Sequential Data Modelling

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Insight **Centre for Data Analytics**

Objective

Develop deep learning methods for event prediction

Convolutional Architecture for event prediction

TCNs architecture for event prediction

 $\Delta t4$

Concatenate

Sequence length

Regression

(linear/relu)

Conv

(k=1,d)

Event

Time

2.0 .

1.5

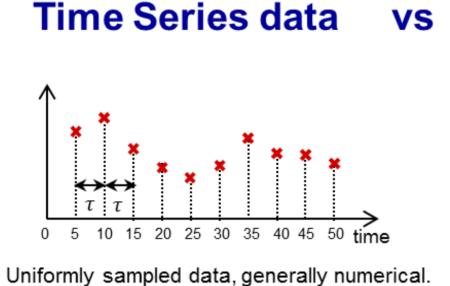
1.0

 $\lim_{n \to \infty} \frac{\Delta t 1}{\Delta t 2} \Delta t 3$

> Modelling time explicitly as an input

Problem

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



Event/Transactional data vs Sequential data

Which is next Given a history of events event?, /hen? <u>have a good day 、</u> 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 Non uniformly generated, generally categorical.

Examples of event sequential data

Transactional data

E-commerce data, medical records

i.e. alarms, customers' shopping behavior

Event prediction task

Artificial Event Sensor Data Threshold-based alarm events

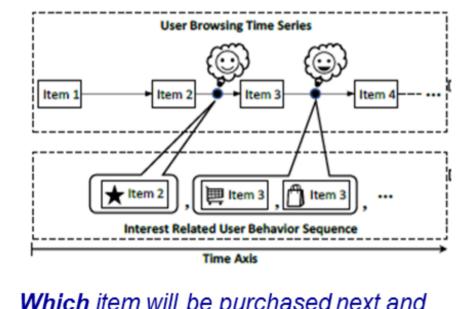
i.e. temperature, number of calls per hour



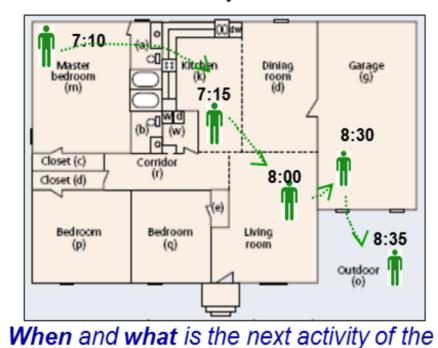
Which alarm will happened next and when?

Related work

Event modelling approaches



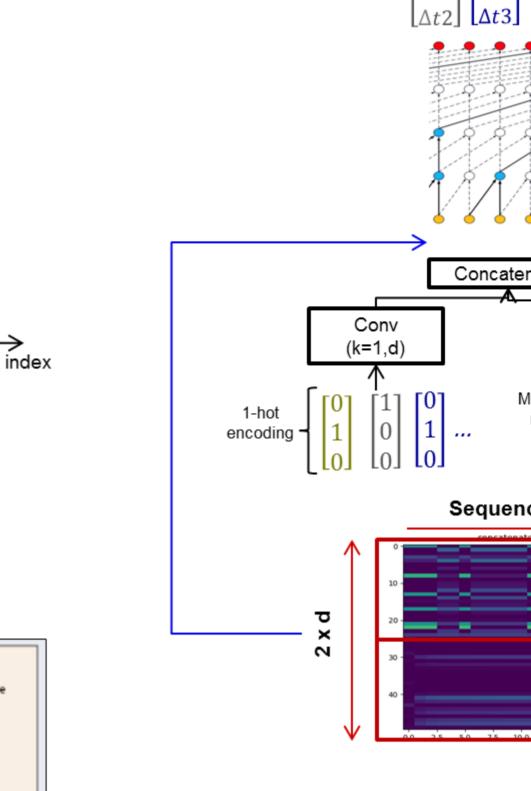
Which item will be purchased next and when?



