Global, Local & Tranductive Model for Multiple Time-Series Analysis and Modelling

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Motivation

Time-series modelling and prediction have been very well researched by both the Statistical and Data Mining communities. However, the multiple time-series problem of modelling and predicting simultaneous movements of a collection of time sensitive variables which are related to each other have received much less attention eventhough the existence of dynamic relationships in multiple time-series data relating real world phenomena has been identified from previous studies.

The study focuses on the anaylsis and modelling of interactions in multiple time-series from a specific setting that take place continuously over time through different learning methodologies, to in the end perform simultaneous prediction. It is expected that various level of knowledge about the dynamics of the relationships in multiple time-series from a specific setting can be acquired to finally construct a complete understanding about the underlying behaviour of the dynamic system under investigation.

Objective

The main objectives of the study are,

- analysis and modelling of dynamic interactions in multiple time-series from a specific setting,
- knowledge extraction of relationships in multiple time-series through diverse learning process, and
- simultaneous prediction of multiple time-series through knowledge integration.

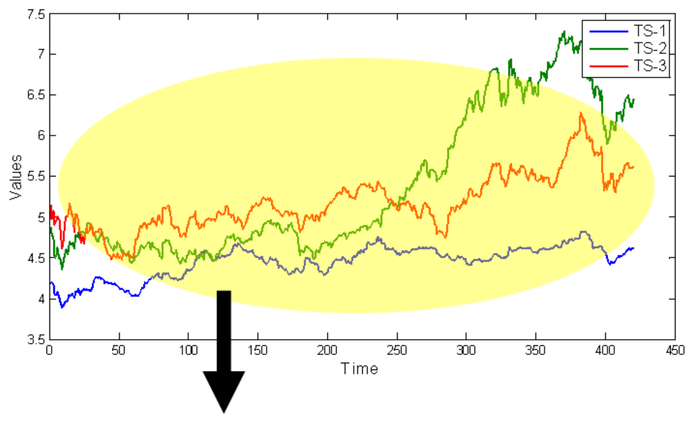
DIN Model

Detecting and evaluating degree of influences in multiple observed variables. Capturing global trends of dynamic interactions.

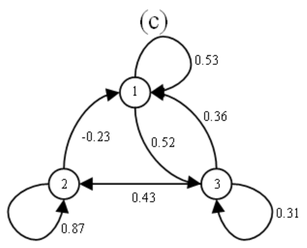
- Dynamic interactions is modelled with the discrete time approximation of first-order differential equations,

$$\mathbf{x}_{t+1} = \mathbf{F}\mathbf{x}_t + \epsilon_t; \mathbf{x}_t = \left(x_t^1, \ldots, x_t^n\right)'$$

- Kalman Filter forward recursions to estimate next states of the dynamic system.
- Kalman Filter backward recursions to compute required statistics for likelihood evaluation and parameter estimation.



$$\begin{bmatrix} 0.53 & -0.23 & 0.36 \\ -0.01 & 0.87 & 0.43 \\ 0.52 & -0.02 & 0.31 \end{bmatrix} \begin{bmatrix} + & - & + \\ 0 & + & + \\ + & 0 & + \end{bmatrix}$$



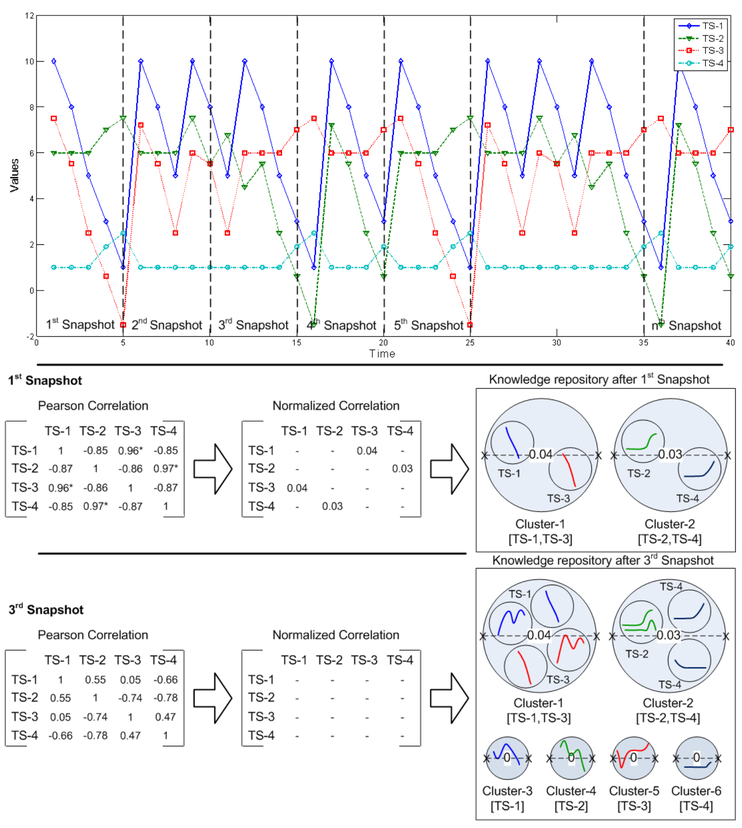
LTM Model

Provides localized profiles of relationships between multiple time-series. Utilizes a 2-level local modelling process;

