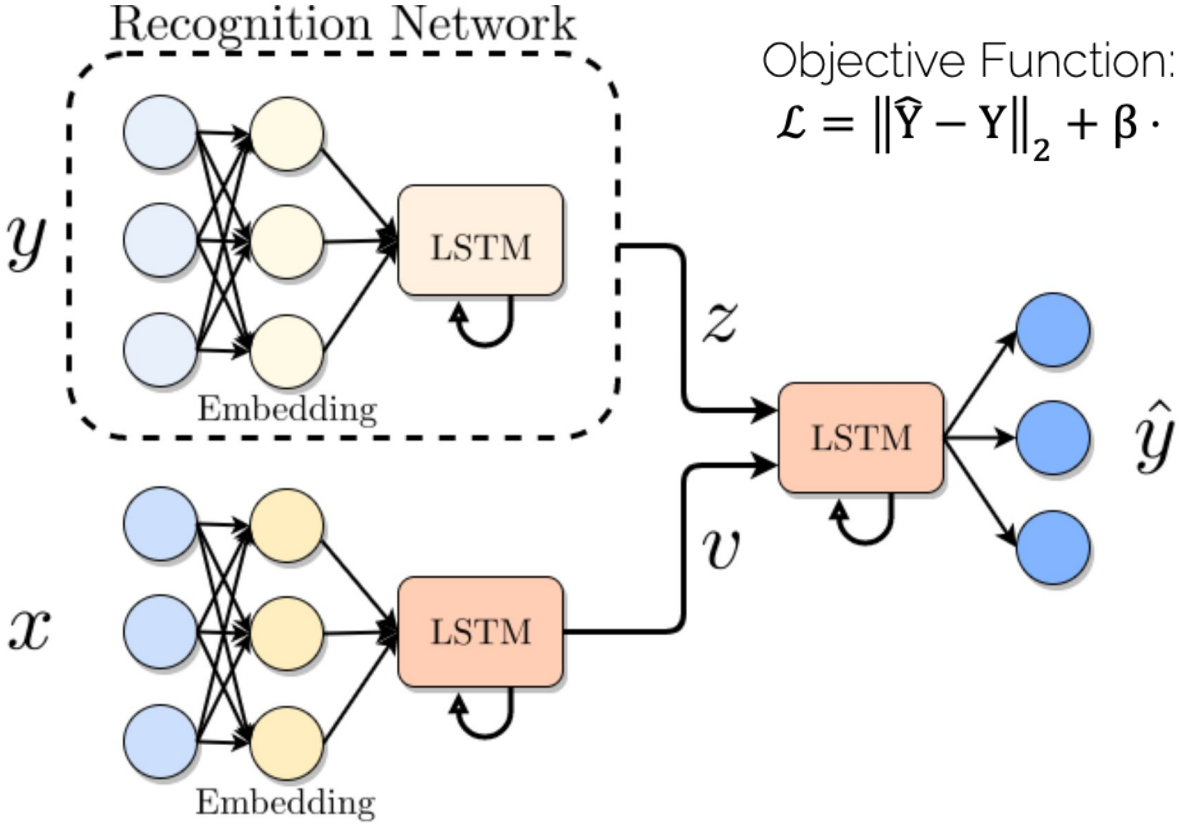
Each element of z encodes a different feature

Variational Autoencoder

Degree of smile

Head pose

Conditional Variational Autoencoder



Objective Function:

$$\mathcal{L} = \left\|\hat{Y} - Y\right\|_2 + \beta \cdot D_{KL}(q_\theta(z|x,y)|N(0,1))$$

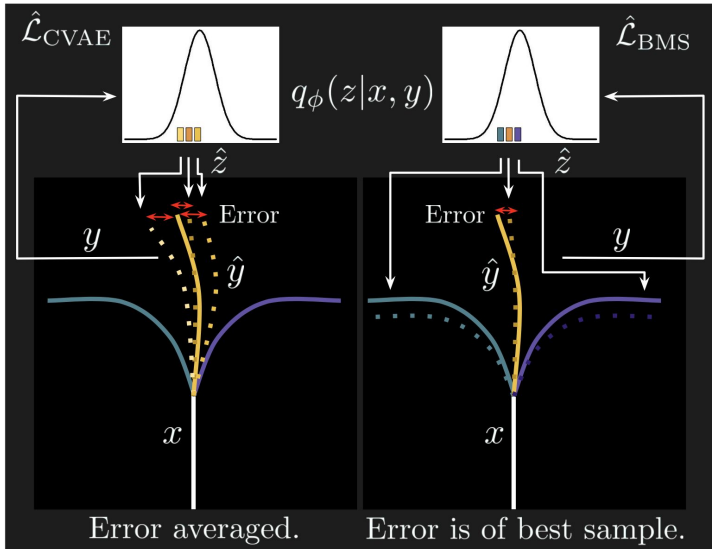
Kulback-Leibler (KL) divergence

[Bhattacharyya et al. 18] Best of Many

Best-of-many-sampling

- Sample multiple trajectories
- Backpropagate sample with minimal error

Before | Best of Many Sampling (BMS)



Objective Function:

$$\mathcal{L} = \min_{j} \left\| \hat{Y} - Y \right\|_2 + \beta \cdot D_{KL}(q_\theta(z|x,y)|N(0,1))$$

