Online Multi-Target Tracking Using Recurrent Neural Networks

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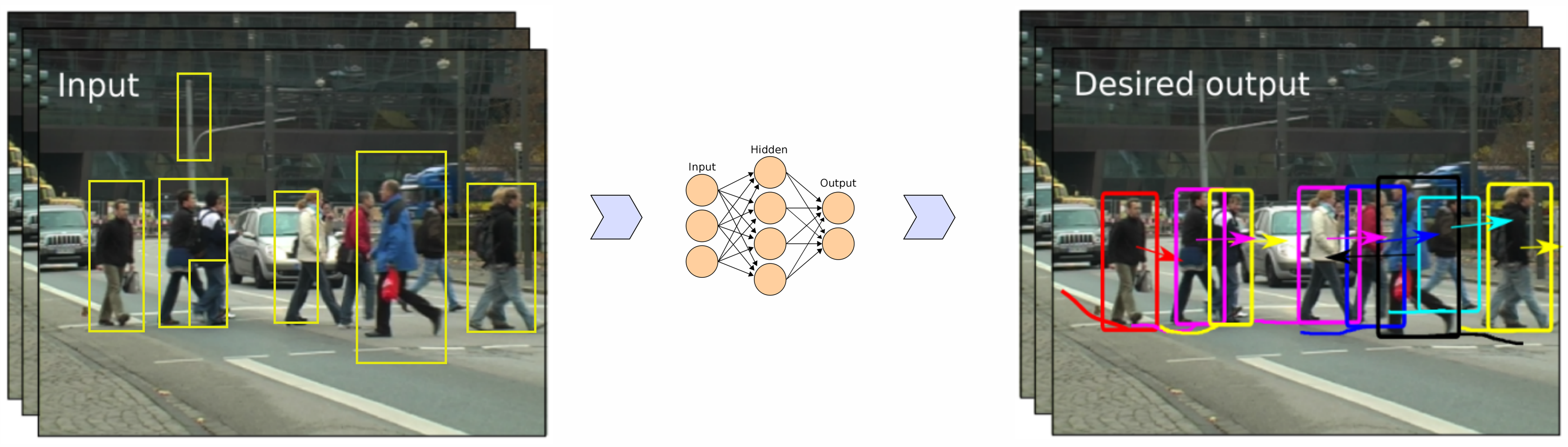
Abstract

We present a novel approach to online multi-target tracking based on recurrent neural networks (RNNs). Tracking multiple objects in real-world scenes involves many challenges, including a) an a-priori unknown and time-varying number of targets, b) a continuous state estimation of all present targets, and c) a discrete combinatorial problem of data association. Our solution addresses all of the above points in a principled way.

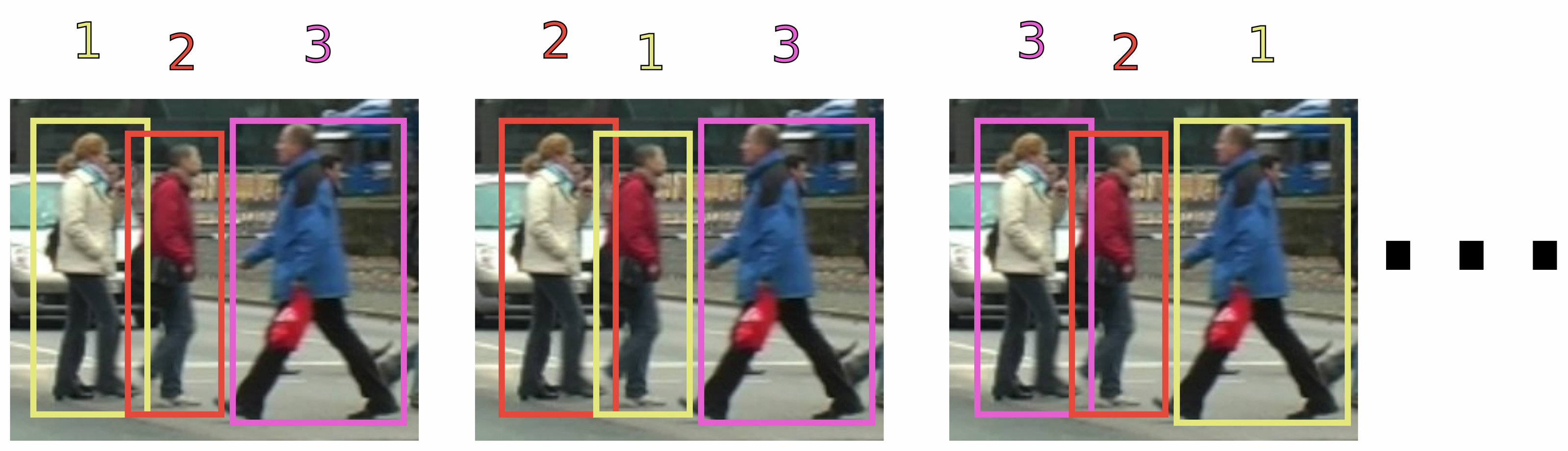
Motivation

- Exploit power of deep learning for multi-target tracking
- Data-driven approach, first step towards end-to-end learning
- Efficient inference (up to 300Hz on a CPU)



