

Online Multi-target Tracking using Recurrent Neural Networks - Milan et al.

Seminar Biomedical Image Analysis Freiburg 01.08.16

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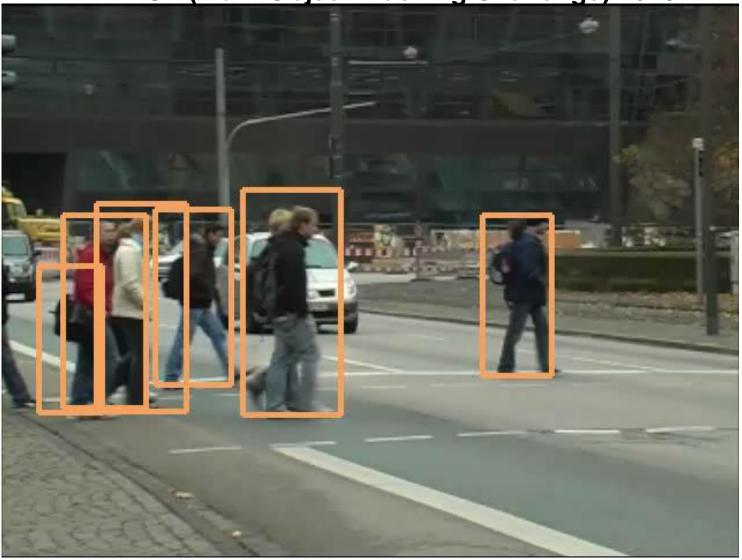
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Introduction: Motivation

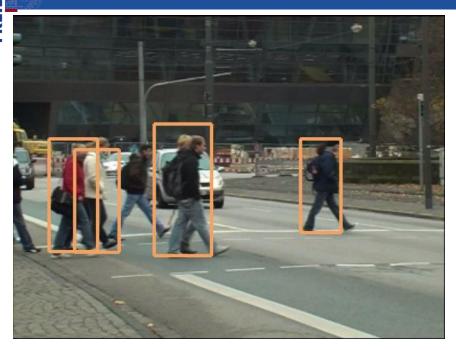
2D MOT (Multi Object Tracking Challenge) 2015



Source: https://motchallenge.net/



Introduction: Problem

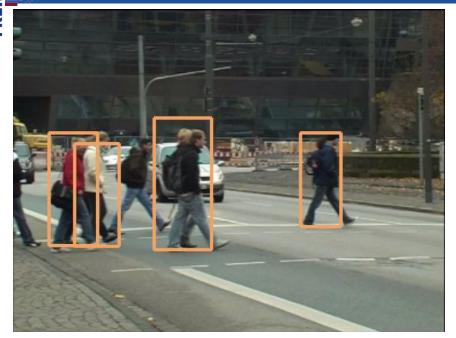


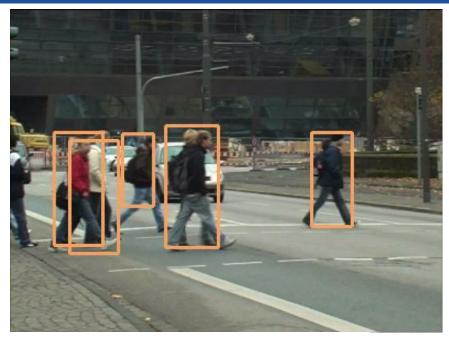
Problem: Locate multiple targets of interest in a video sequence over time

Source: https://motchallenge.net/



Introduction: Problem - Challenges



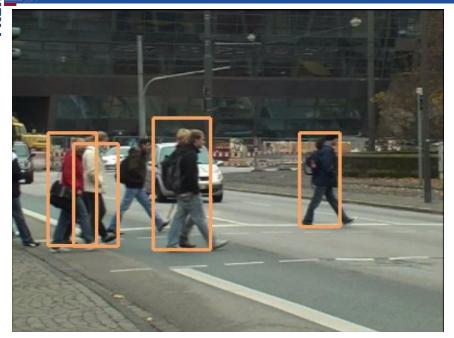


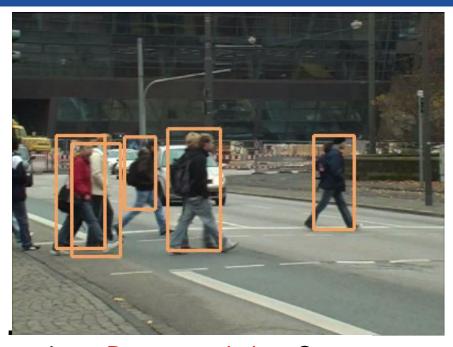
Challenges: Dynamic number of object detections, Data association, State Estimation

