

# Sequential Data Modelling

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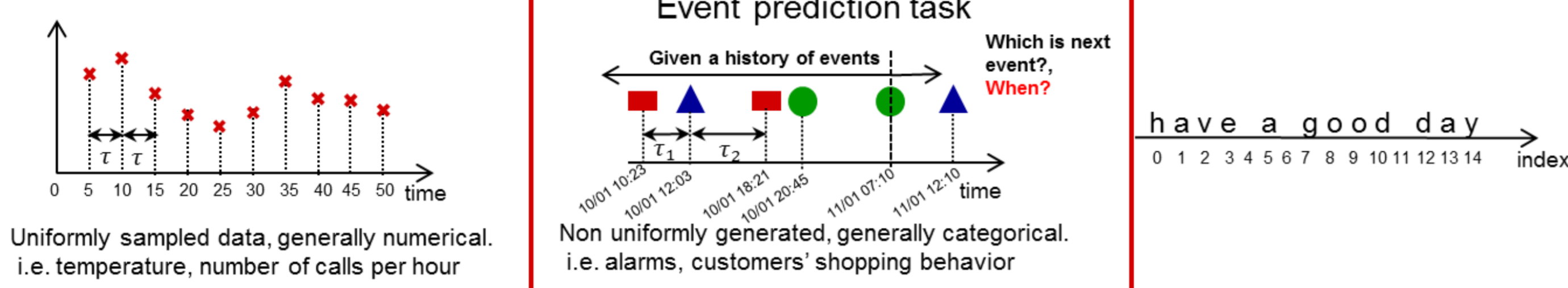
## Objective

Develop deep learning methods for event prediction

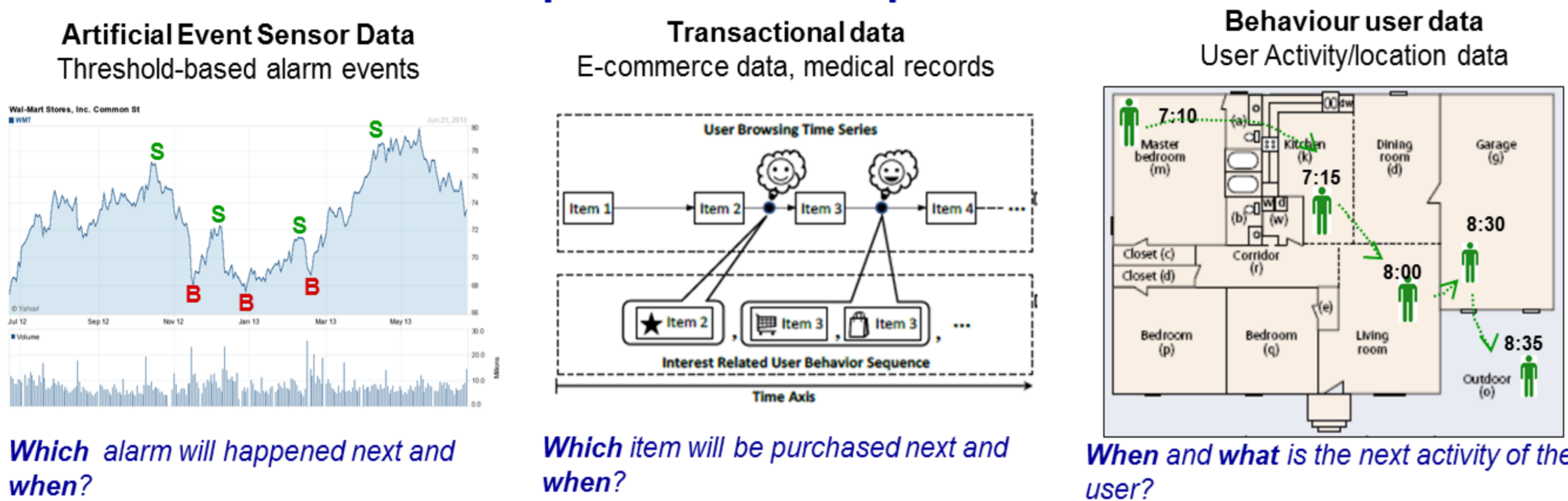
## Problem

Event sequence data are time-stamped **categorical** data collected over time at **no particular frequency**.