[Bhattacharyya et al. 18] Best of Many

Visual results cVAE

K-mean clustered trajectories

[Bhattacharyya et al. 18] Best of Many

Recap: Generative Models

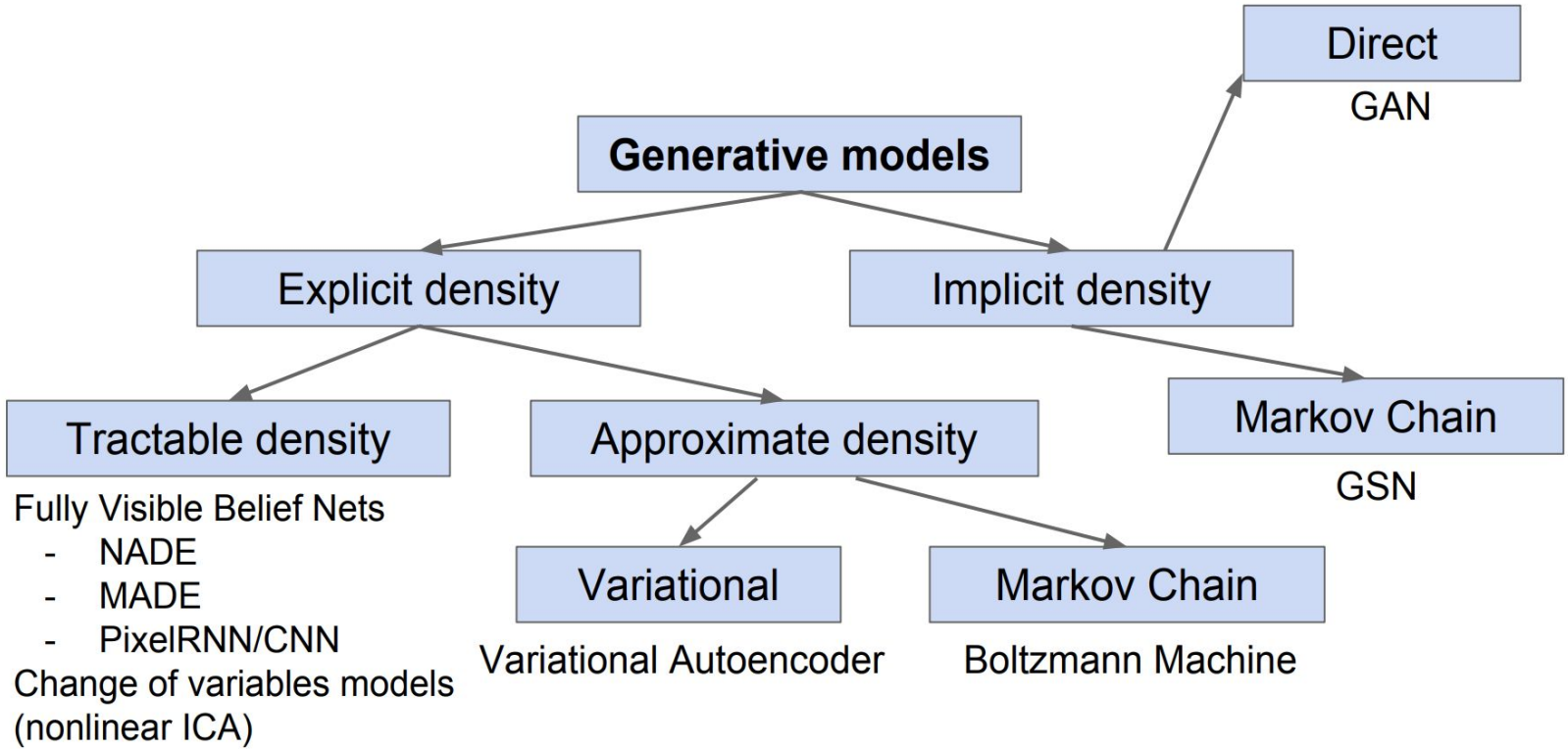


Figure from Ian Goodfellow, Tutorial on Generative Adversarial /networks, 2017

Recap: Generative Models

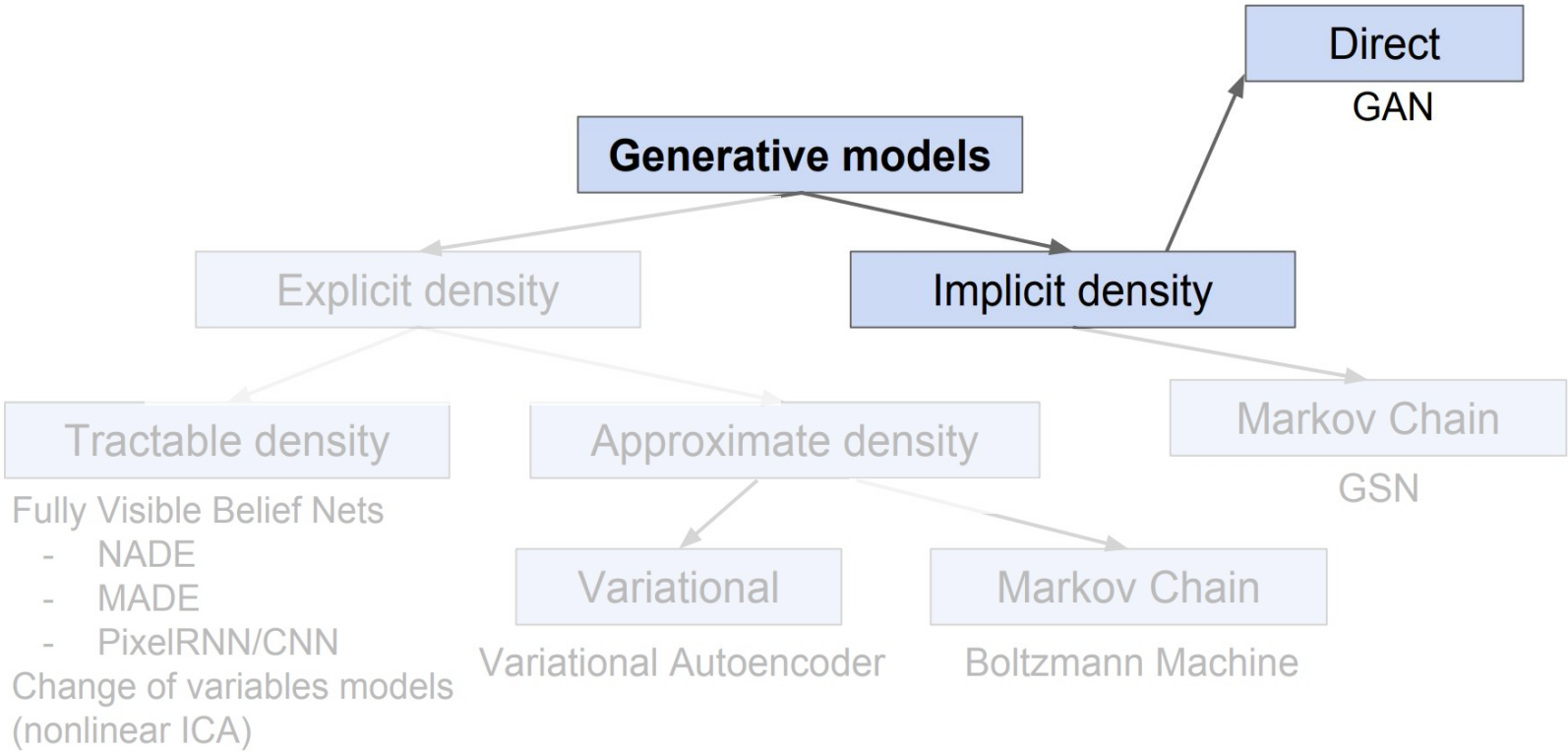
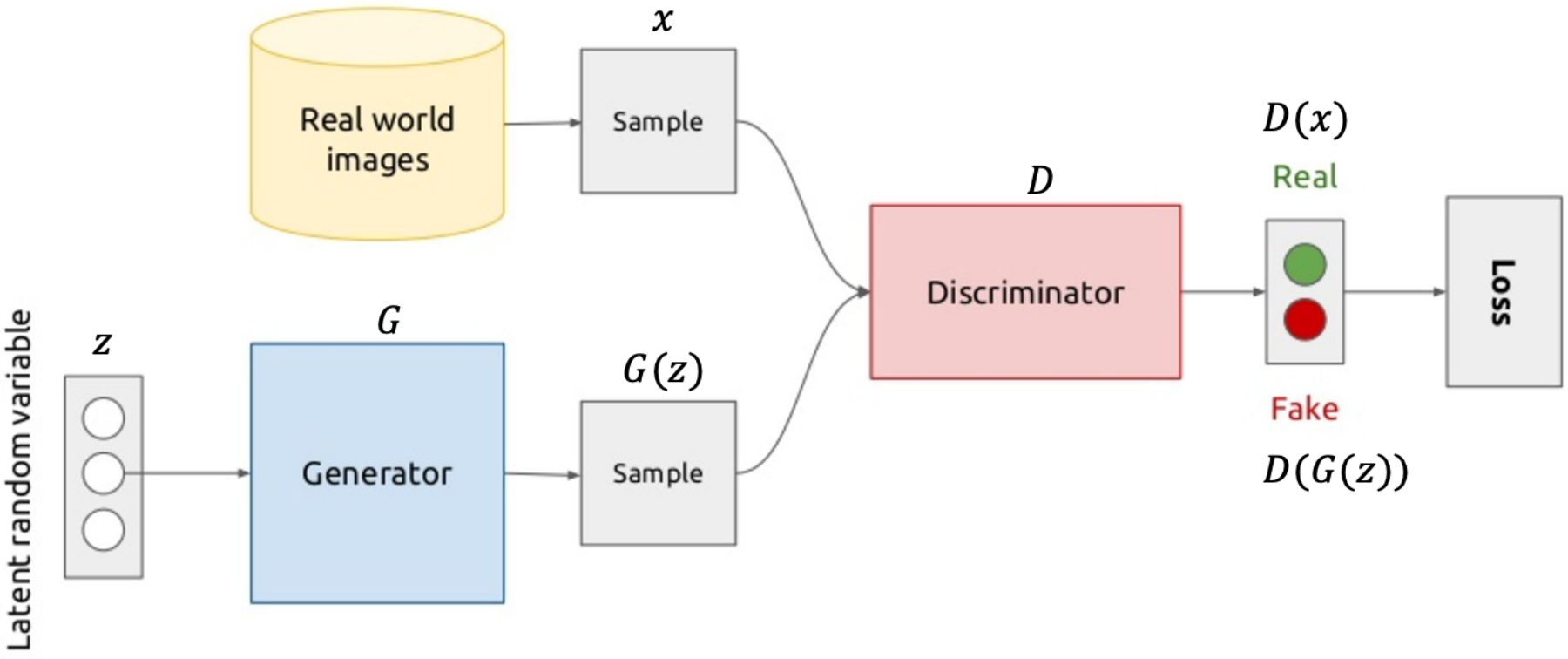