Image source: https://motchallenge.net/



Introduction: Problem – Challenges - Solution





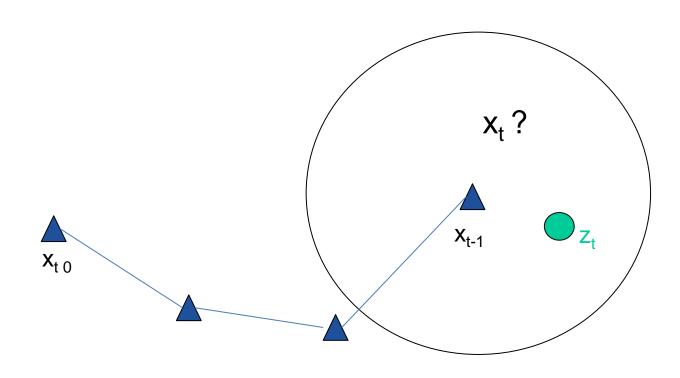
Challenges: Dynamic number of object detections, Data association, State Estimation



- Sequences and RNN, RNN as Bayes Filter!
- Data association can also be "learned"!
- Existence probability



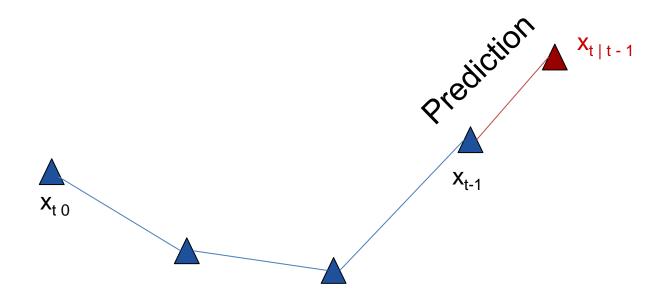
Digression: State Estimation



What is x_t (current estimate) given $x_{0:t-1}$ (previous estimates) and z_t (measurement)??



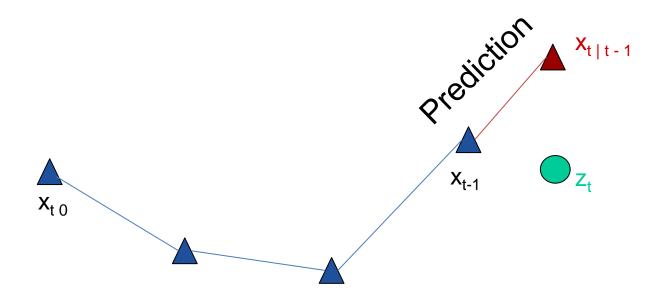
Digression: Bayes Filter



Predict using previous estimate and motion model!



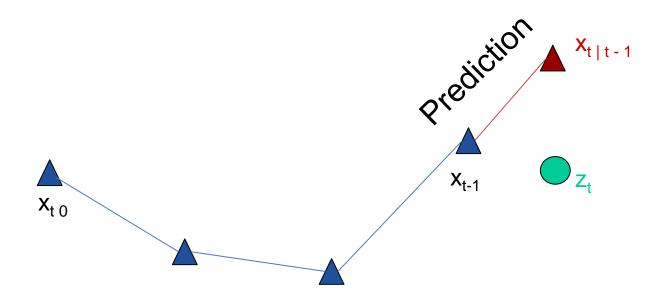
Digression: Bayes Filter



What to trust more: The prediction or measurement?



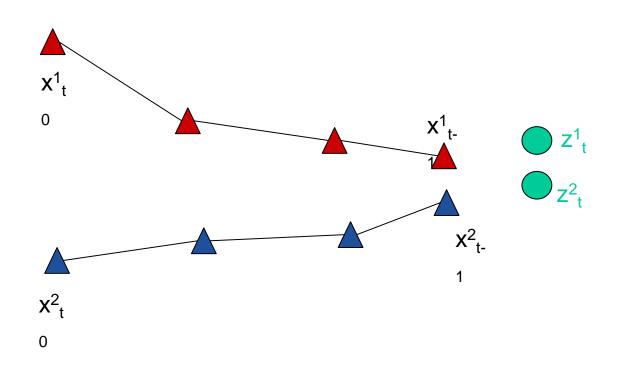
Digression: Bayes Filter



Correct (update) using the measurement!



Digression: Data Association



Which observation belongs to which track?