Challenges

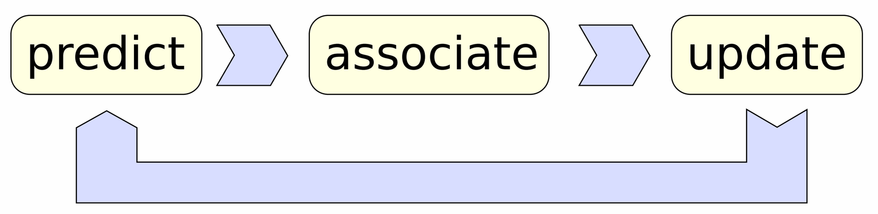
- Unknown and time-varying number of targets
- Missing, false and noisy detections
- Class (ID) assignment is arbitrary

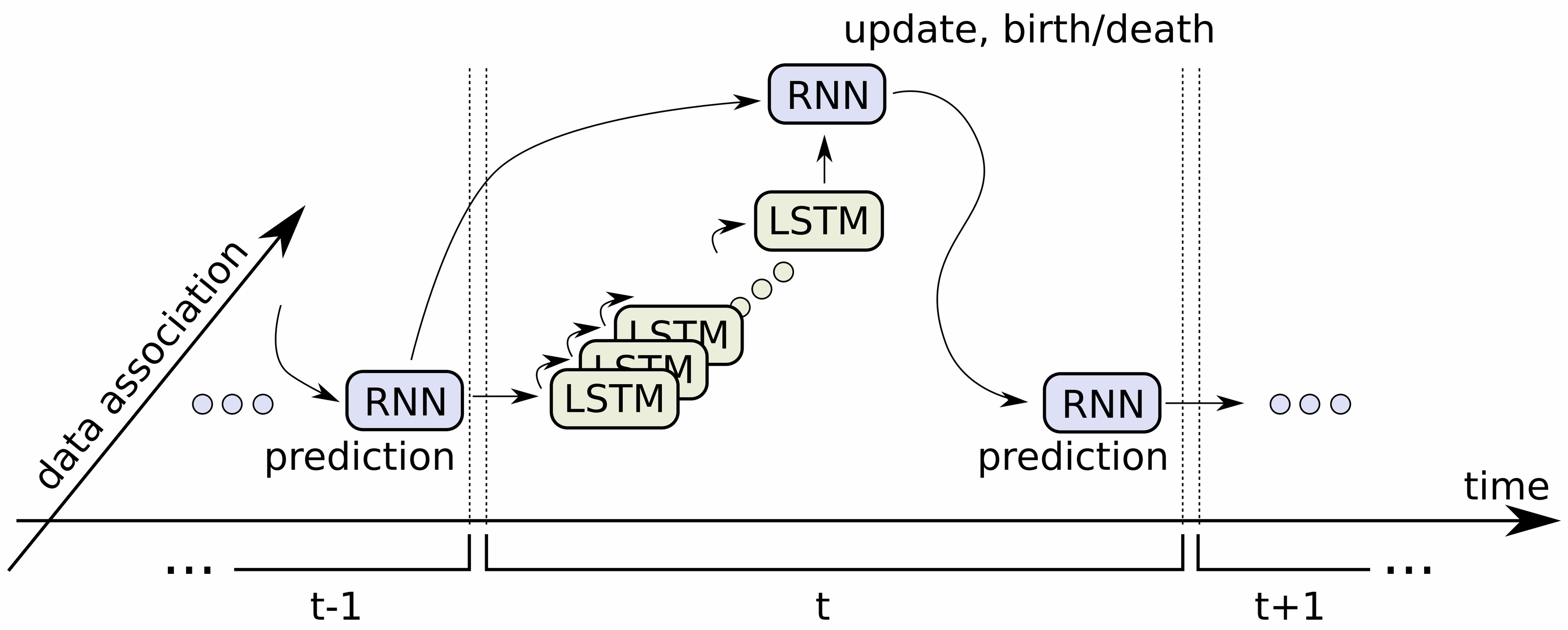