Time Series data vs Event/Transactional data vs Sequential data



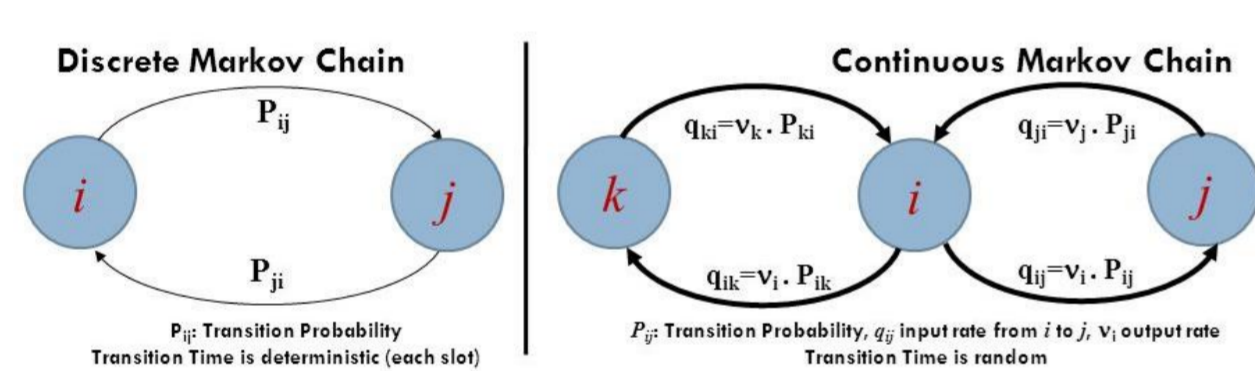
### Examples of event sequential data



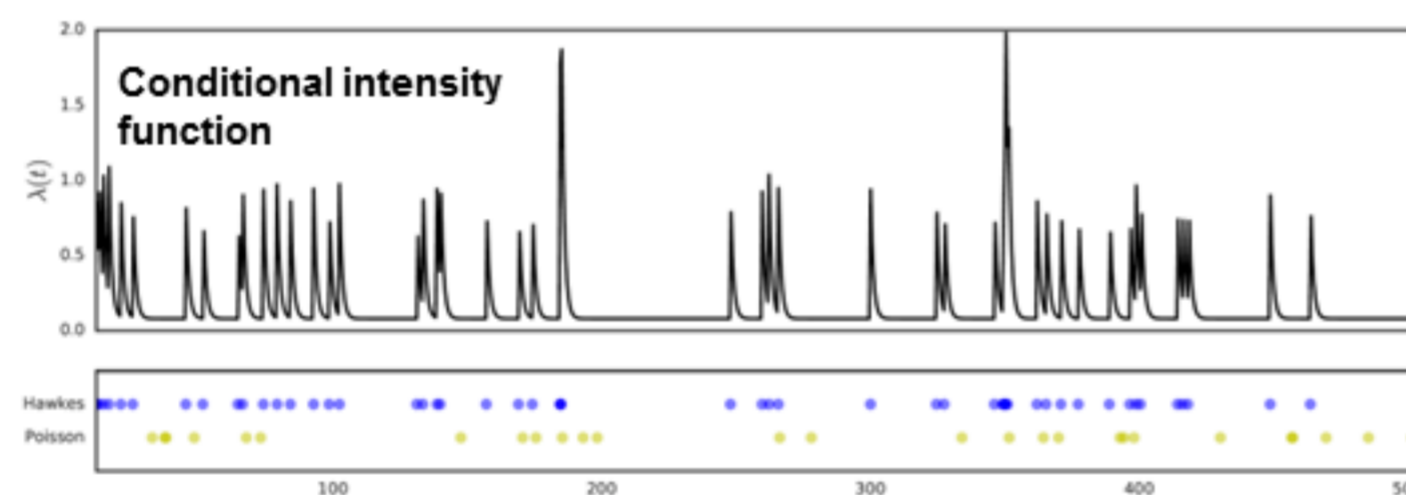