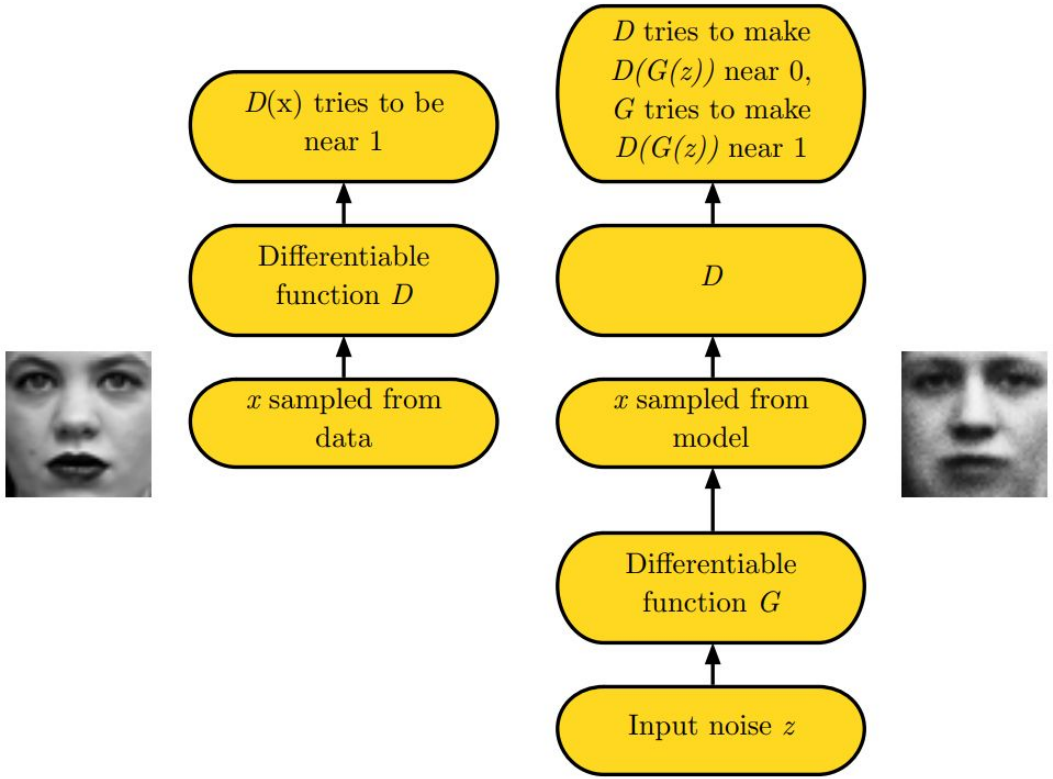
Figure from Ian Goodfellow, Tutorial on Generative Adversarial /networks, 2017

Generative Adversarial Networks (GANs)



[Goodfellow et al. 14] GANs (slide McGuinness)

Generative Adversarial Networks (GANs)



[Goodfellow et al. 14] GANs (slide McGuinness)

GANs: Loss Functions

Discriminator loss

$$J^{(D)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}} \log D(\boldsymbol{x}) - \frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log\left(1 - D\left(G(\boldsymbol{z})\right)\right)$$

binary cross entropy

Generator loss

$$J^{(G)} = -J^{(D)}$$

- Minimax Game:
  - G minimizes probability that D is correct
  - Equilibrium is saddle point of discriminator loss

-> D provides supervision (i.e., gradients) for G

[Goodfellow et al. 14] GANs (slide McGuinness)

GANs: Loss Functions

Discriminator loss

$$J^{(D)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}} \log D(\boldsymbol{x}) - \frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log\left(1 - D\left(G(\boldsymbol{z})\right)\right)$$