Related Work

- Variants of MHT, JPDA used
 - Various simplified models (Linear programs etc.)
 - Numerous numerical optimization techniques



Related Work

- Variants of MHT, JPDA used
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 - Numerous numerical optimization techniques
- Little work on using Deep Learning to Multi-Object tracking: chiefly due to unavailability of training data



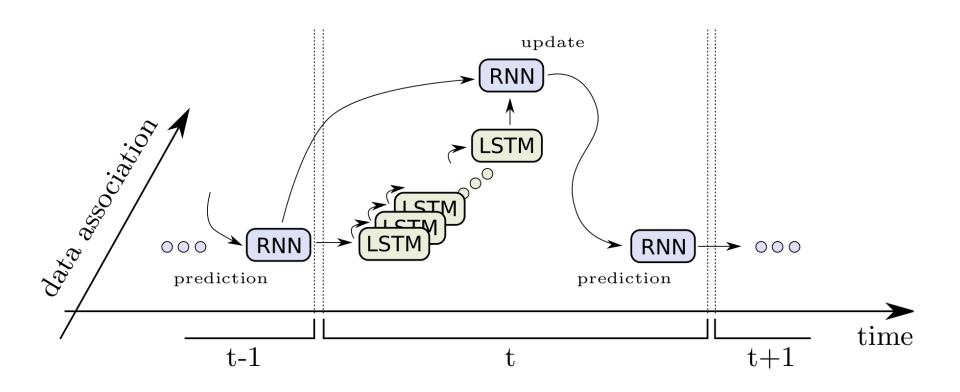
Related Work

- Variants of MHT, JPDA used
 - Various simplified models (Linear programs etc.)
 - Numerous numerical optimization techniques
- Little work on using Deep Learning to Multi-Object tracking: chiefly due to unavailability of training data
- RNN promising, mainly used for language processing
- Issues:
 - Multi dimensional space
 - Includes continuous and discrete variables
 - Multiple outputs possible

Main Contributions

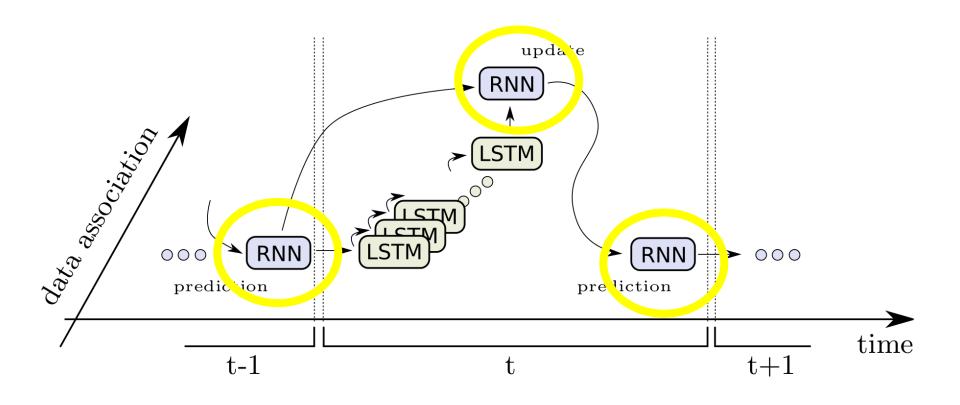
- Bayesian filter by unified RNN approach
 - Model free approach
 - •Linear, nonlinear or higher order dependencies
- Data Association learned from data
- Generated synthetic training data
- Qualitative and quantitative result presented

Approach: Outline



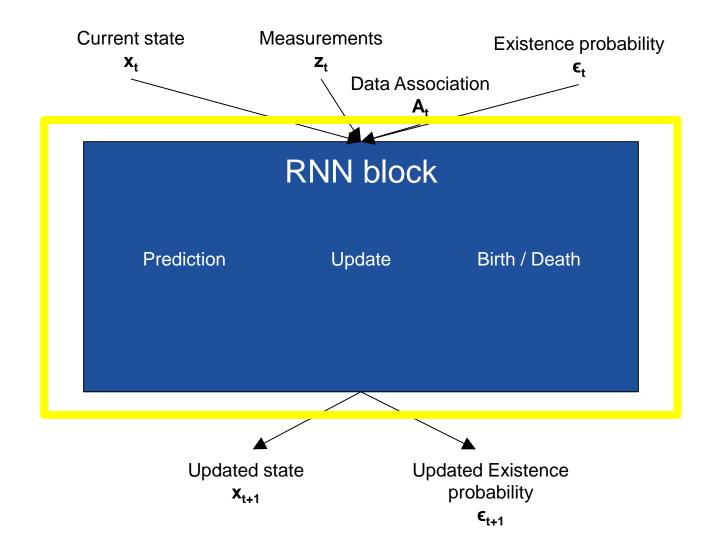
Source: Online Multi-target Tracking using Recurrent Neural Networks, A. Milan et al.