## Related work

### Event modelling approaches

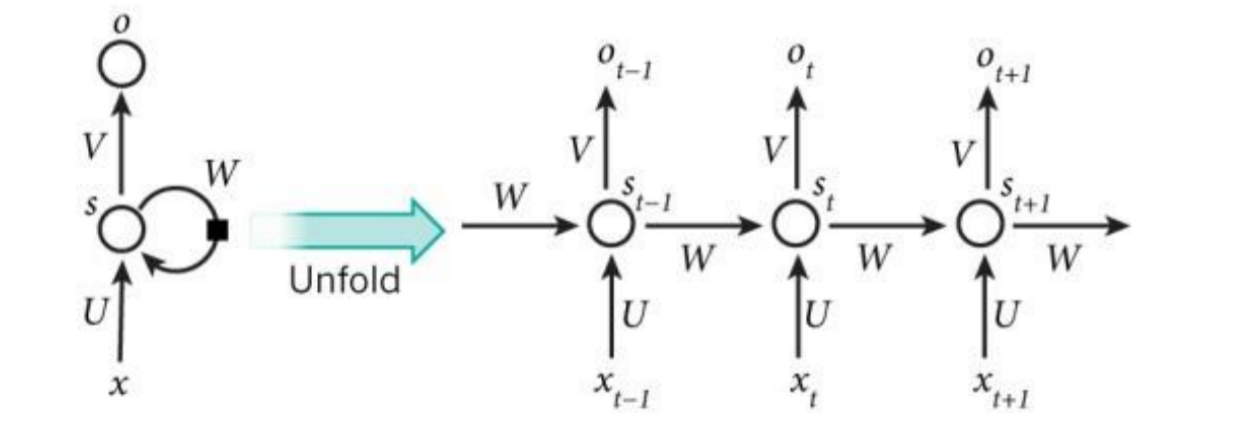
#### Markov Chain Models



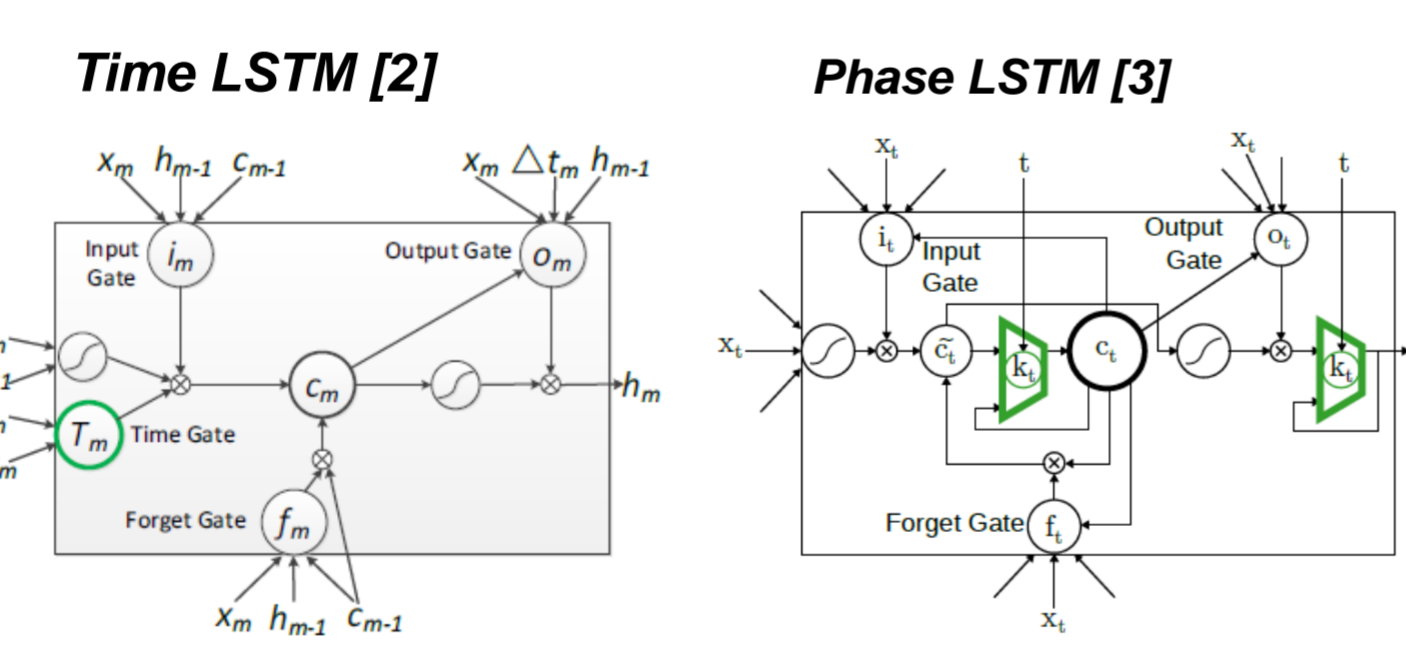
#### Point Processes



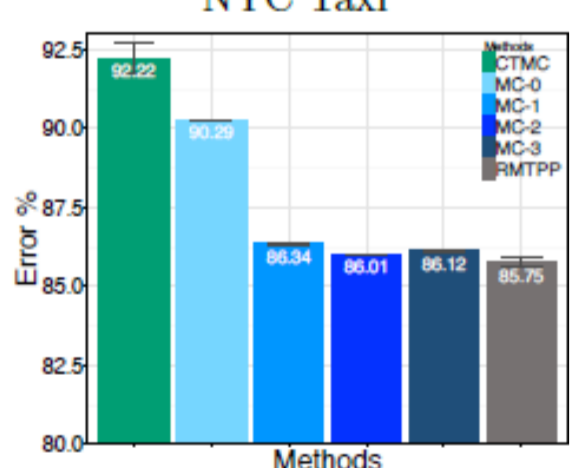