Generator loss

$$J^{(G)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log D\left(G(\boldsymbol{z})\right)$$

- Heuristic Method (often used in practice)
  - G maximizes the log-probability of D being mistaken
  - G can still learn even when D rejects all generator samples

[Goodfellow et al. 14] GANs (slide McGuinness)

Vanilla GAN

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right].$$

end for

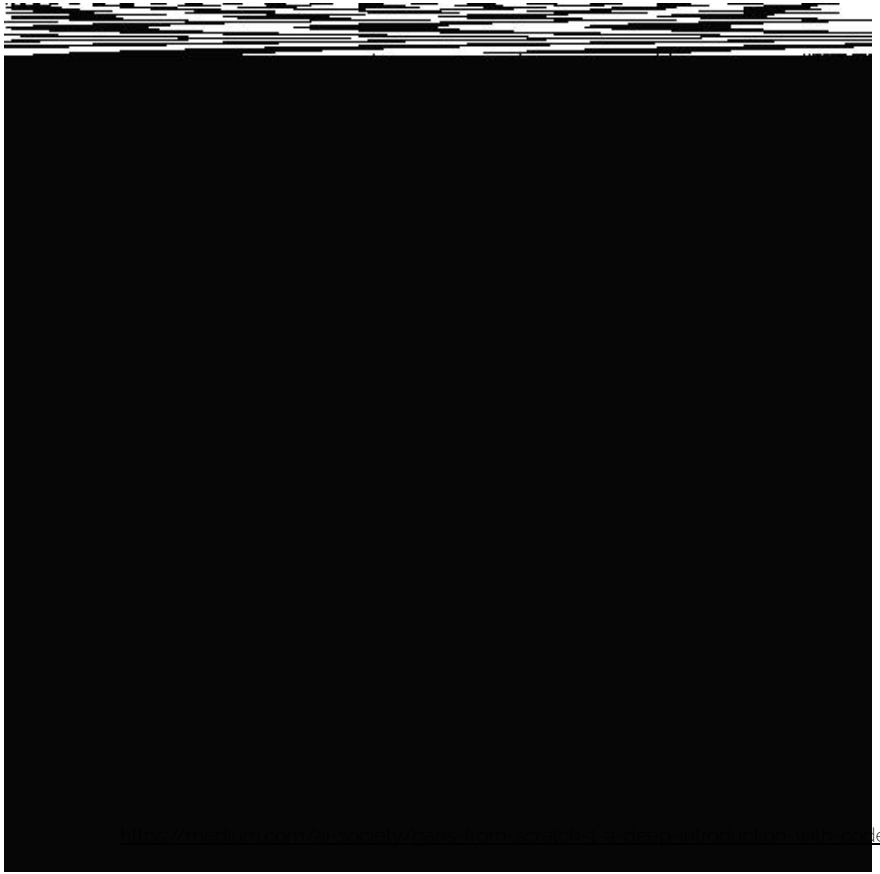
- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

[Goodfellow et al. 14] GANs (slide McGuinness)

Training GAN

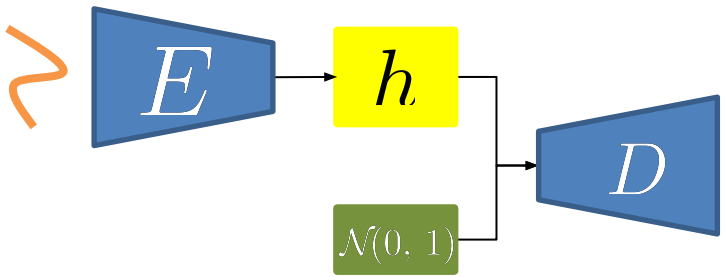


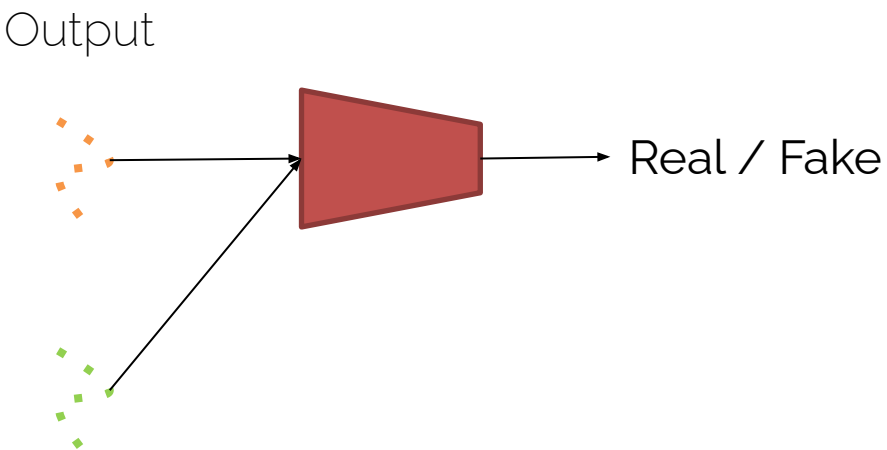
https://medium.com/ai-society/gans-from-scratch-1-a-deep-introduction-with-code-in-pytorch-and-tensorflow-cb03cdcdba0f