Approach: Outline

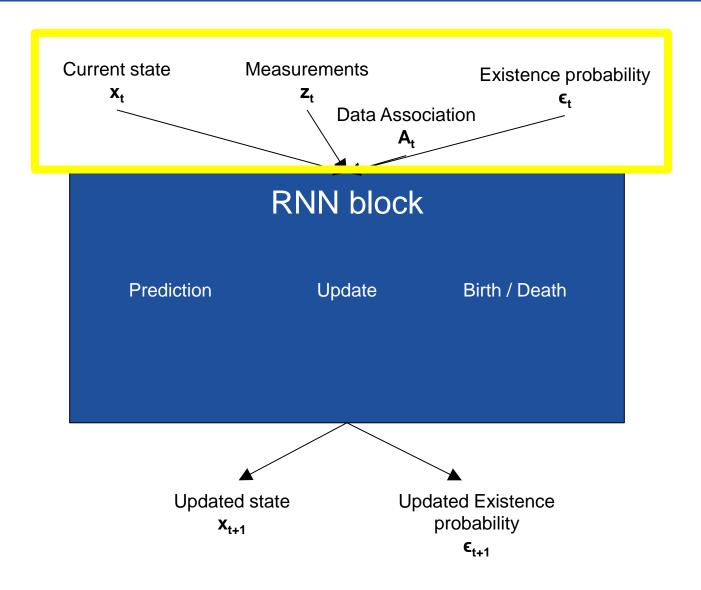


Source: Online Multi-target Tracking using Recurrent Neural Networks, A. Milan et al.

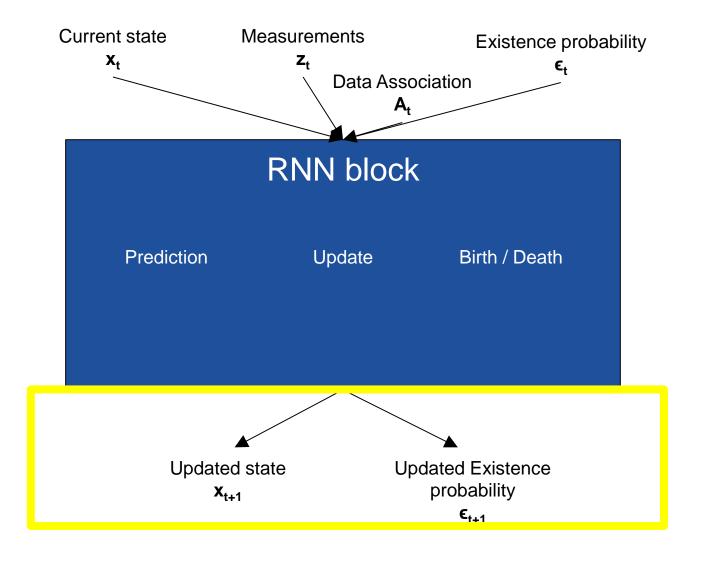








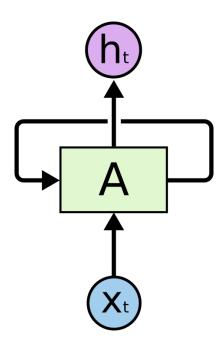






Digression: RNN

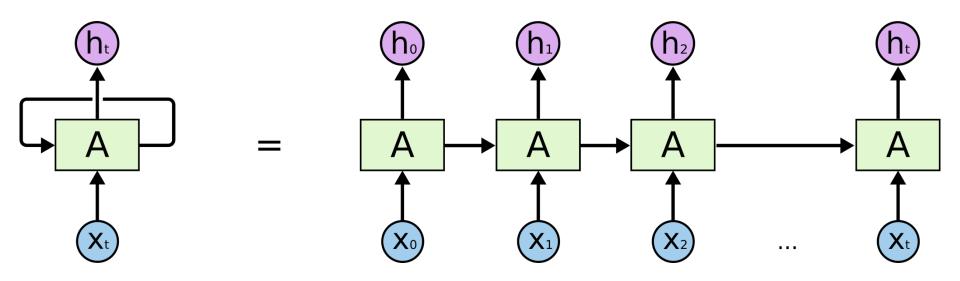
RNNs are neural networks with loops!





