

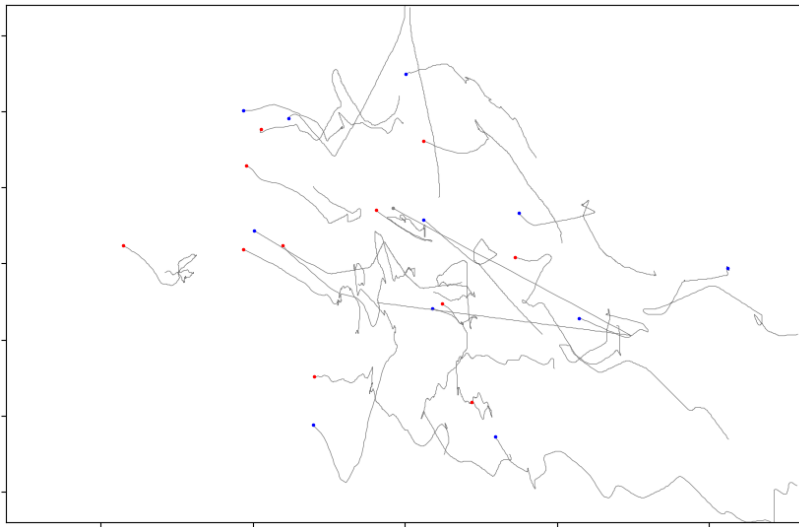
# SciSports: Player evaluation in soccer using 2D tracking data

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## 2D Tracking Data



# Goals

- ▶ Quantifying football.
- ▶ Player Evaluation using 2D tracking data.

# Game Plan towards Player Evaluation

1. Gain insights on player's space-time geometry and statistics of trajectories of players.
2. Generate trajectories of a single player.
3. Generate trajectories of all players.
4. Generate trajectories conditional on players' positions.
5. Use reinforcement learning to evaluate game setup and eventually individual players.

# Dynamic Linear Model and Newtonian Dynamics

$$\mathbf{y}_t = \mathbf{F}_t \boldsymbol{\alpha}_t + \boldsymbol{\epsilon}_t \quad (\text{Observation})$$

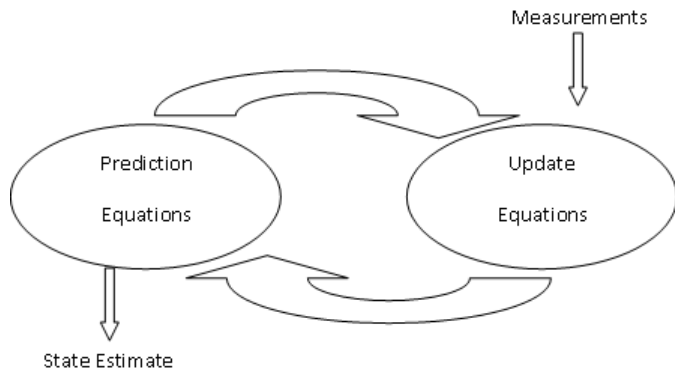
$$\boldsymbol{\alpha}_{t+1} = \mathbf{G}_t \boldsymbol{\alpha}_t + \boldsymbol{\eta}_t \quad (\text{Latent process})$$

$\boldsymbol{\epsilon}_t, \boldsymbol{\eta}_t$  are Gaussian error and innovation

$$\boldsymbol{\alpha}_t = \begin{pmatrix} \text{position } x \\ \text{position } y \\ \text{velocity } x \\ \text{velocity } y \end{pmatrix}$$

