Autoregressive Convolutional Neural Networks for Asynchronous Time Series

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Introduction

- Significance-Offset Convolutional Neural Network for Asynchronous time series
- Combining AR models and Neural Networks
- Inspired by standard AR models and gating mechanisms (used in RNN)
- Focused on time series with multivariate and noisy signals i.e. financial data
- Time series forecasting problem:

$$p(X_{t+d}|X_t, X_{t-1}, ...) = f(X_t, X_{t-1}, ...)$$

Introduction

- Financial time series is challenging to predict due to their low signal-to-noise ratio and heavy-tailed distributions
  - same signal (e.g. price of a stock) obtained from different sources (e.g. financial news) asynchronously, each source may have different bias or noise (Fig1)
  - the traditional econometric models i.e. AR,VAR,VARMA might not be sufficient.
  - combine them with deep neural networks that can learn highly nonlinear relationships

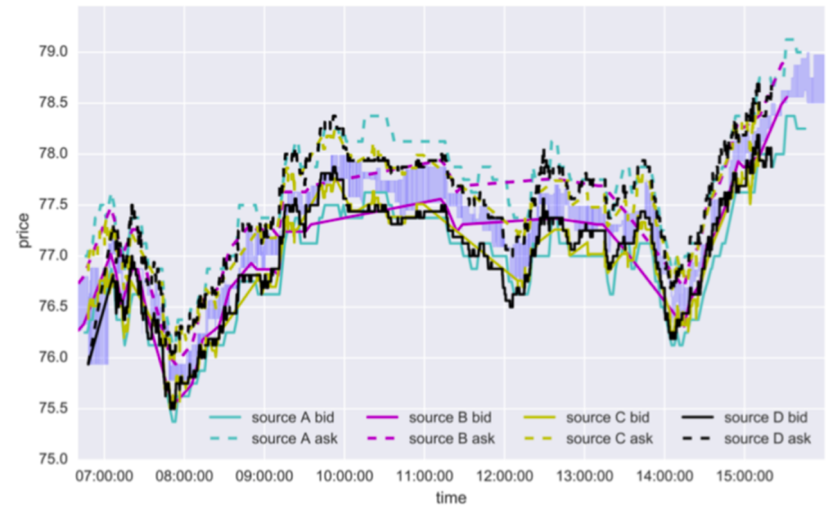

Figure 1. Quotes from four different market participants (sources) for the same CDS[2] throughout one day. Each trader displays from time to time the prices for which he offers to buy (*bid*) and sell (*ask*) the underlying CDS. The filled area marks the difference between the best sell and buy offers (*spread*) at each time.

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Related Work

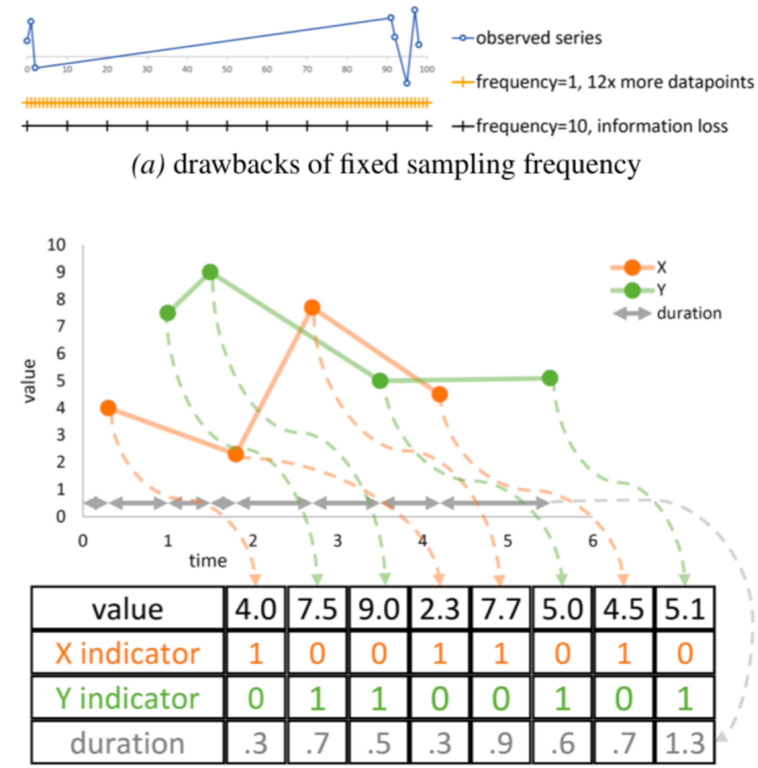
- Stochastic models such as AR, ARIMA and GARCH
  - Explain variables rather than improving out-of-sample prediction
  - Overfit, poor out-of-sample performance
- Gaussian processes, especially irregular sampled time series
  - Combine with econometric models i.e. Gaussian Copula Process Volatility[1]
- 4-layer perceptrons in modeling price change distributions in Limit Order Books[2]
- WaveNet architecture to several short univariate and bivariate time-series (including financial ones)[3]
- Autoencoders with a single hidden layer to compress multivariate financial data.[4]
- Neil et al. (2016): Augmentation of LSTM architecture suitable for asynchronous series[5], which stimulates learning dependencies of different frequencies through time gate.