GANs for Trajectory Prediction

Generator

Discriminator

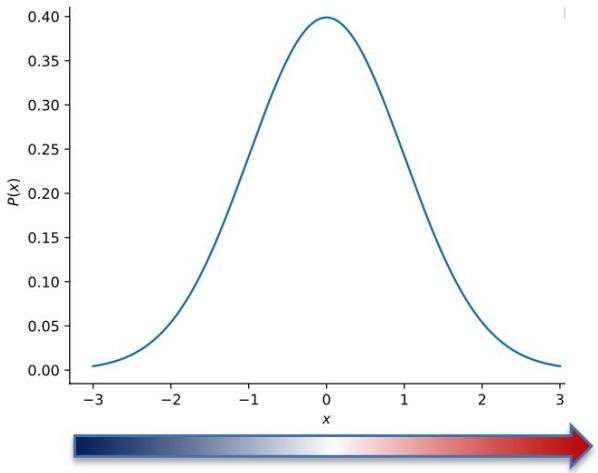




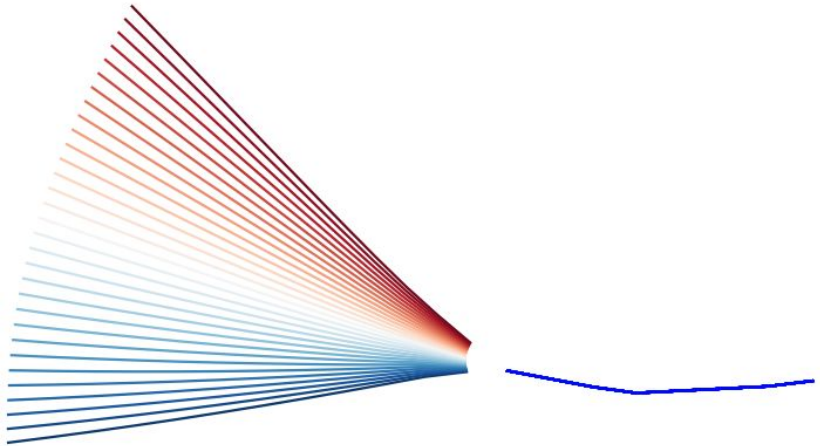
Latent space in GANs

- Different latent space samples result into different real space output

Latent Space



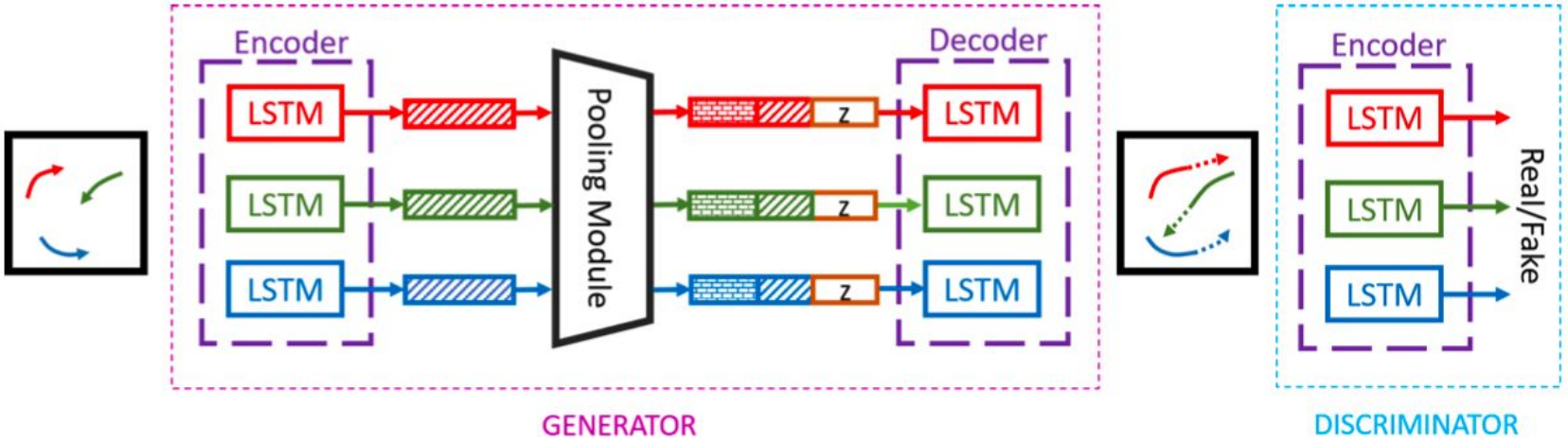
Real Space



[Gupta et al. 18] Social GAN

Social GAN

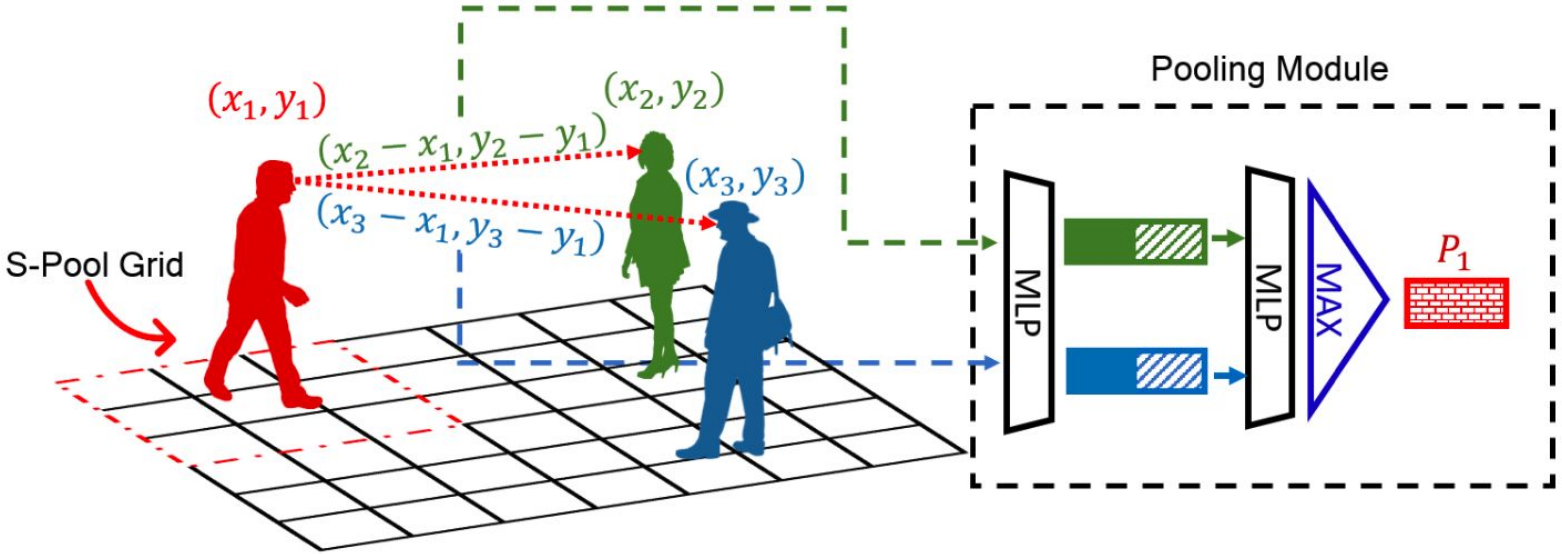
Contribution: GAN + Social Interactions



[Gupta et al. 18] Social GAN

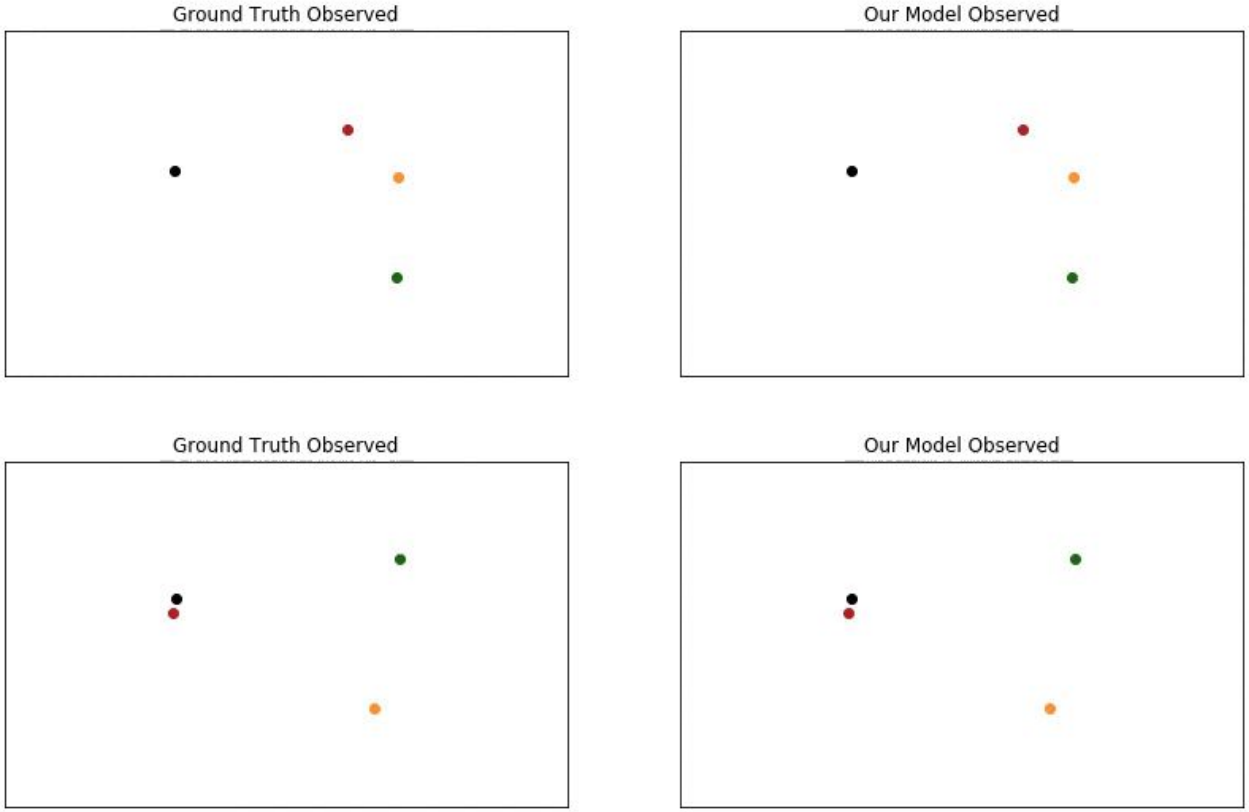
SGAN Pooling Module

- Pooling Vector: $\max_j \mathbf{MLP}\left(\left[\mathbf{x_j} - \mathbf{x_i}, \mathbf{y_j} - \mathbf{y_j}, \mathbf{h_j^{t-1}}\right]\right)$
- max – operation is symmetric (initial order does not matter)
- Pooling is not restricted to grid (S-LSTM)