Digression: RNN

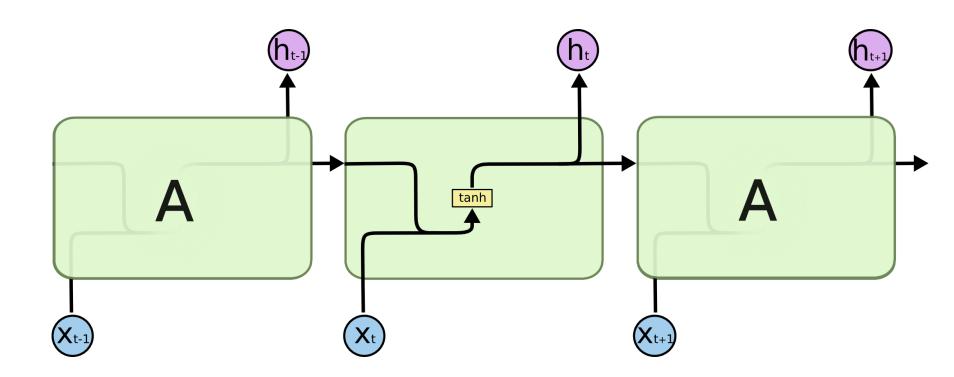
More intuitive way of seeing an RNN!



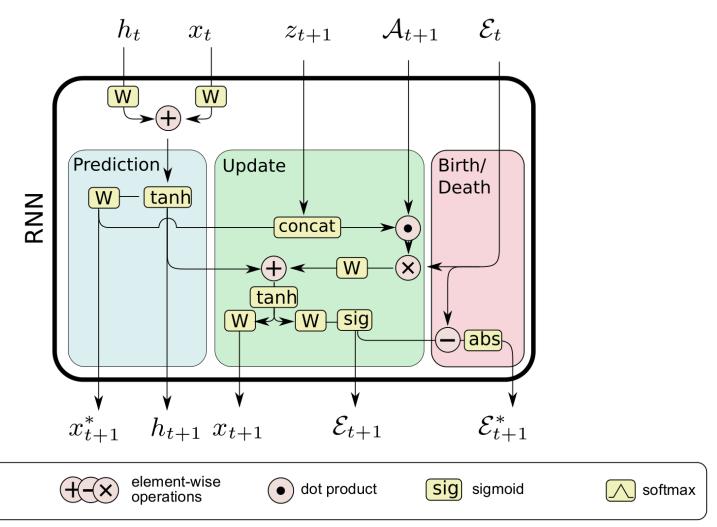


Digression: RNN

A simple RNN!



RNN in their approach



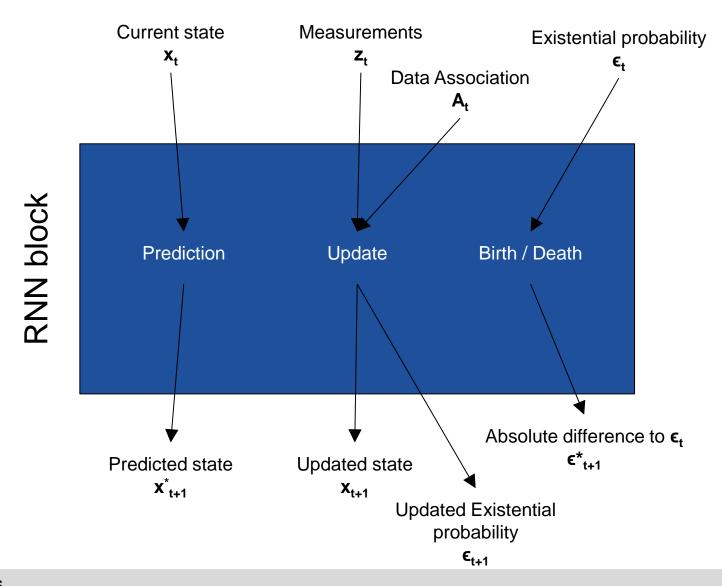
Source: Online Multi-target Tracking using Recurrent Neural Networks, A. Milan et al.

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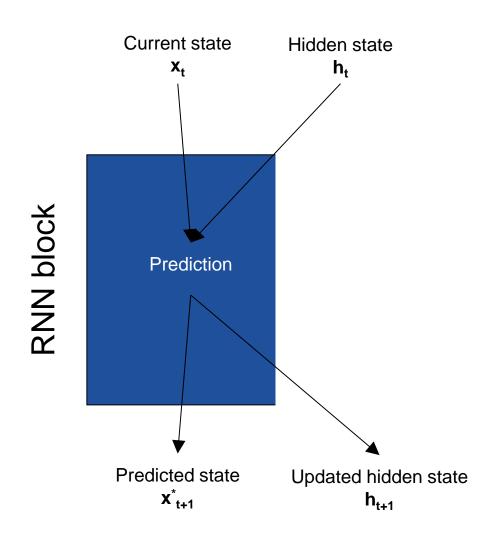
learnable