Related Work

- **Gating and weighting mechanisms**
  - overcome the problem of vanishing gradient
  - $f(x) = c(x) \otimes \sigma(x)$
  - f(x): output function, c: nonlinear function of x, $\otimes$: an element-wise(Hadamard) matrix product, $\sigma(x)$: a sigmoid nonlinearity that controls the amount of output passed to the next layer
  - Appropriate composition of functions may lead to popular recurrent architecture such as LSTM and GRU.

Motivation

- Econometrics and machine learning communities done independently. AR models are not sufficient.
- Gaussian processes follow heavy-tailed distribution for financial datasets.
- Irregular sampled time series involve highly nonlinear functions.
- The dimension of multivariate time series are often observed separately and asynchronously, fix frequency may lead to lose information or enlarge the dataset (Fig2).
  - Treats varying durations as additional feature
  - uses the indicator feature to indicate whether the value of the observation is in this duration or not.
- LSTM increases computation complexity.



(a) drawbacks of fixed sampling frequency

(b) representation

Figure 2. (a) Fixed sampling frequency and its drawbacks; keeping all available information leads to much more datapoints. (b) Proposed data representation for the asynchronous series. Consecutive observations are stored together as a single *value* series, regardless of which series they belong to; this information, however, is stored in *indicator* features, alongside durations between observations.

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Model Architecture

- Given multivariate time series $(x_n)_{n=0}^{\infty} \subset \mathbb{R}^d$
- Predict the conditional future values