Our Proposed Approach

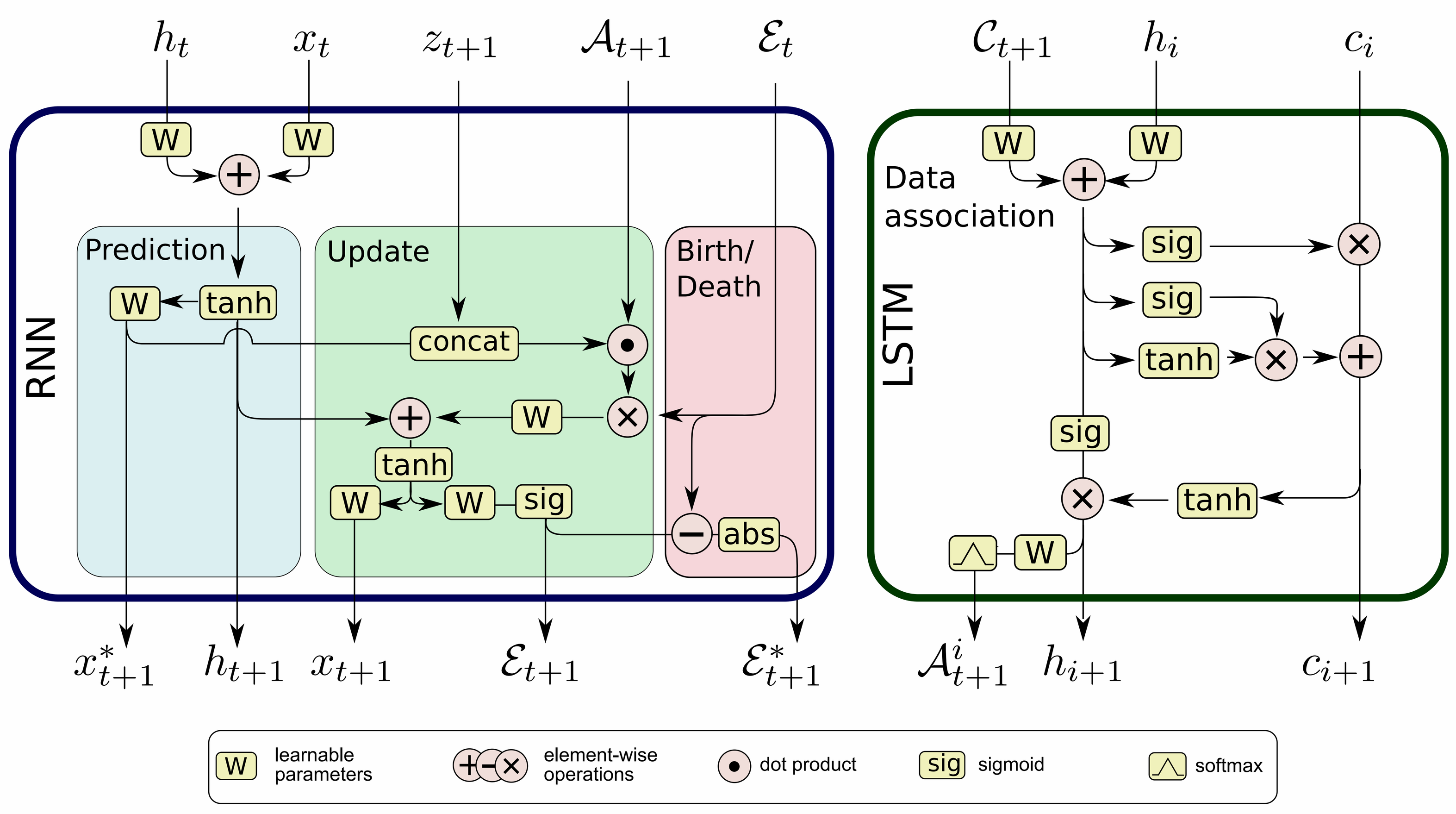
Based on **Bayesian filtering**

$$p(x_t|z_{1:t}) \propto p(z_t|x_t) \int p(x_t|x_{t-1}) p(x_{t-1}|z_{1:t-1}) dx_{t-1}$$