[Gupta et al. 18] Social GAN

SGAN Results

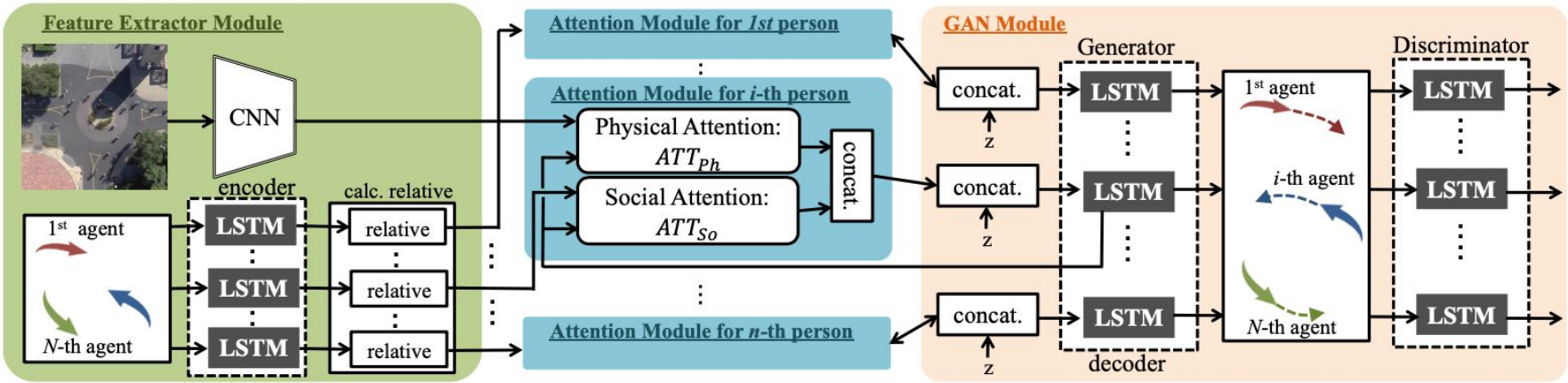


[Gupta et al. 18] Social GAN

SoPhie

Contribution: Combining physical and social interactions

- SoPhie uses soft attention istead of max-pooling



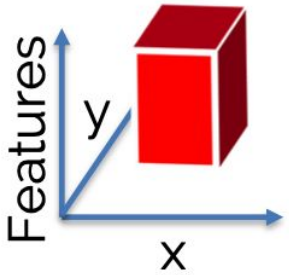
[Sadeghian et al. 19] SoPhie

Visual Attention

- Spatial Attention selects relevant features for each region in scene

e.g. VGG

Visual Features $F_{i,j,k}$



Attention Network

Softmax Layer

- Attention values weight visual features for each spatial position

$$\alpha_{ijk} = Softmax(MLP(F_{ij}))$$

$$A_{ij} = \sum_{k} \alpha_{ijk} \cdot F_{ijk}$$

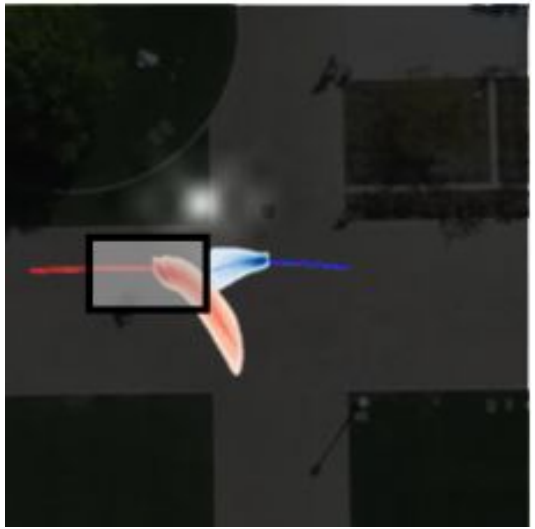
[Sadeghian et al. 18] SoPhie
[Xu et. al. 15] Show, Attend and Tell