#### Recurrent Neural Networks



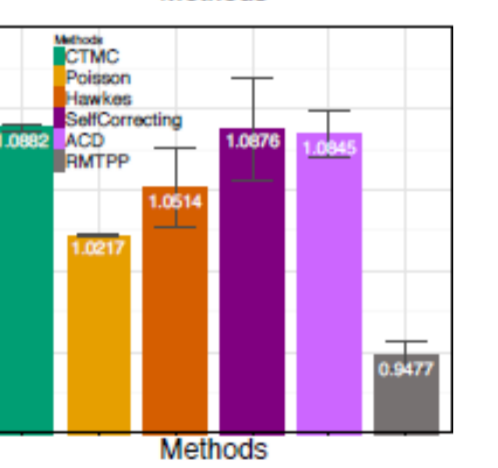
#### New RNN Architectures



#### Event prediction [1]



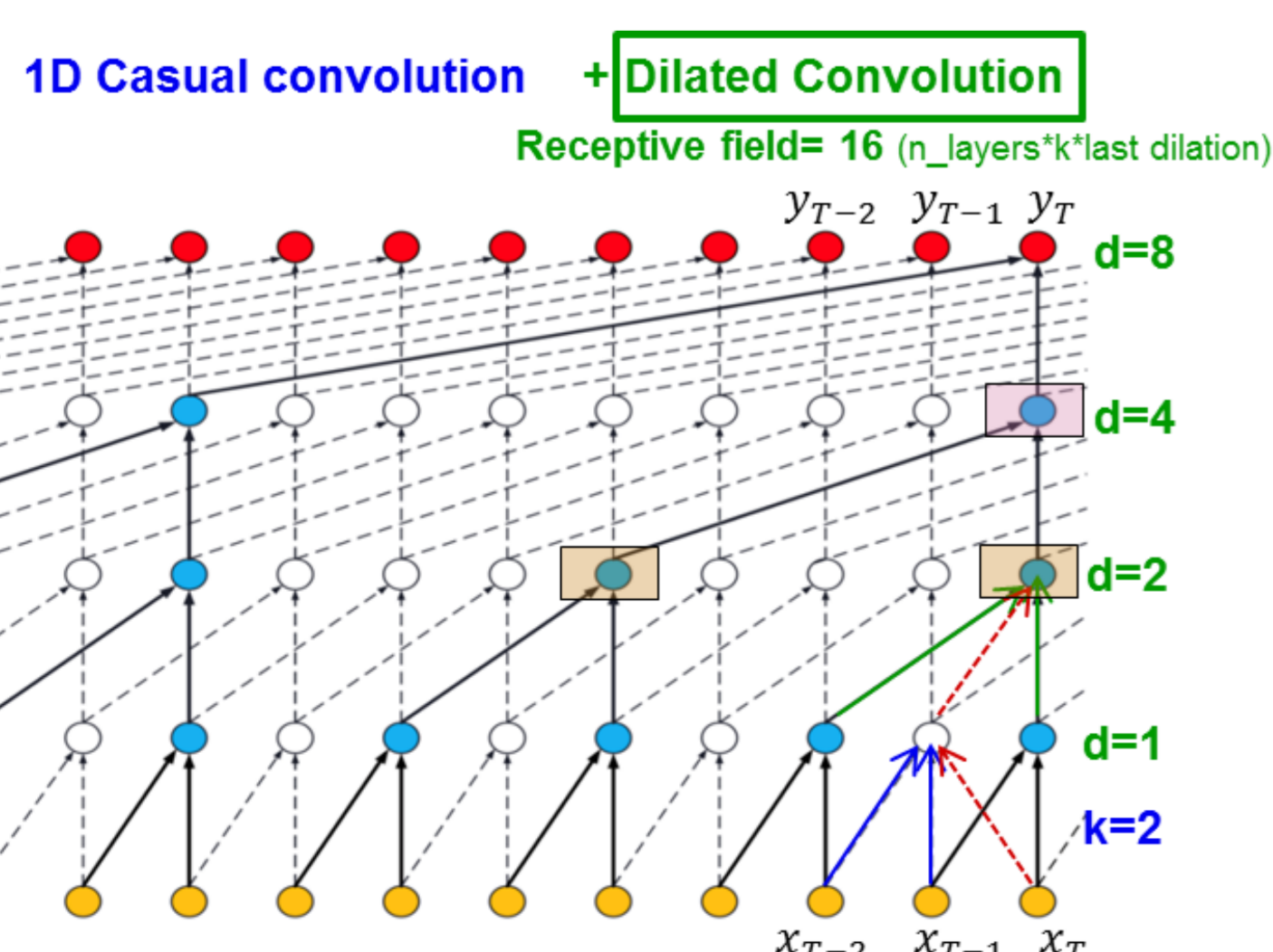
#### Time prediction [1]