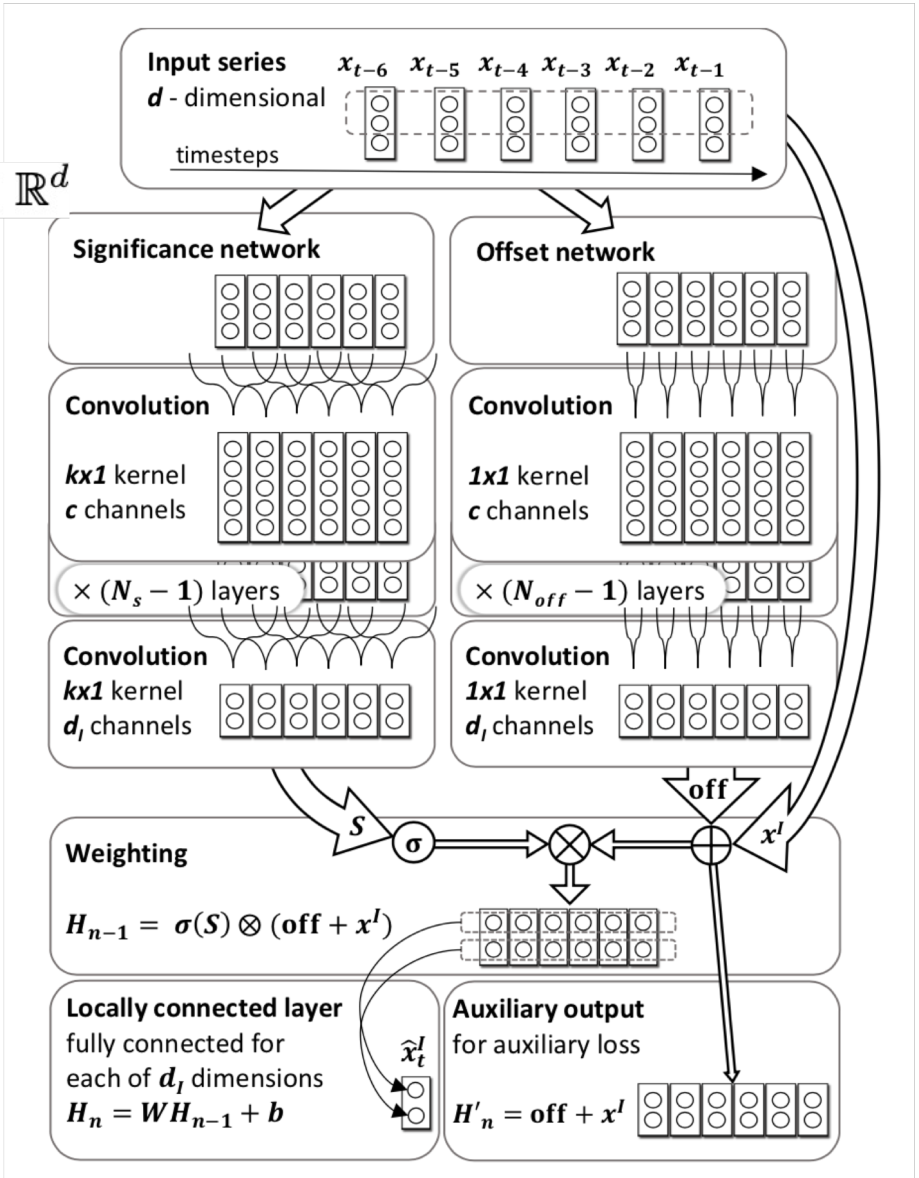
$$y_n = \mathbb{E}[x_n^I | \underbrace{x_{n-m}, m = 1, 2, \ldots]}_{\mathbf{x}_n^{-M}}$$

- The general equation for SOCNN (Significance-Offset Convolutional Neural Network):

$$\hat{y}_n = \sum_{m=1}^{M} [F(\mathbf{x}_n^{-M}) \otimes \sigma(S(\mathbf{x}_n^{-M}))]_{\cdot,m}$$

(similar to Gating and weighting mechanisms mentioned before $f(x) = c(x) \otimes \sigma(x)$)

- F,S are neural networks. S is a fully convolutional network which is composed of convolutional layers only and called significance network.
- σ is a normalized activation function
- ⊗ is element-wise (Hadamard) matrix multiplication.



Model Architecture

- The Eq. of estimator yn can be rewritten as:

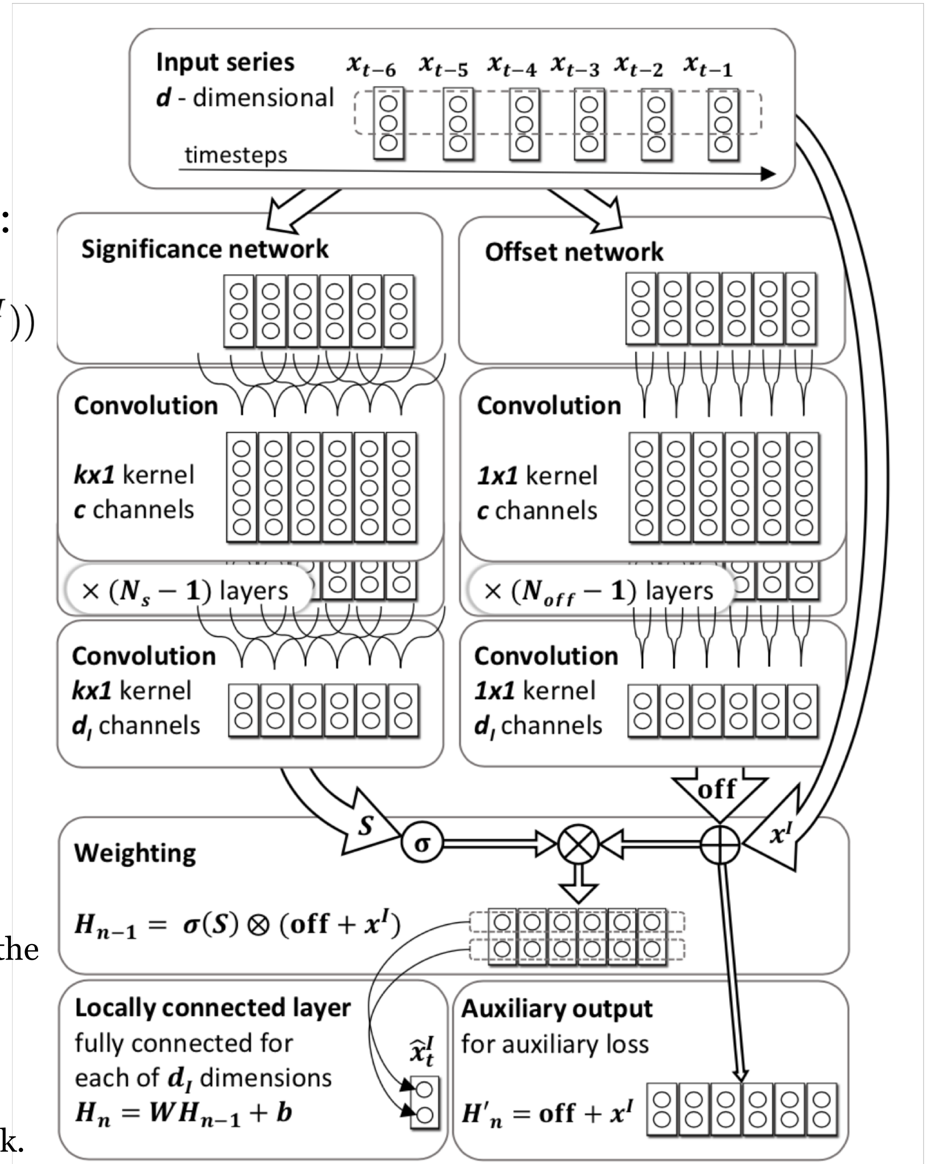
$$\hat{y}_n = \sum_{m=1}^{M} \underbrace{W_{\cdot,m} \otimes (off(x_{n-m}) + x^{I}_{n-m})}_{F(\mathbf{x}_n^{-M})} \otimes \sigma(S_{\cdot,m}(\mathbf{x}_n^{-M}))$$

Significance-Offset Convolutional Neural Network (SOCNN)

- Auxiliary Loss Function:

$$L^{aux}(\mathbf{x}_n^{-M}, y_n) = \frac{1}{M}\sum_{m=1}^{M} ||off(x_{n-m}) + x^{I}_{n-m} - y_n||^2$$

- The eq. enforces the separation of temporal dependence, the local significance of observations Sm, and the predictors off(xn−m) that are completely independent of position in time.
- Each of the past observations provides an adjusted single regressor for the target variable through the offset network.
- Significance network provides data-dependent weights for all regressors and sums them up in an autoregressive manner.



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Experiments

- Three datasets:
  - Artificially generated datasets: They generated 4 artificial series, $X_{K \times N}$, where $K \in \{16,64\}$. Therefore there is a synchronous and an asynchronous series for each K value.
  - Household electric power consumption dataset: 7 different features excluding date and time.
  - Quotes dataset: 2.1 million quotes from 28 different sources from different market participants, each quote is characterized by 31 features.
- Comparing SOCNN performance with simple CNN, single and multiplayer LSTM and 25-layer ResNet.

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Training

- Training and validation set: first 80%, sampled by ratio 3:1
  Test set: the remaining 20%
- Adam optimizer
- Batch size=128 for artificial and electricity data
  Batch size =256 for quotes dataset
  batch normalization
- Randomly sampled at the beginning of each epoch
- Dropout and early stopping
- Tensorflow, Keras
- K20s NVIDIA GPU and 8-core Intel Core i7-6700 CPU

Training

- Grid search over some of the hyperparameters
  - depth of offset subnetwork
  - auxiliary weight α
- LeakyReLU activation function, with leak rate a=0.1 :

$$\sigma^{LeakyReLU}(x) = \begin{cases} x & \text{if } x \geq 0 \\ ax & \text{otherwise} \end{cases}$$

  used in all layers except the top layer
- CNN: same number of layers , same stride, similar kernel size, max pooling with pool size=2 every two convolutional layers