SoPhie Results

Scene Interaction

Social Interaction

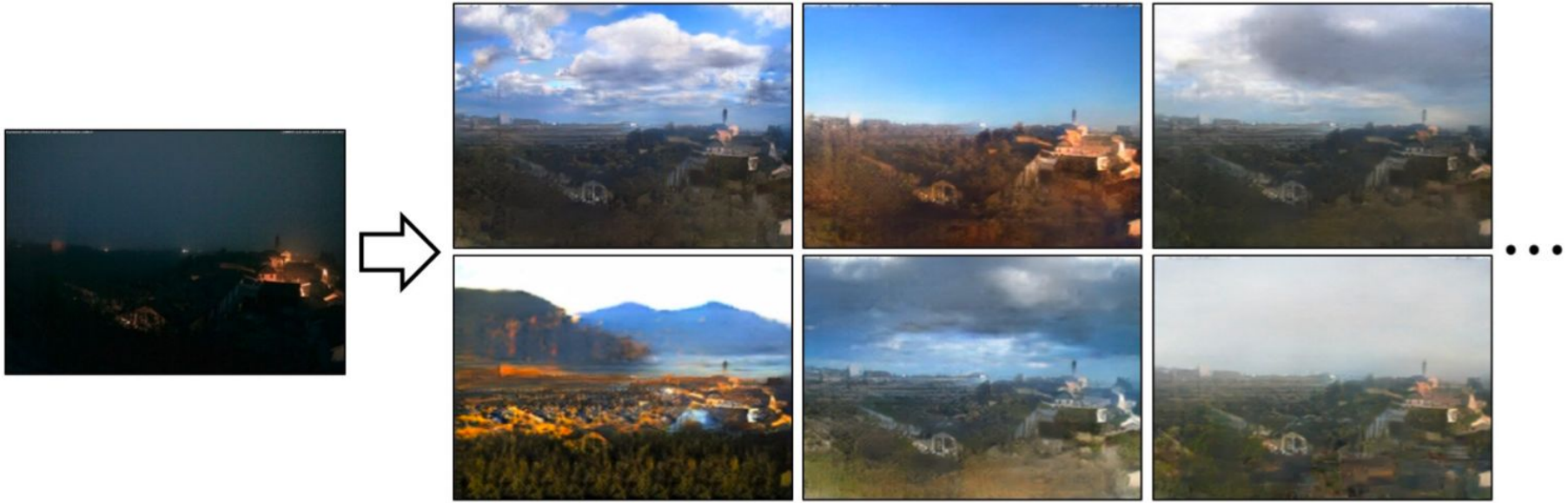
Scene + Social Interaction



[Sadeghian et al. 19] SoPhie

Multimodal Image-to-Image Translation

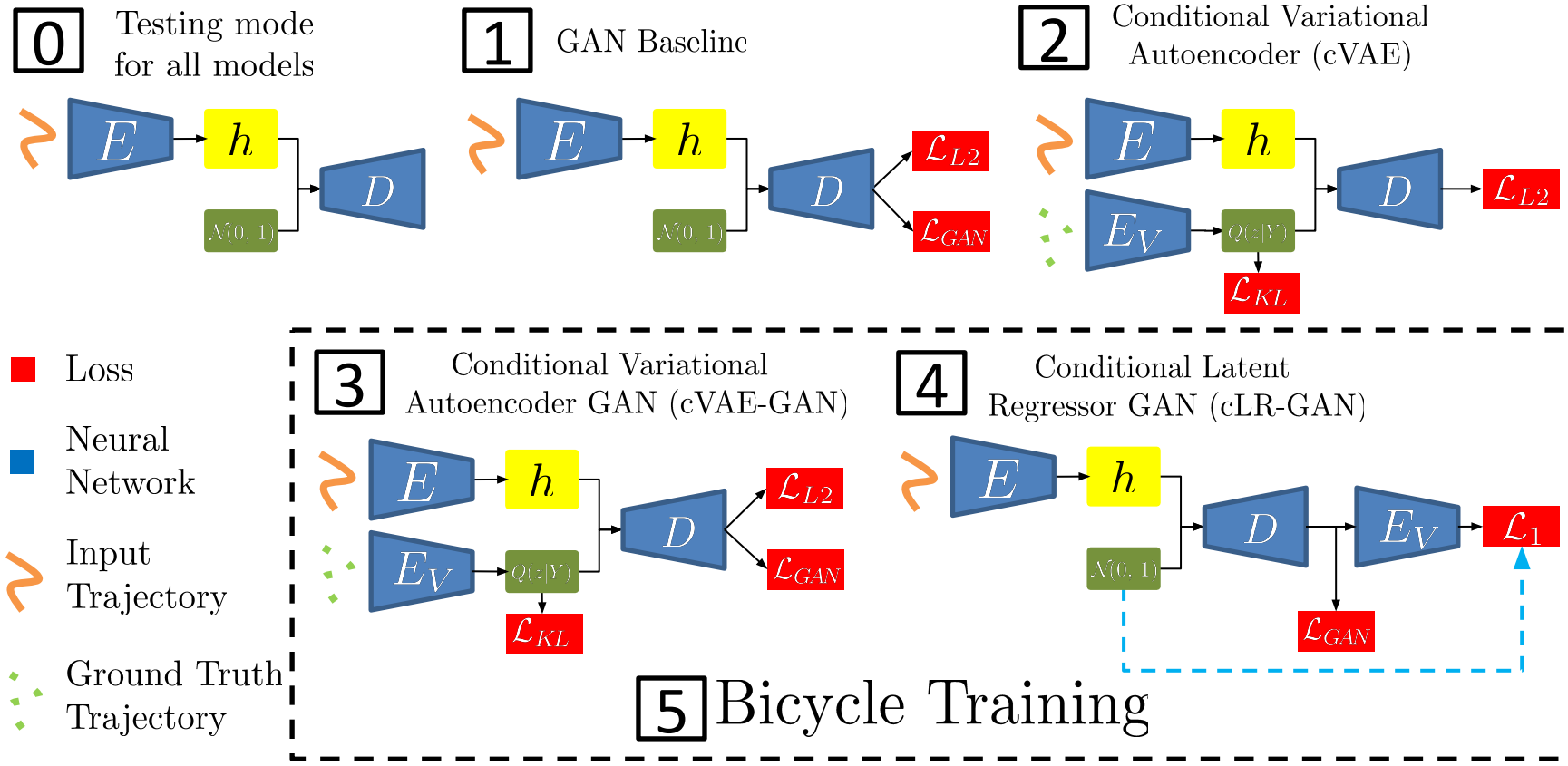
- Multimodality in image-to-image translation