✓ RNN and point process combination is SOA in event prediction

### SOA in sequence modelling

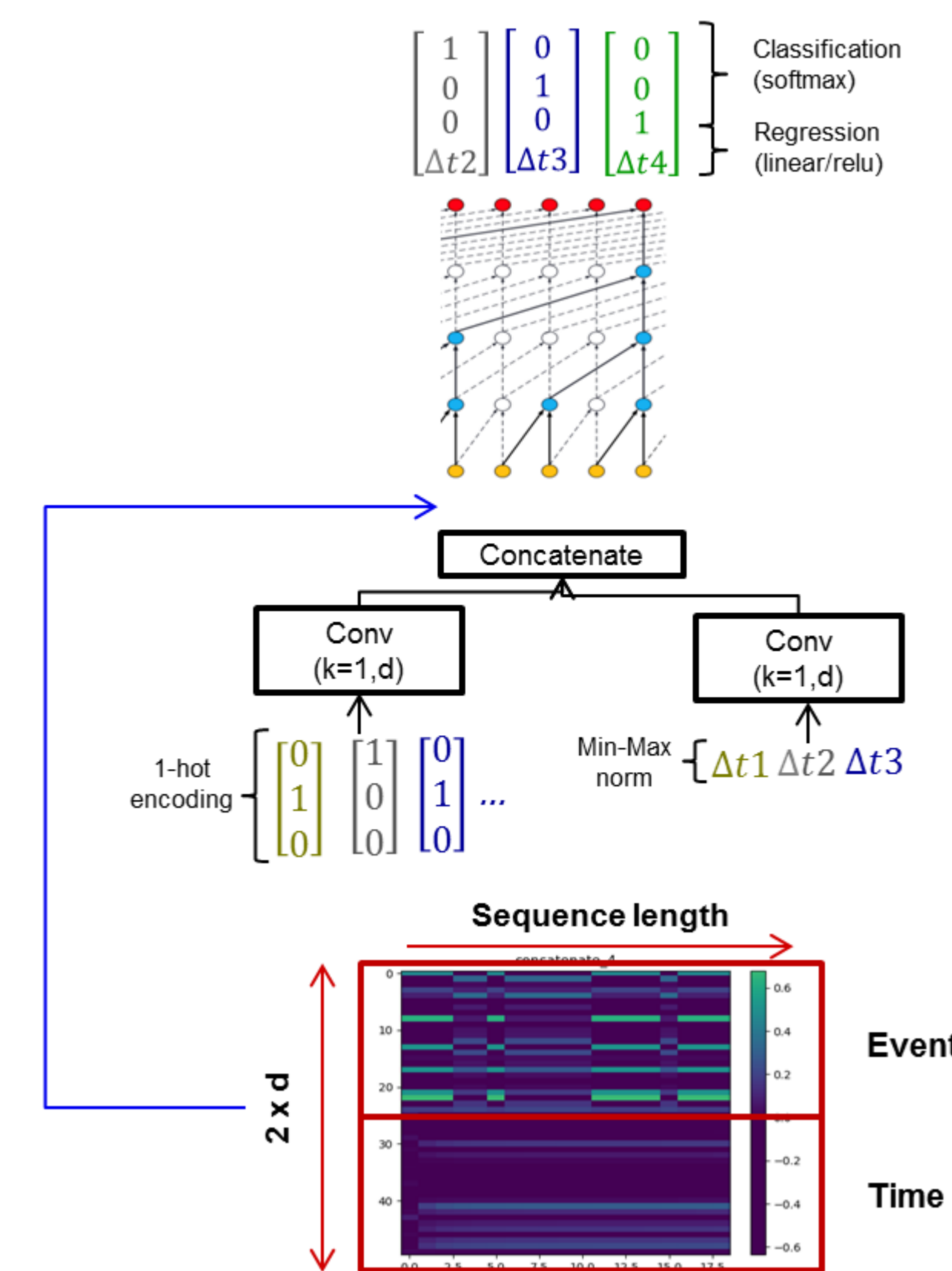
#### Temporal Convolutional Neural Networks (TCNs) [5]