Table 1. Configurations of the trained models. *f* - number of convolutional filters/memory cell size in LSTM, *ks* - kernel size, *p* - dropout rate, *clip* - gradient clipping threshold, *conv* - $(k \times 1)$ convolution with kernel size k indicated in the ks column, *conv1* - (1×1) convolution. Apart from the listed layers, each network has a single fully connected layer on the top. Kernel sizes (3, 1) ((1, 3, 1)) denote alternating kernel sizes 3 and 1 (1, 3 and 1) in successive convolutional layers. We also optimized a parameter specific to Phased LSTM, the *initialized period*, considering two: settings: [1, 1000] and [.01, 10].

Artificial & Electricity Datasets					
Model	layers	f	ks	p	clip
SOCNN	10conv + $\{1, 10\}$conv1	$\{8, 16\}$	$\{(3, 1), 3\}$	0	$\{1, .001\}$
CNN	7conv + 3pool	$\{16, 32\}$	$\{(3, 1), 3\}$	$\{0, .5\}$	$\{1, .001\}$
LSTM	$\{1, 2, 3, 4\}$	$\{16, 32\}$	-	$\{0, .5\}$	$\{1, .001\}$
Phased LSTM	1	{16, 32}	-	0	$\{1, .001\}$
ResNet	22conv + 3pool	16	(1, 3, 1)	{0, .5}	$\{1, .001\}$
Quotes Dataset					
Model	layers	f	ks	p	clip
SOCNN	7conv + $\{1, 7\}$conv1	8	$\{(3, 1), 3\}$	.5	.01
CNN	7conv + 3pool	$\{16, 32\}$	$\{(3, 1), 3\}$	.5	.01
LSTM	$\{1, 2, 3\}$	$\{32\}$	-	.5	.0001[10]
Phased LSTM	1	{16, 32}	-	0	.01
ResNet	22conv + 3pool	16	(1, 3, 1)	.5	.01

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Results

Table 2. Detailed results for all datasets. For each model, we present the average and standard deviation (in parentheses) mean squared error obtained on the out-of-sample test set. The best results for each dataset are marked by bold font. *SOCNN1* (*SOCNN1+*) denote proposed models with one (10 or 7) offset sub-network layers. For quotes dataset the presented values are averaged mean-squared errors from 6 separate prediction tasks, normalized according to the error obtained by VAR model.

model	VAR	CNN	ResNet	LSTM	Phased LSTM	SOCNN1	SOCNN1+
Synchronous 16	0.841 (0.000)	0.154 (0.003)	0.152 (0.001)	**0.151 (0.001)**	0.166 (0.026)	0.152 (0.001)	0.172 (0.001)
Synchronous 64	0.364 (0.000)	0.029 (0.001)	0.029 (0.001)	**0.028 (0.000)**	0.038 (0.004)	0.030 (0.001)	0.032 (0.001)
Asynchronous 16	0.577 (0.000)	0.080 (0.032)	0.059 (0.017)	0.038 (0.008)	1.021 (0.090)	**0.019 (0.003)**	0.026 (0.004)
Asynchronous 64	0.318 (0.000)	0.078 (0.029)	0.087 (0.014)	0.065 (0.020)	0.924 (0.119)	**0.035 (0.006)**	0.044 (0.118)
Electricity	0.729 (0.005)	0.371 (0.005)	0.394 (0.013)	0.461 (0.011)	0.744 (0.015)	**0.163 (0.010)**	0.165 (0.012)
Quotes	1.000 (0.019)	0.897 (0.019)	2.245 (0.179)	0.827 (0.024)	0.945 (0.034)	**0.387 (0.016)**	–

- SOCNN outperforms in asynchronous artificial, electricity and quotes datasets.
- For synchronous data, LSTM slightly better, but SOCNN almost has the same results with LSTM.
- Phased LSTM and ResNet have performed bad on artificial asynchronous dataset and quotes dataset respectively.
- SOCNN1+ has negligible or negative impact.