- Relationship profiling in a sub-space of multiple time-series data through dissimilarity measurement by the *RNOMC* matrix,

$$\text{RNOMC}(a,b) = \sqrt{\frac{1 - corr(a,b)}{2}}$$

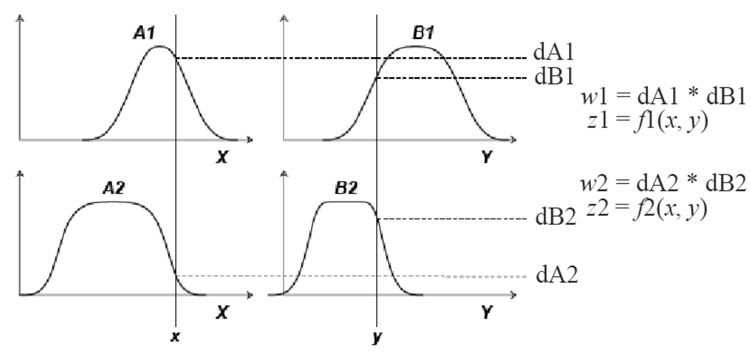
- Recurring trends extraction and clustering across pairs of time-series using the *non-parametric regression* and the ECM algorithm.



mTNFI Model

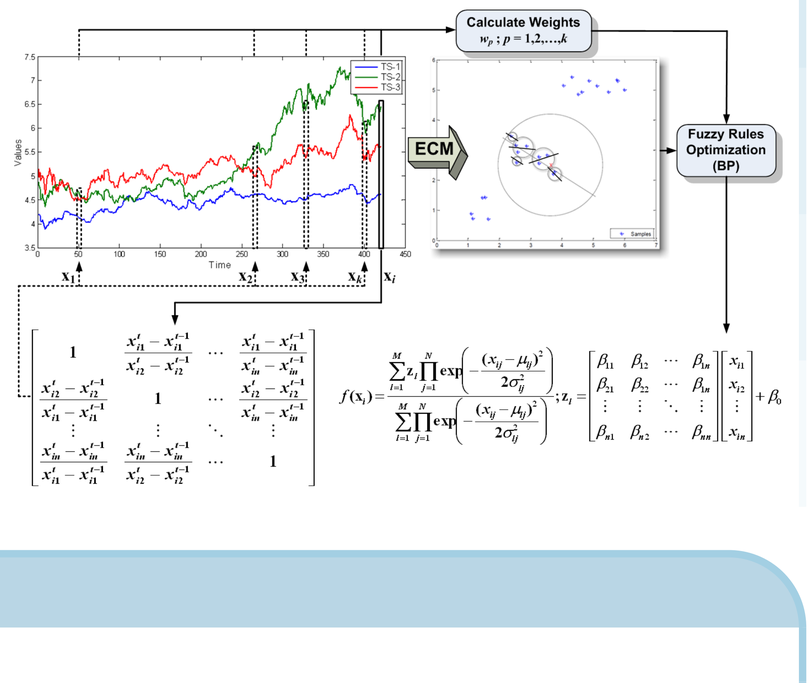
Constructs a localized multivariate fuzzy inference system using k training samples that are "closest" to the state of input vector.

- Nearest Neighbour method.
- Constructs multiple local models using ECM with Takagi-Sugeno inference system.