- ✓ Outperform RNNs
- ✓ Exhibit longer memory
- ✓ Training and evaluation faster (parallelism)
- ✓ Has stables gradients
- Not used for event prediction tasks

## Convolutional Architecture for event prediction

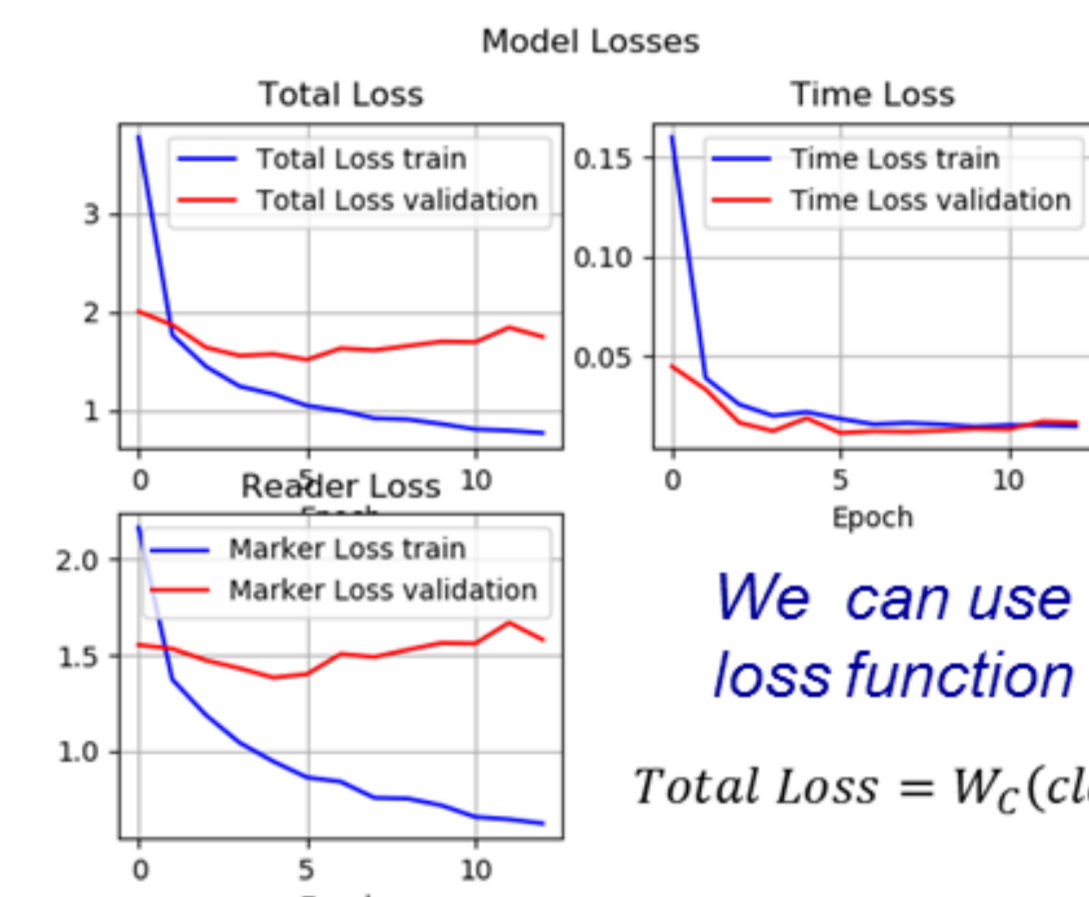
### TCNs architecture for event prediction