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Results

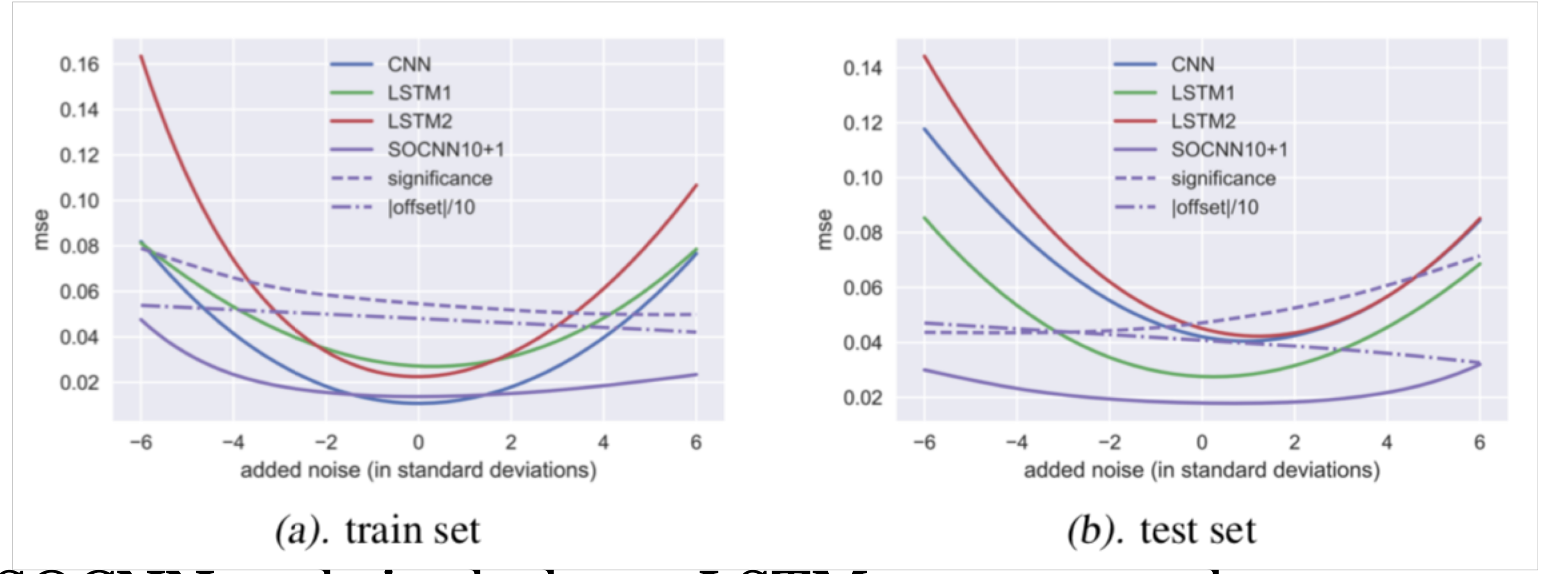
- the higher α improved asynchronous artificial generated dataset, but has negligible impact on other datasets.
- In general, SOCNN had significantly lower variance of the test and validation errors.

Table 3. MSE for different values of α for two artificial datasets.

α	Async 16	async 64
0.0	0.0284	0.0624
0.01	0.0253	0.0434
0.1	0.0172	0.0323

Results

- Test the robustness of the proposed model SOCNN:
  - add noise terms to asynchronous 16 dataset



- SOCNN and single-layer LSTM are most robust compared to other networks.

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Conclusion

- Significance-Offset Convolutional Neural Network: AR-like weighting mechanism and convolutional neural network.
- High-noise asynchronous time series
- Achieves outperformance in forecasting several asynchronous time series
- Extension:
  - adding intermediate weighting layers
  - not just 1×1 convolutional kernels on the offset sub-network
- econometric datasets

Critique

- The paper is most likely an application paper, and the proposed new architecture shows improved performance over baselines in the asynchronous time series.

BUT

- The quote data cannot be reached, only two datasets available.
- The 'Significance' network was described as critical to the model in paper, but they did not show how the performance of SOCNN with respect to the significance network.
- The transform of the original data to asynchronous data is not clearly stated.
- The experiments on the main application are not reproducible because the data is proprietary.
- The paper didn’t state clearly about the impact and advantage of auxiliary loss function.

Reference

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THANK YOU! ☺