Behaviour user data

User Activity/location data





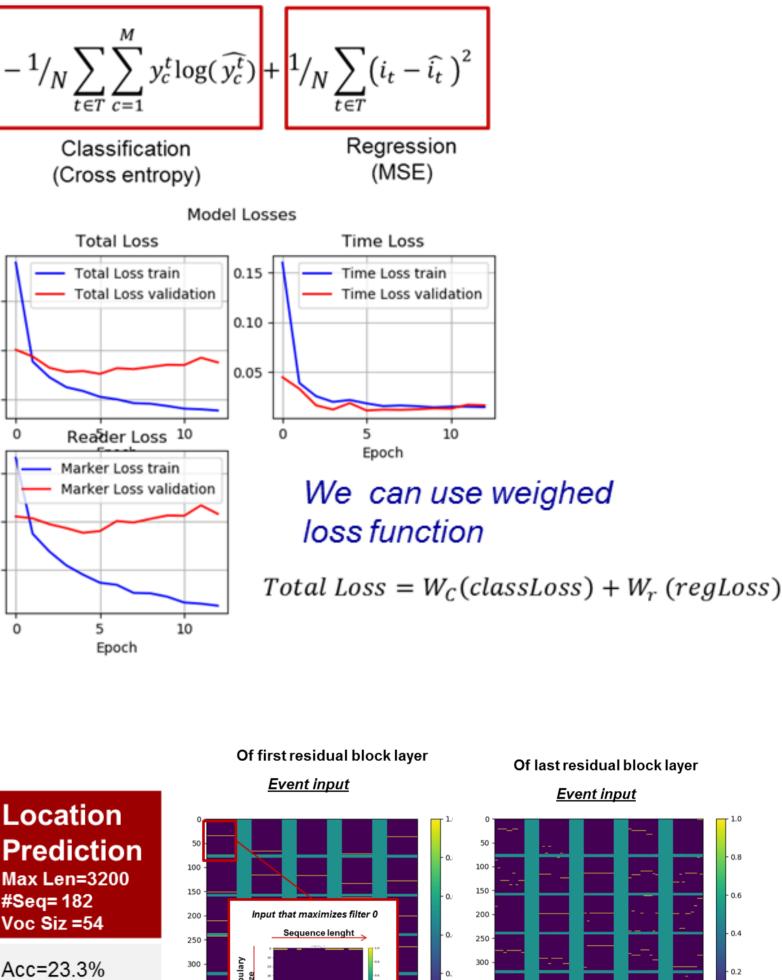
Results

D	B	MIMIC Max Len=33 #Seq= 650 Voc Siz =75	Financial Max Len=3319 #Seq= 200 Voc Siz =2	SO Max Len=736 #Seq= 6633 Voc Siz =22	Location Prediction Max Len=3200 #Seq= 182 Voc Siz =54
M y(t	a selines ost Frequent t)=x(t) ean time	Acc=30.5% Acc= 64.8 % RMSE(day)= 1.3		Acc=43% Acc=30.9% RMSE(day)= 12	Acc=23.3% Acc=57.6% RMSE(hr)=1.5

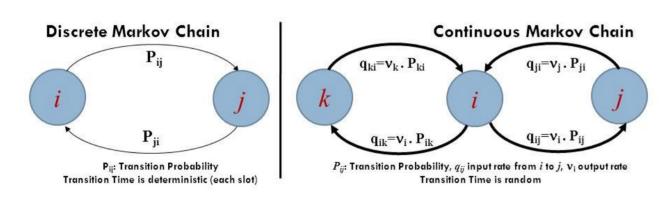
SOA with DNNe

(time interval)