➤ Modelling time explicitly as an input (time interval)

### Combined loss function

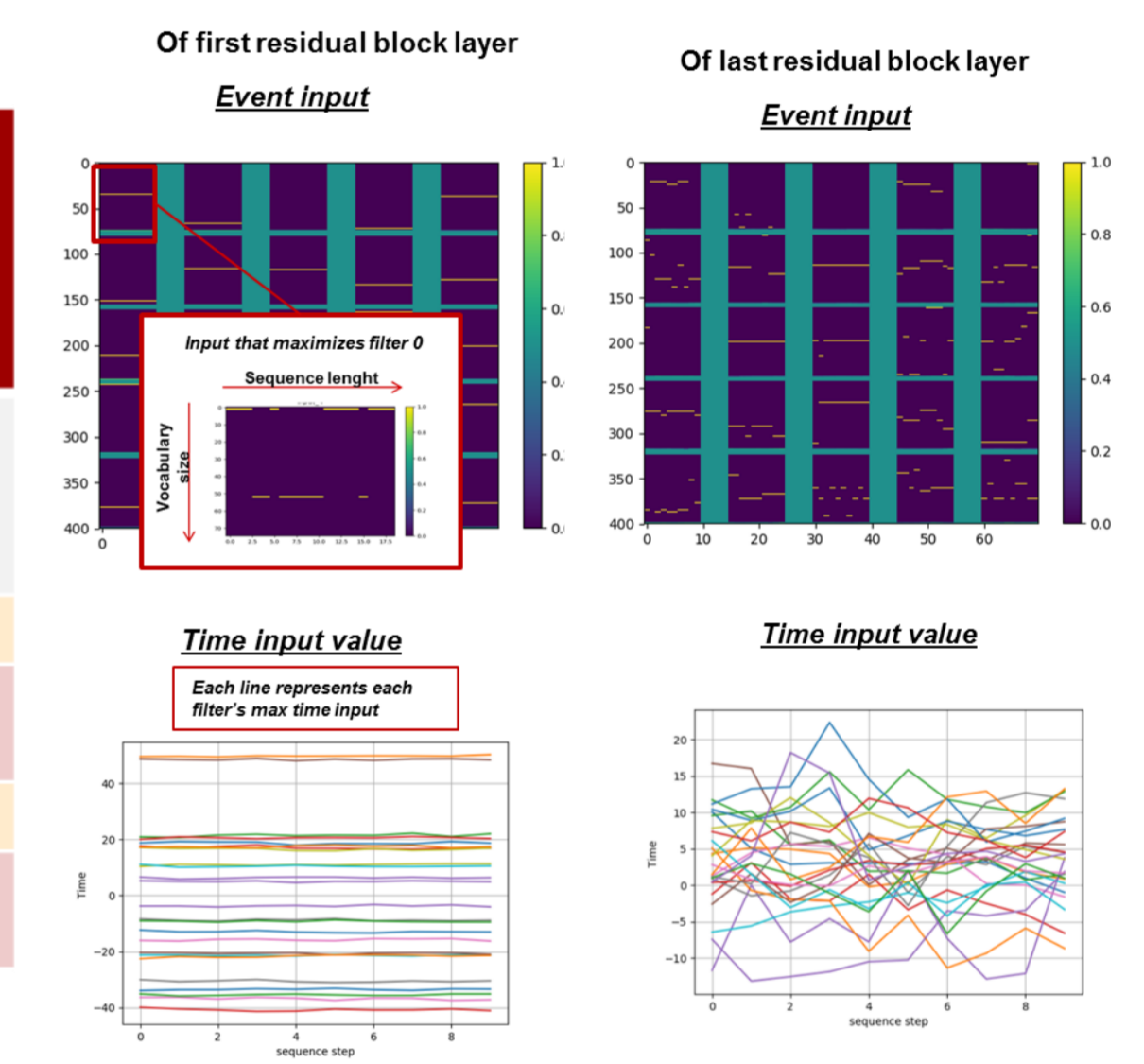
$$-\frac{1}{N} \sum_{t \in T} y_t^c \log(\hat{y}_t^c) + \frac{1}{N} \sum_{t \in T} (t_t - \hat{t}_t)^2$$