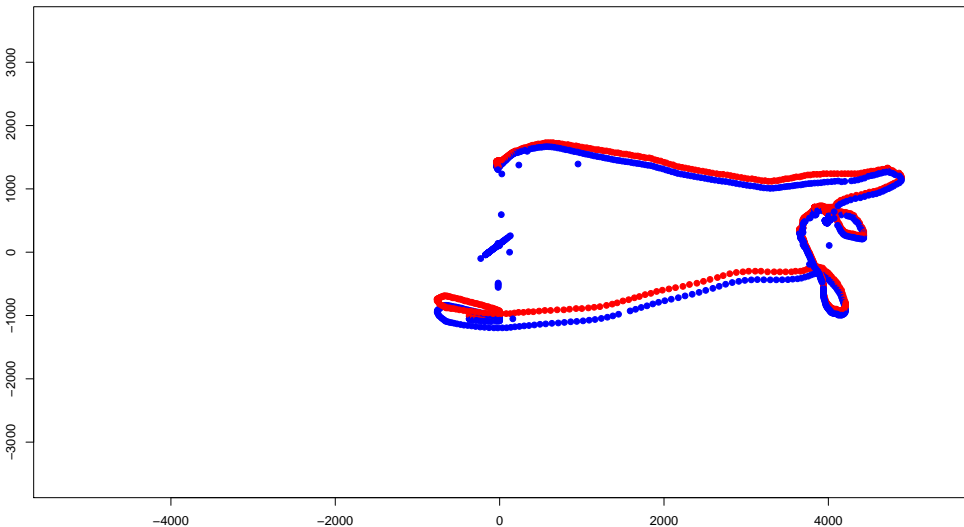
We only observe the  $(x, y)$  positions. The entries of  $\mathbf{G}_t$  are based on  $s = vt + \frac{1}{2}at^2$

# Kalman Filter

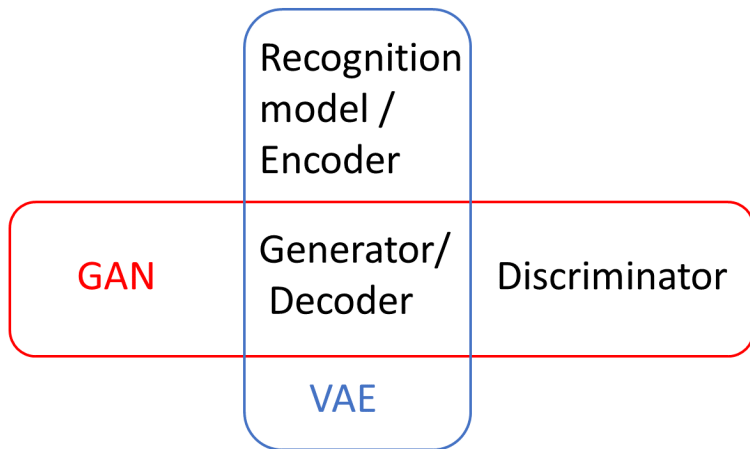


# One-step ahead online prediction

Red: Actual footballer's position, Blue: Predicted



# Generative Adversarial Network and Variational Autoencoder

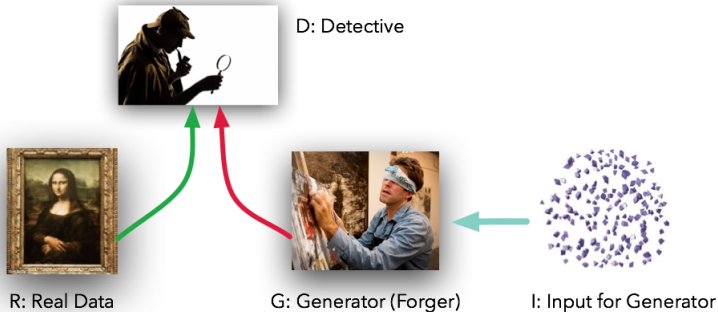




# Generative Adversarial Network

Two competing neural networks:

1. One tries to generate the best trajectories possible
2. One tries to distinguish generated and real trajectories



# Generative Adversarial Network

GAN works well for generating images

## Generating Pokémon



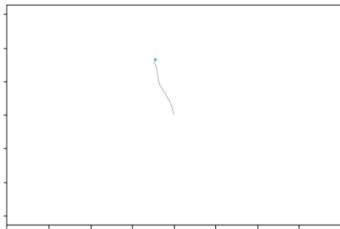
# Generative Adversarial Network

Can we generate trajectories instead?

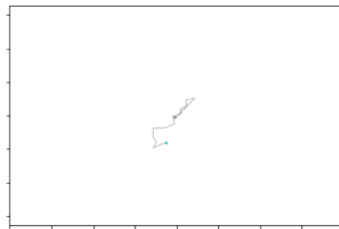
## Generating Pokémon



# Results



(a) Realised Trajectory



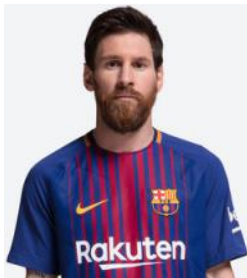
(b) Generated Trajectory

# Generative Adversarial Network

- ▶ Problem with GAN: Not enough computation power to train two Neural Networks.
- ▶ We train the discriminator to distinguish between players.
- ▶ We train the discriminator to distinguish between artificial and realised trajectories.