parameters



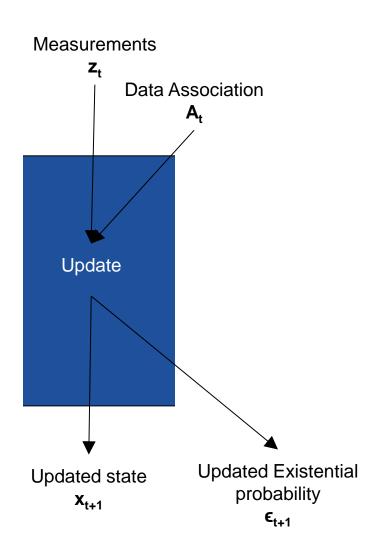






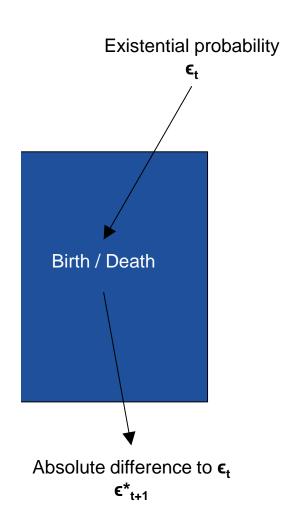


RNN block





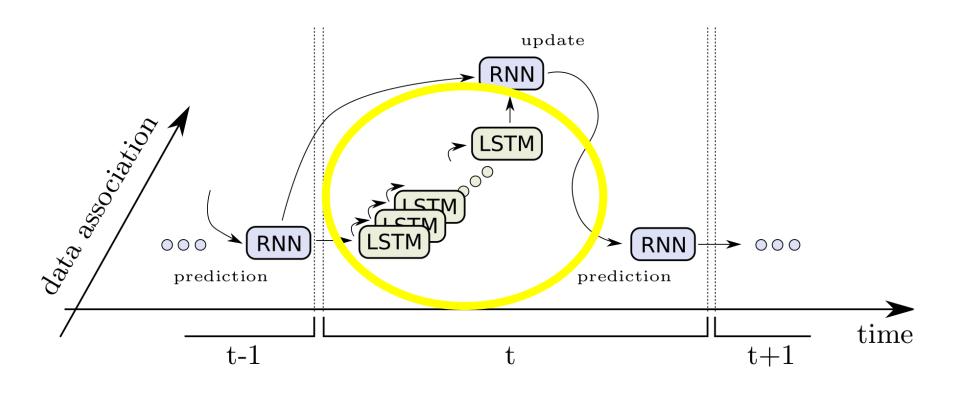
RNN block



$$\mathcal{L}(x^*, x, \mathcal{E}, \widetilde{x}, \widetilde{\mathcal{E}}) = \underbrace{\frac{\lambda}{ND} \sum \|x^* - \widetilde{x}\|^2}_{\text{prediction}} + \underbrace{\frac{\kappa}{ND} \|x - \widetilde{x}\|^2}_{\text{update}} + \underbrace{\nu \mathcal{L}_{\mathcal{E}} + \xi \mathcal{E}^*}_{\text{birth/death + reg}},$$

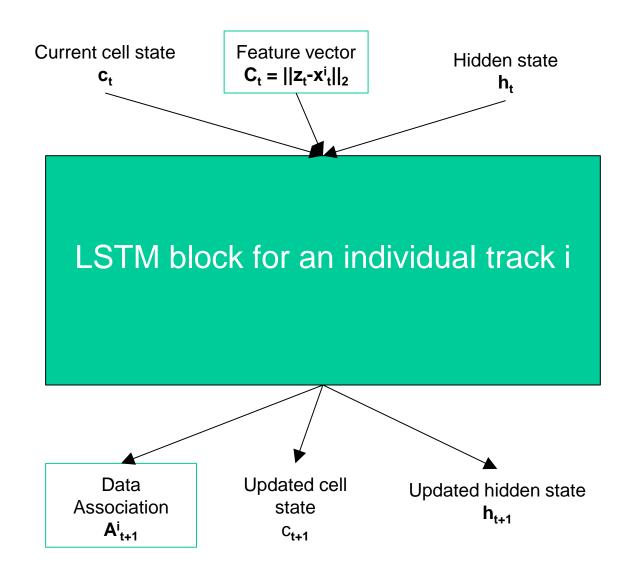
Source: Online Multi-target Tracking using Recurrent Neural Networks, A. Milan et al.