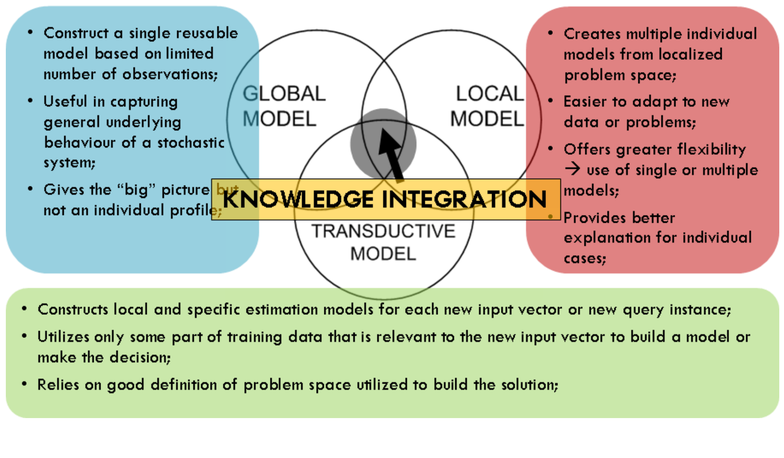


$$\text{R}_1 : \text{If } x \text{ is } \text{A}_1 \text{ and } y \text{ is } \text{B}_1 \text{ then } z_1 \text{ is } f_1(x,y)$$
$$\text{R}_2 : \text{If } x \text{ is } \text{A}_2 \text{ and } y \text{ is } \text{B}_2 \text{ then } z_2 \text{ is } f_2(x,y)$$

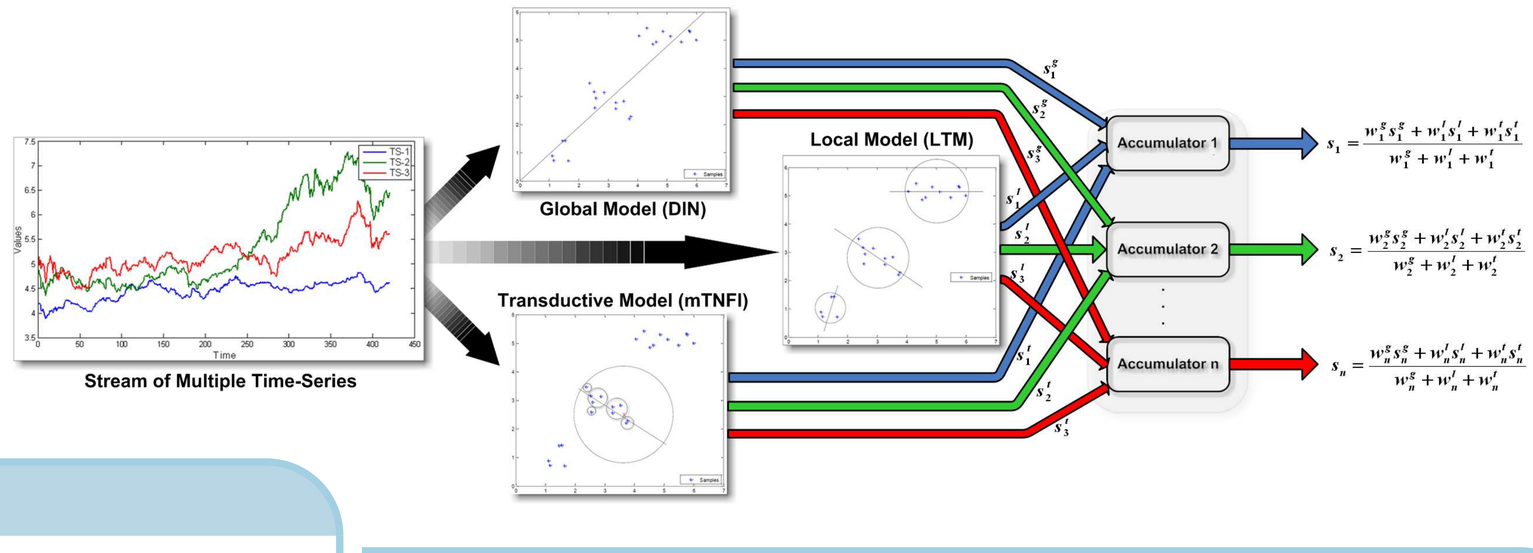
$$z = \frac{w_1 z_1 + w_2 z_2}{w_1 + w_2}$$



Knowledge Integration



Integrated Framework



Experimental Result

Location	DIN MTSP	LTM MTSP	mTNFI MTSP	MLR STSP	MLP STSP	R-Walk STSP
Auckland	3.2673	1.3219	**1.2965**	3.5236	3.0371	1.6340
Paeroa	2.8343	1.3890	**1.1973**	3.4257	3.1592	1.6868
Hamilton	2.8810	1.4513	**1.4045**	3.7263	3.4958	1.8316
Reefton	3.0067	**1.8351**	1.9612	4.1725	3.9125	2.4708

Root Mean Squared Error in mPa, 100 days air pressure level prediction in New Zealand.
Note: MTSP is Multiple Time-series Prediction; STSP is Single Time-series Prediction.

Summary

- Three methodologies to extract different types and levels of knowledge about the dynamics of relationships in multiple time-series have been introduced and proposed.
- Based on results from conducted experiments with climate data set from New Zealand, knowledge integration is expected to increase the prediction accuracy of multiple time-series data.