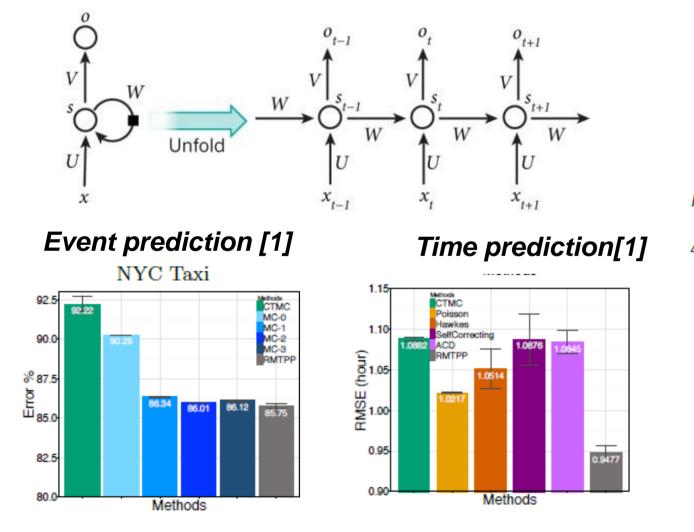
Combined loss function

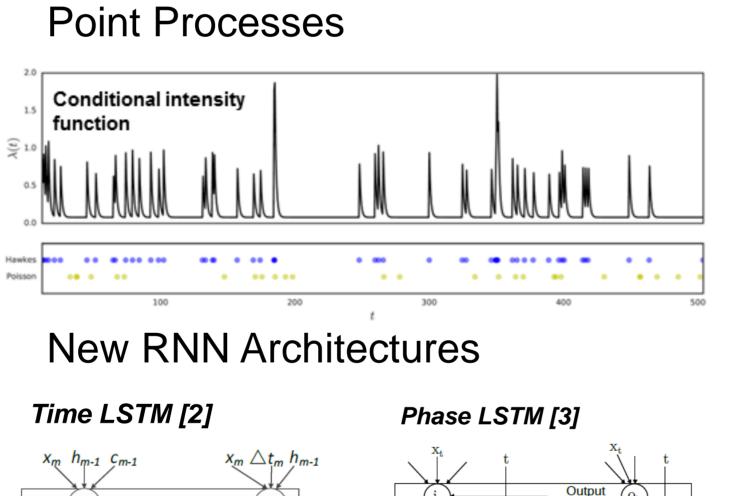


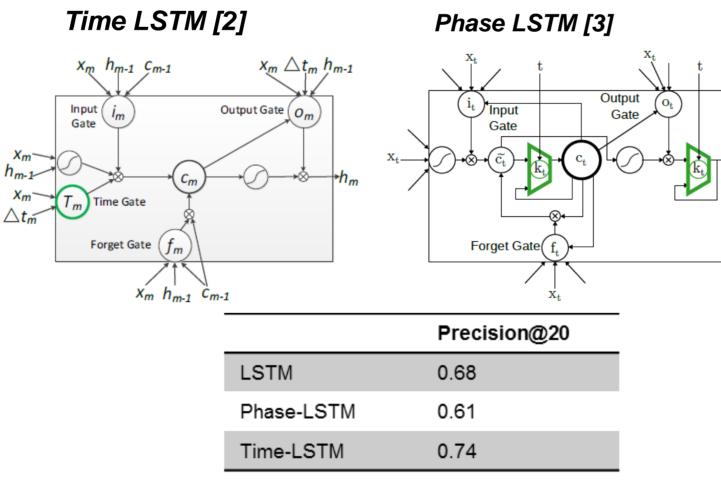
Markov Chain Models



Recurrent Neural Networks







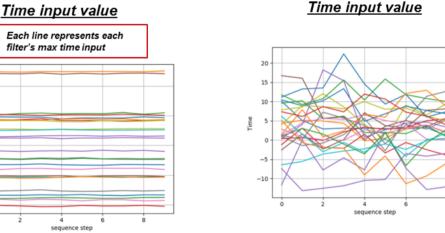
✓ RNN and point process combination is SOA in event prediction

SOA in sequence modelling

Temporal Convolutional Neural Networks (TCNs) [5]

1D Casual convolution + Dilated Convolution

SUA WITH KNNS								
RMTPP[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	Acc= 87%	Acc= 62.7 %	Acc= 45.5%	Acc= 66.7 %				
events	RMSE(day)= 0.9	RMSE(s)= 0.9	RMSE(day)=11.8	RMSE(hr)= 0.6				



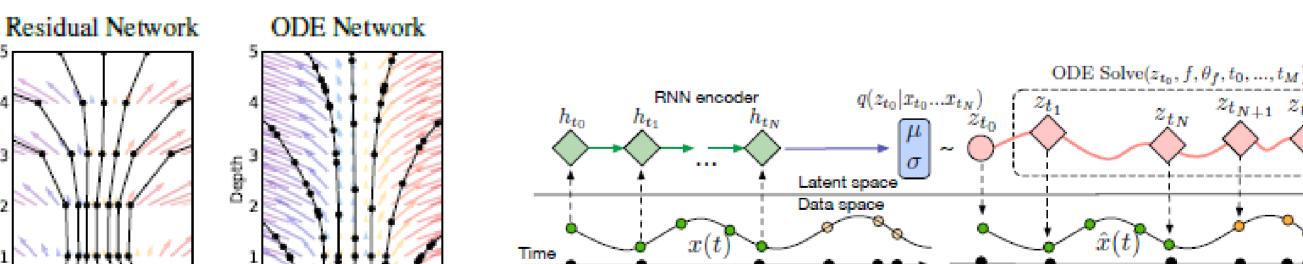
TCNs improves event prediction compared with RNN SOA approach

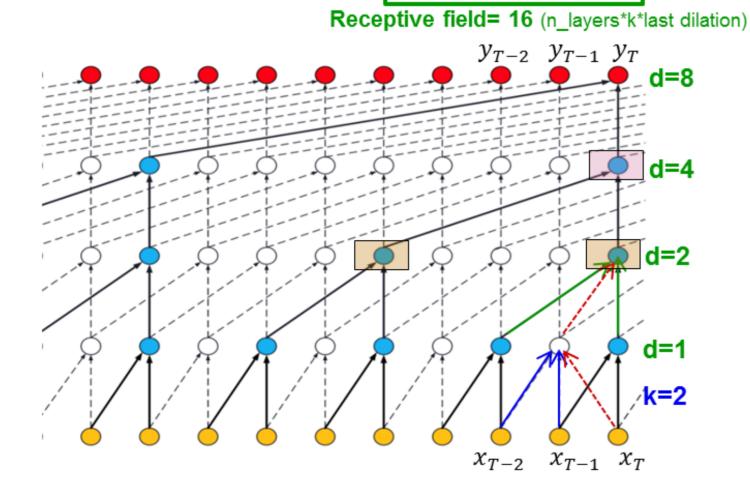
- \succ Time prediction also improves but still error is high compared with baselines
- Lower convolutional layers learn low frequency patterns and higher layers high frequency patterns

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]





✓ Outperform RNNs

✓ Exhibit longer memory

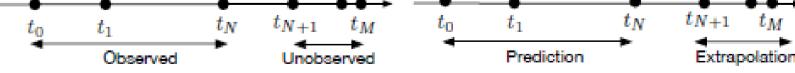
✓ Training and evaluation faster

(parallelism)

✓ Has stables gradients

 \rightarrow Not used for event prediction tasks





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).

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