Approach: Outline ...



Source: Online Multi-target Tracking using Recurrent Neural Networks, A. Milan et al.

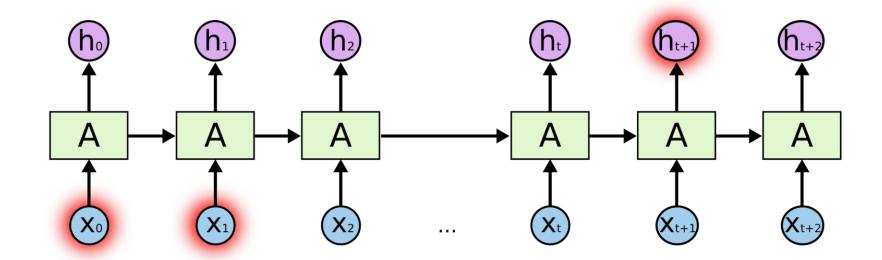
Approach: LSTM for Data Association





Digression: LSTM

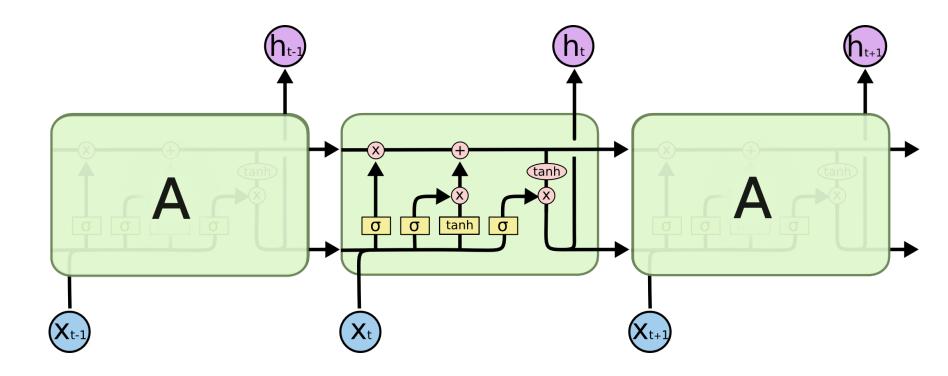
Long term dependency!



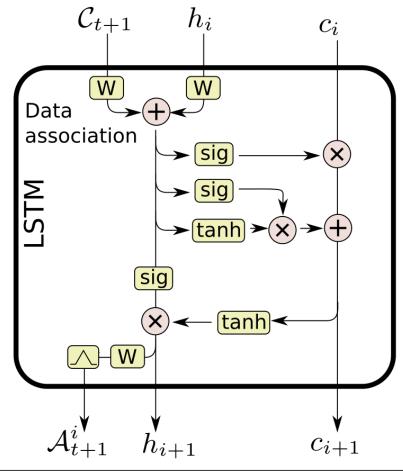
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Digression: LSTM

- A simple LSTM
- Cell state -- Conveyor belt!



Approach: LSTM for Data Association ...



learnable parameters element-wise operations object sigmoid softmax

Source: Online Multi-target Tracking using Recurrent Neural Networks, A. Milan et al.



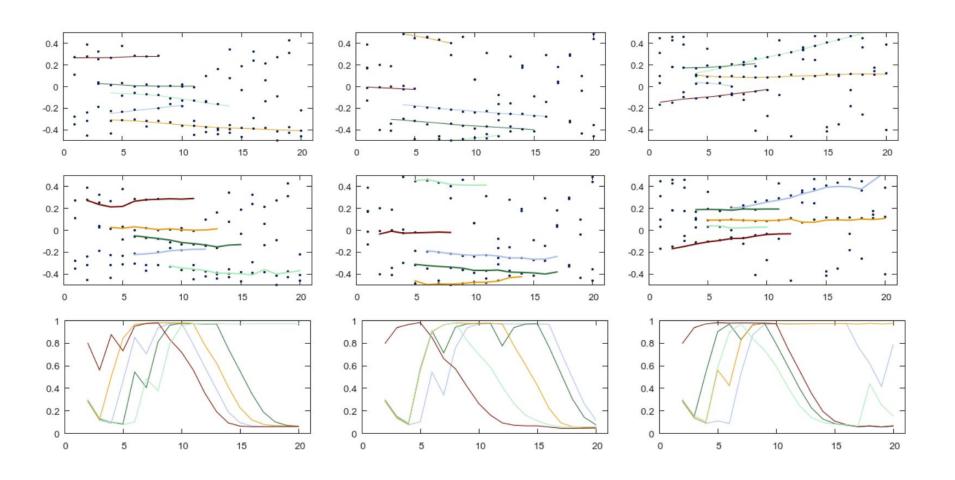
Experiments: Training data generation

- Few training data available
- Perturbation of real data
 - Mirroring
 - Translation
 - Rotation
- Sampling from a generative model
 - Learn trajectory model from each available training sequence
- Physically-based trajectory generation
 - Simulating real world motion and cameras