Model



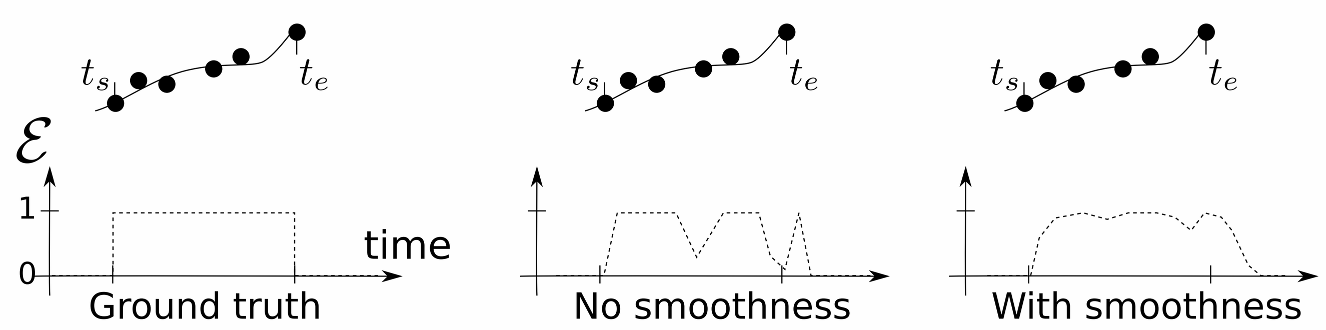
Loss

$$\mathcal{L} = \underbrace{\lambda \sum \|x^* - \tilde{x}\|^2}_{\text{prediction}} + \underbrace{\kappa \|x - \tilde{x}\|^2}_{\text{update}} + \underbrace{\nu \mathcal{L}_{\mathcal{E}} + \xi \mathcal{E}^*}_{\text{birth/death + reg.}}$$

$$\mathcal{L}_{\mathcal{E}} = \tilde{\mathcal{E}} \log \mathcal{E} + (1 - \tilde{\mathcal{E}}) \log(1 - \mathcal{E})$$

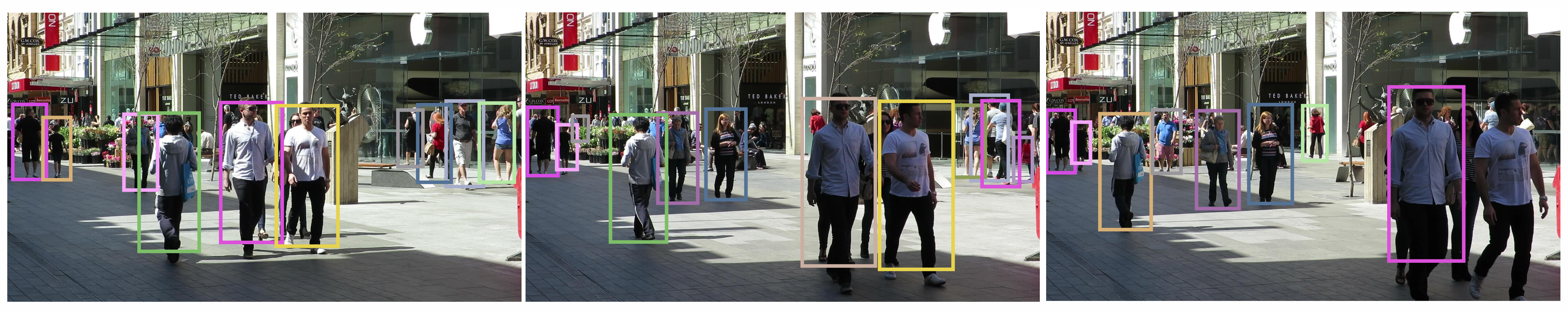
$$\mathcal{L}_{\mathcal{A}}(\mathcal{A}^i, \tilde{a}) = -\log(\mathcal{A}_{i\tilde{a}})$$

Existence smoothness $\mathcal{E}$



Experiments

MOTChallenge 2015 [4]



Baseline comparison

Method	MOTA	Recall	Precision	ID Sw.
Kalman+HA (O)	19.2	28.5	79.0	685
Kalman+HA+Post	22.4	28.3	**83.4**	**105**
RNN+HA (O)	**24.0**	**37.8**	75.2	518
RNN+LSTM (O)	22.3	37.1	73.5	572

(O) = Online method

Benchmark result

Method	MOTA	FN	FP	ID Sw.	FPS
MDP [1]	**30.3**	**32,422**	9,717	680	1.1
JPDAm [2]	23.8	40,084	**6,373**	**365**	32.6
TC_ODAL [3]	15.1	38,538	12,970	637	1.7
RNN+LSTM	19.0	38,706	11,578	1,490	**165.2**

bitbucket.org/amilan/rnntracking

Acknowledgements

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References

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[4] Leal-Taixé, L.; Milan, A.; Reid, I.; Roth, S.; and Schindler, K. 2015. MOTChallenge 2015: Towards a benchmark for multi-target tracking. arXiv:1504.01942 [cs].