Transfer Learning in Financial Time Series with Gramian Angular Field (Student Abstract)

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Abstract

Transfer learning enhances model performance in financial time series by leveraging data from related domains. The selection of appropriate source domains is crucial to avoid negative transfer. We propose using Gramian Angular Field (GAF) transformations to improve time series similarity functions for better domain alignment. Extensive experiments with DNN and LSTM models show that GAF-based similarity functions, specifically Coral (GAF) for DNN and CMD (GAF) for LSTM, significantly reduce prediction errors, demonstrating their effectiveness in complex financial environments.

Introduction

Transfer learning enhances the performance of models in data-scarce domains by leveraging knowledge from related domains. It has shown success in time series analysis, including financial forecasting. However, the risk of negative transfer, where irrelevant source data degrades model performance, remains a challenge (Rosenstein et al. 2005) (Wang and Oates 2015) (Wang et al. 2020). This study focuses on enhancing source domain selection by using GAF transformations to improve similarity functions, thereby reducing transfer learning errors.

Methodology

We introduce a GAF-based approach to enhance domain discrepancy measurement, transforming time series into two-dimensional images. According to (Wang and Oates 2015), GAF transformation captures temporal and angular relationships. This transformation enables more accurate similarity measurements between source and target domains.

Turning 1-d Time Series to 2-d Gramian Angular Field

There are three steps in transforming time series to GAF. The first step is to scale the time series to [-1,1] using:

$$\tilde{x}_i = \frac{(x_i - \max(X)) + (x_i - \min(X))}{\max(X) - \min(X)} \tag{1}$$

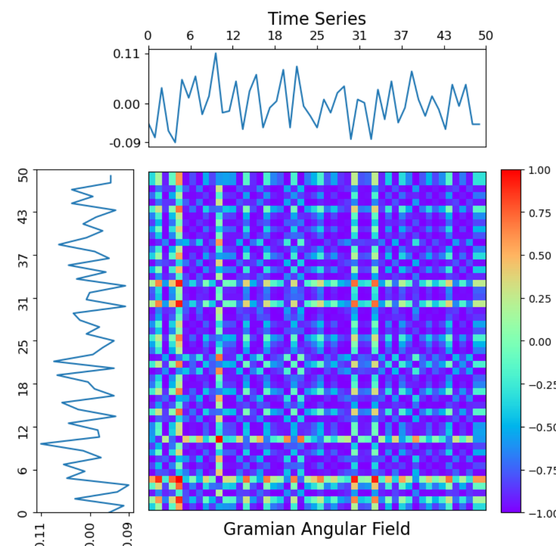

Figure 1: GAF Transformation on Time Series

x_i represents an individual data point in the time series. X denotes the entire time series dataset. The equation scales each data point to a range of [-1,1] by adjusting it relative to the maximum and minimum values in the entire dataset X.

Next, the scaled time series is transformed to polar coordinates:

$$\begin{cases} \phi = \arccos(\tilde{x}_i), & -1 \leq \tilde{x}_i \leq 1, \tilde{x}_i \in \tilde{X} \\ r = \frac{t_i}{N}, & t_i \in N \end{cases} \tag{2}$$

Finally, the polar coordinates are converted to Gramian Angular Summation Field (GASF) as shown in transform:

$$GASF = [\cos(\phi_i + \phi_j)] \tag{3}$$

GASF is a specific type of GAF that focuses on the summation of angular values (Wang et al. 2020). In this study, we generally refer to these transformations as GAF to encompass both GASF and other potential variations.

Transfer Learning Based on Gramian Angular Field (GAF)

In single-source transfer learning, a neural network is trained on a source dataset (D), fine-tuned on the target dataset (D_t),