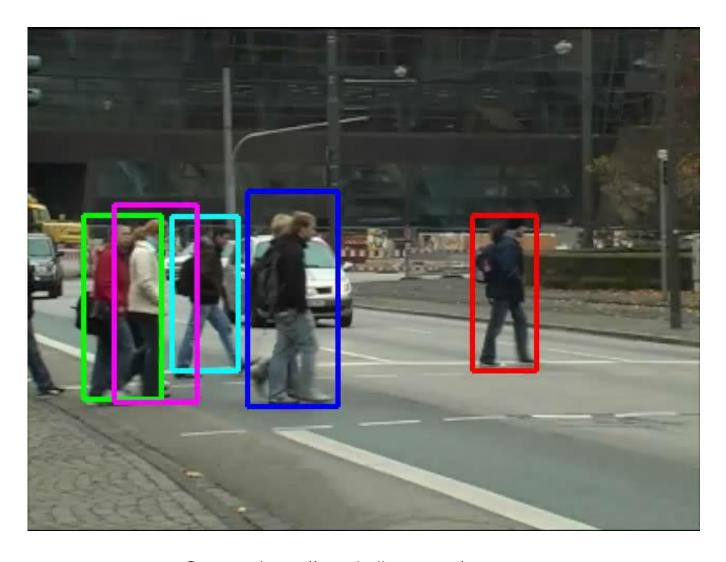
Implementation: other details

- Platform: Lua and Torch7
- •Network size:
 - •RNN: 1 layer, 300 hidden units
 - •LSTM: 2 layers, 500 hidden units
- Optimization:
 - RMSprop
 - Convergence under 200,000 iterations
- Data:
 - •100,000 20-frame long sequences
 - Mini batches of 10 samples per batch
 - •Normalized to [-0.5, 0.5]



Source: Online Multi-target Tracking using Recurrent Neural Networks, A. Milan et al.





Source: https://motchallenge.net/



Table 1. Tracking results on the MOTChallenge training dataset. *Denotes offline post-processing.

Method	Rcll	Prcn	MT	ML	FP	FN	IDs	FM	MOTA	$\overline{\text{MOTP}}$
Kalman-HA	28.5	79.0	32	334	3,031	28,520	685	837	19.2	69.9
Kalman-HA2*	28.3	83.4	39	354	$2,\!245$	28,626	105	342	22.4	69.4
$JPDA_m^*$	30.6	81.7	38	348	2,728	27,707	109	380	23.5	69.0
RNN_HA	37.8	75.2	50	267	4,984	24,832	518	963	24.0	68.7
RNN_LSTM	37.1	73.5	50	260	$5,\!327$	25,094	572	983	22.3	69.0

Source: Online Multi-target Tracking using Recurrent Neural Networks, A. Milan et al.

Table 2. Tracking results on the MOTChallenge test dataset. *Denotes an offline (or delayed) method.

Method	MOTA	MOTP	FAR	MT%	ML%	FP	FN	IDs	Frag.	FPS
MDP [48]	30.3%	71.3%	1.7	13.0	38.4	9,717	32,422	680	1,500	1.1
$JPDA_m^*$ [13]	23.8%	68.2%	1.1	5.0	58.1	6,373	40,084	365	869	32.6
TC_ODAL [49]	15.1%	70.5%	2.2	3.2	55.8	12,970	38,538	637	1,716	1.7
RNN_LSTM	19.0%	71.0%	2.0	5.5	45.6	11,578	36,706	1,490	2,081	165.2

Source: Online Multi-target Tracking using Recurrent Neural Networks, A. Milan et al.



Conclusions

- RNN's and its relation to sequences makes it look promising
- Their approach showed that RNN can be utilized to design a Bayes Filter
- LSTM for Data Association not a trivial task
- •First approach that employs end-to-end training for multi-target tracking



References

- 1. Online Multi-target Tracking using Recurrent Neural Networks, A. Milan et al.
- https://motchallenge.net/
- 3. colah.github.io/posts/2015-08-Understanding-LSTMs
- 4. http://pages.cs.wisc.edu/~bolo/shipyard/neural/local.html

Thanks:)