# Distinguishing between two players

Given a trajectory, can we guess which player it belongs to?



# Discriminator

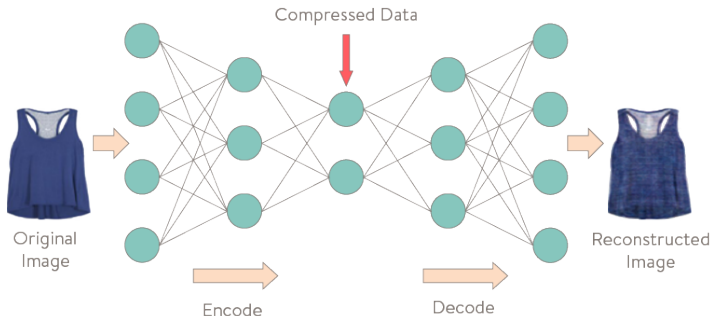
Using neural network:

When trajectories represent  $(x, y)$  coordinates, accuracy  $\approx 90\%$

When using centered trajectories, accuracy  $\approx 60\%$

(Longer training period may improve results)

# Variational Autoencoder





# Results

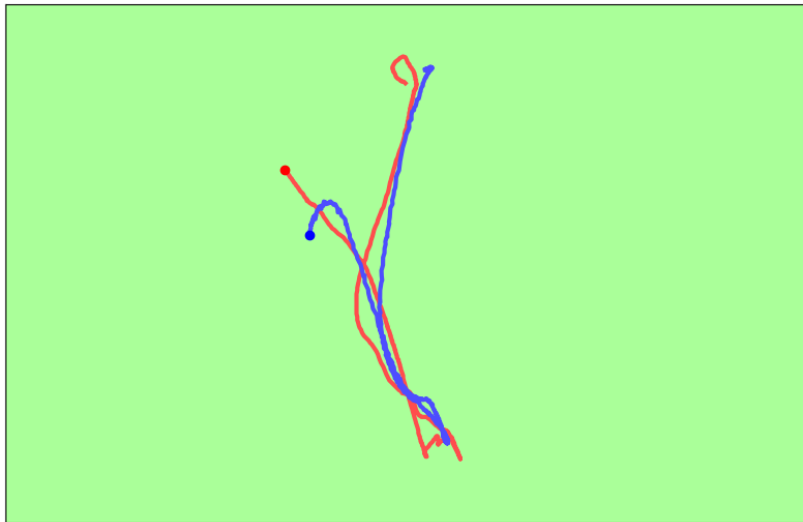
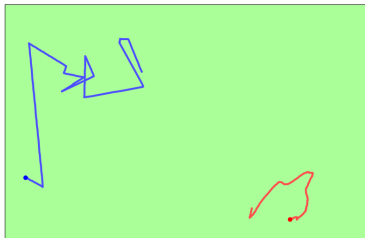


Figure: Generated (red) and Realised (blue) Trajectory.

# Results

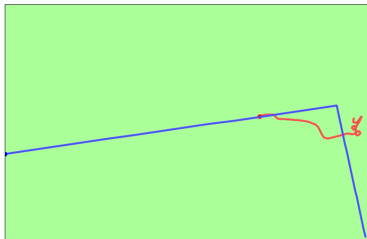


(a) Realised Trajectory: Player and Ball

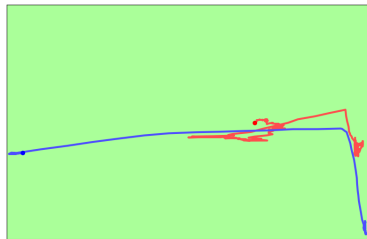


(b) Generated Trajectory: Player and Ball

# Results



(a) Realised Trajectory: Player and Ball



(b) Generated Trajectory: Player and Ball

# Summary, Recommendations and Future Work

- ▶ Kalman Filter, GAN, VAE
- ▶ Preliminary results seem promising: individual player's trajectory can be predicted and generated

## Recommendations:

- ▶ Kalman Filter suitable for short-term fast/online prediction
- ▶ Longer horizons might need more sophisticated (deeper) methods, e.g. GAN + VAE or deep Kalman
- ▶ However need lots of data and GPUs to speed up computations

## Future Research:

- ▶ All trajectories of 22 players and ball, complex interactions, extract underlying strategy