Asymmetrical Bi-RNNs, 3rd place solution at the ICCV Trajnet++ Challenge

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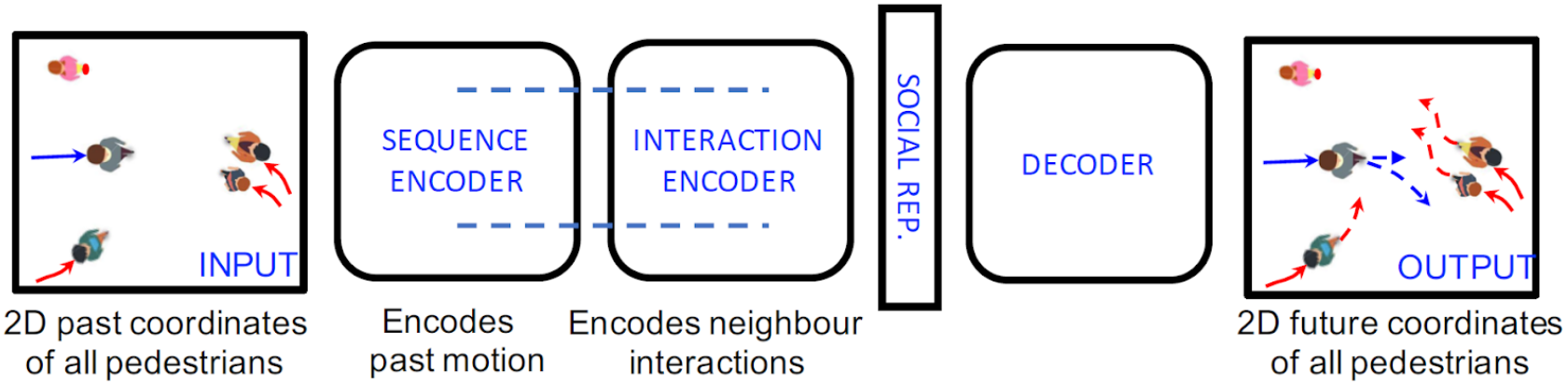
Typical pipeline



- Modern approaches specifically focused on the presence of social interactions.
- We focus on the encoding part of the trajectories of individual people.

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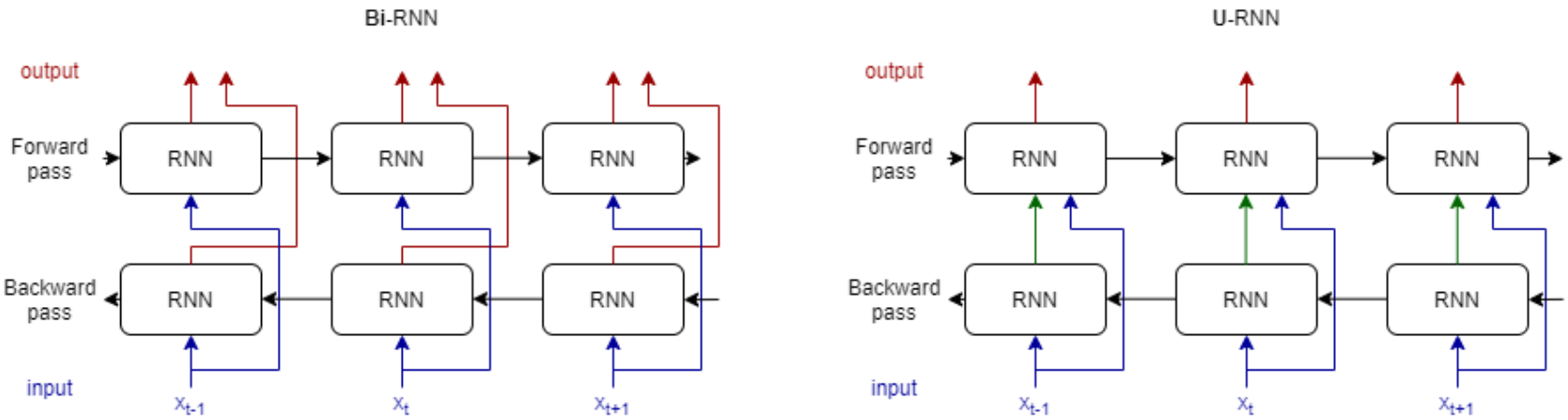
[1] [Kothari et al., 2021], "Human trajectory forecasting in crowds: A deep learning perspective"

[2] [Alahi et al., 2016] "Social lstm: Human trajectory prediction in crowded spaces"

A better encoder? From RNNs & Bi-RNNs to U-RNNs

The data has a **preferred direction** in time: the forward direction.



$\longrightarrow$ We accumulate information while knowing which part of the information will be useful in the future.

[1] [Xue et al., 2017], "Bi-prediction: pedestrian trajectory prediction based on bidirectional LSTM classification."

Results on Trajnet++ real world dataset

Model (Encoder - Decoder)	**Interaction**	**ADE (m)** ± 0.01 m	**FDE (m)** ± 0.01 m	**Col-I (%)** ± 0.5%	**Col-II (%)** ± 1%
Constant velocity	None	0.68	1.42	14.3	15.2
None - GRU	Dir.	0.63	1.33	6.9	12.1
LSTM - LSTM	Occ.	0.58	1.23	11.5	13.9
U-LSTM - LSTM	Occ.	**0.57**	**1.22**	**10.2**	14.9
GRU - GRU	Dir.	0.58	1.24	6.5	12.4
Bi-GRU - GRU	Dir.	0.59	1.26	6.7	11.7
U-GRU - GRU	Dir.	0.58	1.25	6.5	11.7
reversed U-GRU - GRU	Dir.	0.58	1.25	6.5	**11.0**
LSTM - LSTM	Dir.	0.58	1.25	6.4	11.4
Bi-LSTM - LSTM	Dir.	0.59	1.28	6.2	11.9
U-LSTM - LSTM	Dir.	**0.56**	**1.22**	**5.2**	11.9
reversed U-LSTM - LSTM	Dir.	0.58	1.26	6.6	**11.1**
LSTM - LSTM	Soc.	0.55	1.18	6.9	12.7
U-LSTM - LSTM	Soc.	**0.53**	**1.15**	**6.5**	11.5
Social NCE	Soc. + contr.	**0.53**	**1.14**	**5.3**	11.3

[1] [Liu et al., 2021], "Social NCE: Contrastive Learning of Socially-aware Motion Representations"

Conclusion

- A new sequence encoder.
- Interactions are **NOT** the only aspect on which pedestrian trajectory prediction can progress.
- Could be used to significantly **improve current trajectory prediction algorithms**:
  - TrouSPI-Net [Gesnouin et al., 2021]
  - (GO)-Home [Gilles et al., 2021a, Gilles et al., 2021b]

$\longrightarrow$ [Rozenberg et al., 2021], "Asymmetrical Bi-RNN for pedestrian trajectory encoding", *https://arxiv.org/abs/2106.04419*

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