We can use weighed loss function  
Total Loss =  $W_c(classLoss) + W_r(regLoss)$

### Results

DB	MIMIC	Financial	SO	Location Prediction
	Max Len=33 #Seq=650 Voc Siz=75	Max Len=3319 #Seq=200 Voc Siz=2	Max Len=736 #Seq=8633 Voc Siz=22	Max Len=3200 #Seq=182 Voc Siz=54
Baselines	Acc=30.5%	Acc=51%	Acc=43%	Acc=23.3%
Most Frequent	Acc=64.8%	Acc=61.9%	Acc=30.9%	Acc=57.6%
Mean time	RMSE(day)=1.3	RMSE(s)=1.6	RMSE(day)=12	RMSE(hr)=1.5
SOA with RNNs				
RMTTP[1]	Acc=82.51%	Acc=62.3%	Acc=48.6%	Acc=61%
	RMSE(day)=5.7	RMSE(s)=1.4	RMSE(day)=10	RMSE(hr)=2.1
My TCN				
TCN for events	Acc=87%	Acc=62.7%	Acc=45.5%	Acc=66.7%
	RMSE(day)=0.9	RMSE(s)=0.9	RMSE(day)=11.8	RMSE(hr)=0.6

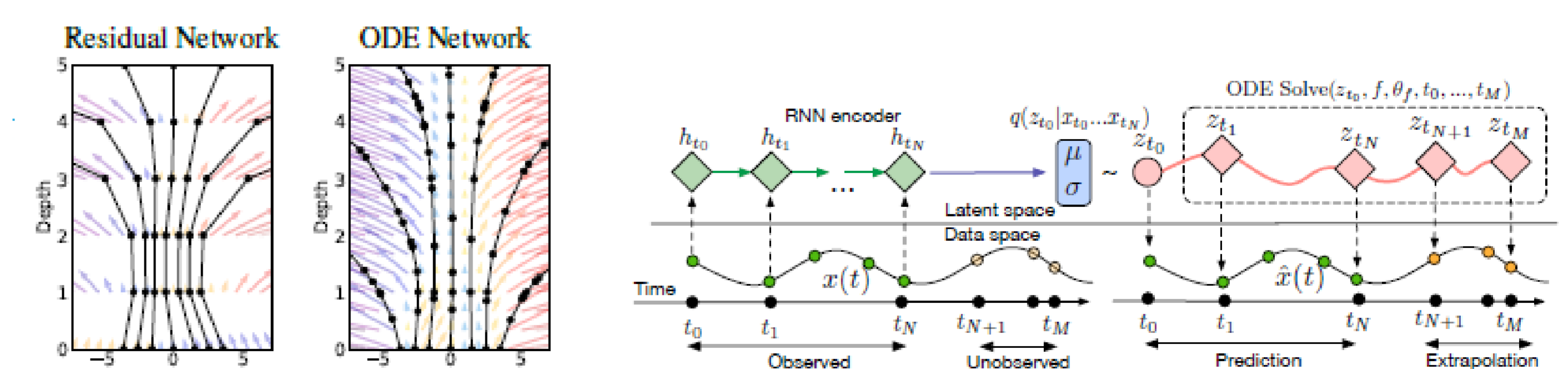


- TCNs improves event prediction compared with RNN SOA approach
- Time prediction also improves but still error is high compared with baselines
- Lower convolutional layers learn low frequency patterns and higher layers high frequency patterns

## Next steps

- Fine tune TCN for event prediction
- Investigate Differential Neural networks for event prediction to leverage ODEs properties and solvers

### Neural ordinary Differential Equations [4]



## References

[1] Du, Nan, et al. "Recurrent marked temporal point processes: Embedding event history to vector." KDD 2016  
[2] "What to Do Next: Modeling User Behaviors by Time-LSTM" JCAI 2017  
[3] Phased LSTM: Accelerating Recurrent Network Training for Long or Event-based Sequences  
[4] Chen, Tian Qi and Rubanova, et al. "Neural Ordinary Differential Equations" NIPS (2016)  
[5] Bai, Shaojie, J. Zico Kolter, and Vladlen Koltun. "An empirical evaluation of generic convolutional and recurrent networks for sequence modeling." (2018).