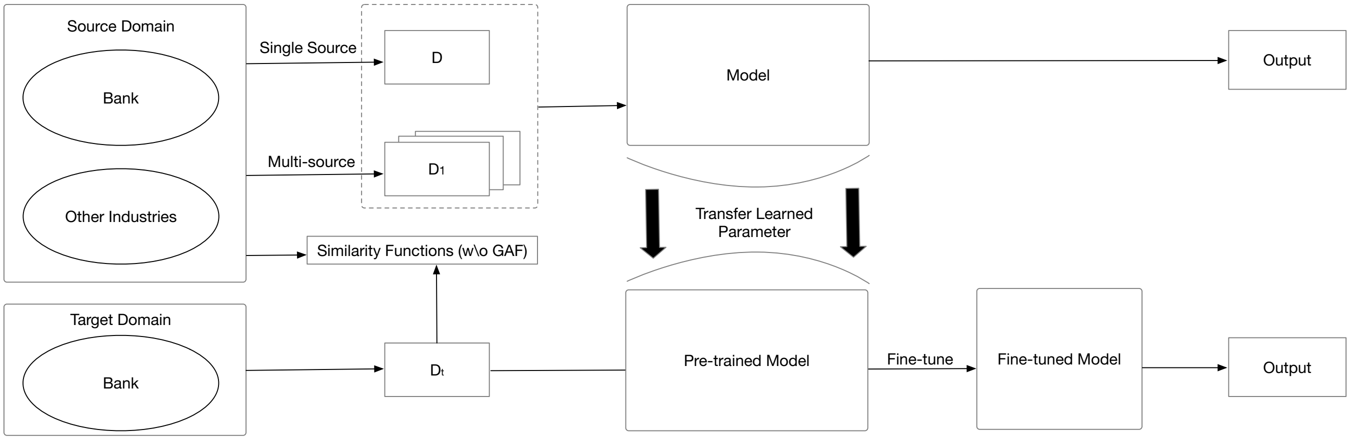

Figure 2: The Procedure of GAF-based Transfer Learning

and evaluated on D_t. Multi-source transfer learning extends this by training on multiple datasets (D_1, D_2) before fine-tuning on D_t.

The selection of source domains is critical. The process starts by applying similarity functions to compare each source dataset (D) with the target (D_t). If using the GAF transformation, both D and D_t are transformed first. The algorithm selects the source dataset with the highest similarity for Pearson correlation or the lowest for other functions, and this dataset is used for training. In multi-source transfer learning, D_1 is selected first, then removed from the pool, and the process is repeated to find D_2. These selected datasets are used for training, ensuring the model is well-tuned for the target domain.

Experiments

We evaluated the performance of similarity functions, with and without GAF transformation (see TABLE 1), using Hong Kong stock market time series data on DNN and LSTM models. These similarity functions include (i) Euclidean distance, (ii) Coral, (iii) CMD, (iv) Wasserstein distance, (v) Pearson, (vi) DTW, (vii) TWED, (viii) MMD, (viv) ARE, (x) PSNR and (xi) SSIM. The baseline evaluations and experiments (see TABLE 2) demonstrate that GAF-based methods, especially Coral (GAF) and CMD (GAF), outperform traditional similarity functions in reducing prediction errors.

Evaluation&Experiment	Source (S_A)	Source (S_B)	Target
Evaluation&Experiment 1	Bank	—	Bank
Evaluation&Experiment 2	Other Industries	—	Bank
Evaluation&Experiment 3	Bank	Bank	Bank
Evaluation&Experiment 4	Other Industries	Other Industries	Bank
Evaluation&Experiment 5	Bank	Other Industries	Bank

Table 1: Single Source and Multi-source Transfer Learning Baseline Evaluations and Experiments

	DNN	LSTM
(S_A: Bank, T: Bank)	**Coral (GAF)**	**CMD (GAF)**
(S_A: Other Industries, T: Bank)	Coral (GAF), CMD	Coral (GAF), CMD
(S_A: Bank, S_B: Bank, T: Bank)	CMD	CMD
(S_A: Other Industries, S_B: Other Industries, T: Bank)	MMD	**ARE (GAF)**
(S_A: Bank, S_B: Other Industries, T: Bank)	**Coral (GAF)**	**CMD (GAF)**

Table 2: Summary of Results

Conclusion

This study evaluated the performance of baseline and Gramian Angular Field (GAF)-based similarity functions in transfer learning for financial time series. The Central Moment Discrepancy (CMD) consistently minimized prediction errors and performed well in multi-source transfer learning, particularly in scenarios involving multiple data sources. GAF-based similarity functions significantly improved transfer learning performance in certain contexts, especially in single-source transfer learning within the banking sector, with Coral (GAF) for DNN and CMD (GAF) for LSTM showing strong results. However, GAF's effectiveness varied in multi-source transfer learning, particularly when sources included mixed industries. While some GAF-based functions like Adapted Rand Error (ARE) improved LSTM model performance, the benefits were less pronounced for DNNs. This highlights that while GAF can enhance transfer learning by capturing complex temporal structures, its utility depends on the specific model and scenario. Future work should address the computational complexity of GAF transformations and explore broader applications beyond financial data to validate the methods' generalizability.

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