Bicycle GAN training

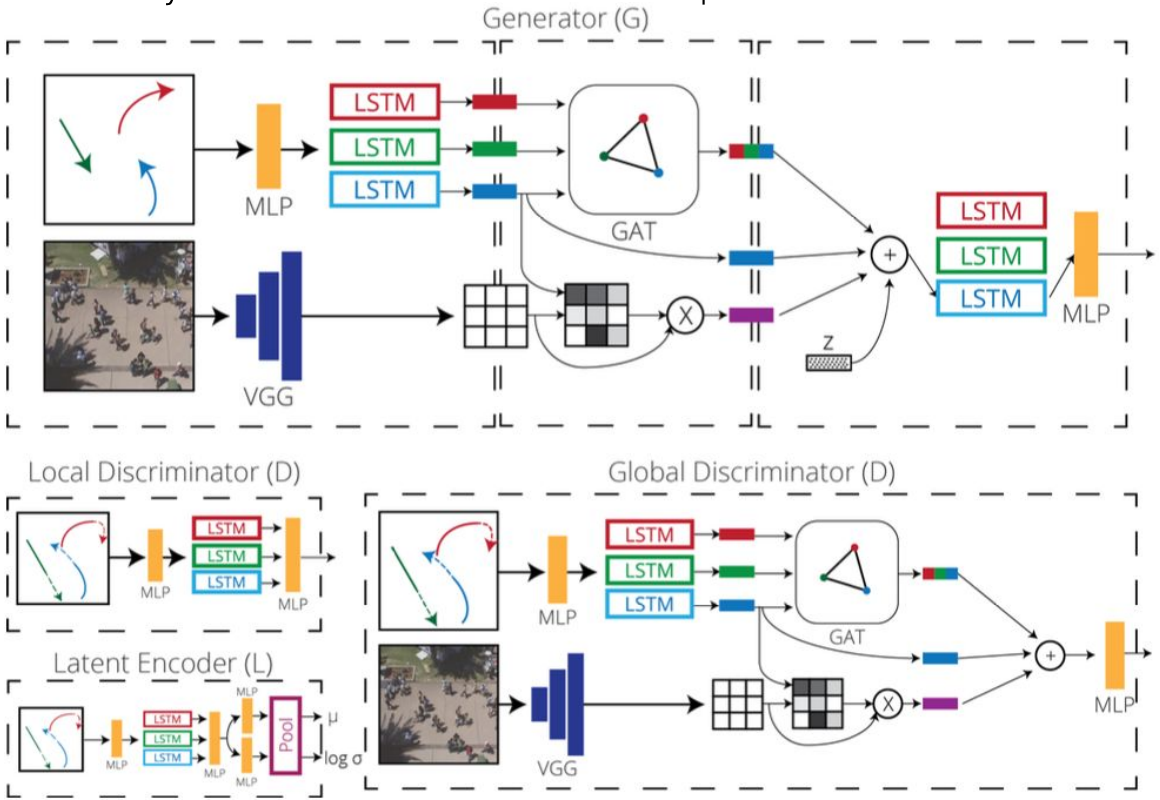
[Zhu et al. 17] Image-to-image translation

Bicycle GAN


0
Testing mode for all models
E
h
D
$\mathcal{N}(0, 1)$
1
GAN Baseline
$\mathcal{L}_{L2}$
$\mathcal{L}_{GAN}$
2
Conditional Variational Autoencoder (cVAE)
E_V
$Q(z|Y)$
$\mathcal{L}_{KL}$
Loss
Neural Network
Input Trajectory
Ground Truth Trajectory
3
Conditional Variational Autoencoder GAN (cVAE-GAN)
4
Conditional Latent Regressor GAN (cLR-GAN)
$\mathcal{L}_1$
5
Bicycle Training

Social BiGAT

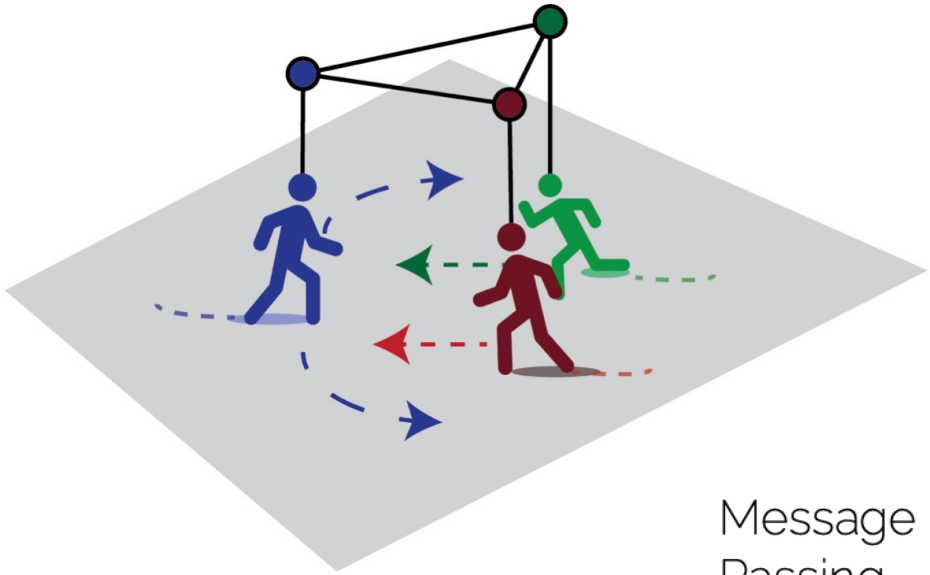
Contribution: Bicycle GAN (Bi) + Graph Attention Network GAT)



[Kosaraju et al. 19] Social BiGAT

Social BiGAT: Graph Attention Network

- Modeling social interactions with graph attention network



Attention network

Encoder features

$$e_{ij} = a\left(W_{gat}V_s(i), W_{gat}V_s(j)\right)$$

Parameters

$$a_{ij} = Softmax_j(e_{ij})$$

Message Passing Steps l

$$e_s^l(i) = \sum_j \alpha_{ij} W_{gat} V_s(j)$$

[Kosaraju et al. 19] Social BiGAT

Summary

- Pedestrian Trajectory Prediction is relevant for numerous problem, e.g. autonomous driving and tracking
- Multimodal nature of trajectories requires generative models (VAE and GAN)
- Most methods use LSTM encoder-decoder architecture
- Interactions are modelled with attention modules or graph networks

Thank you for you attention!

Interested in working on Pedestrian Trajectory Prediction?
Contact me for MA or guided research: Patrick.dendorfer@tum.de