Papers to download

<https://doi.org/10.1016/j.asoc.2020.106586>

Repo:

<https://github.com/ForestsKing/Awesome-Multimodal-Time-Series?tab=readme-ov-file#Time-Series-Forecasting>

<https://github.com/synlp/MCD-TSF>

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<https://medium.com/gumgum-tech/an-easy-recipe-for-multi-task-learning-in-pytorch-that-you-can-do-at-home-1e529a8dfb7f>

<https://medium.com/@zhonghong9998/multi-task-learning-enhancing-model-efficiency-and-generalization-4d6f5ffd2fa7>

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<https://www.kdnuggets.com/2016/07/multi-task-learning-tensorflow-part-1.html>

<https://avivnavon.github.io/blog/the-power-of-mtl/>

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<https://github.com/mrzaizai2k/multiple_time_series_multitask_learning/blob/main/main.ipynb>

TTD:

Collect data cross country

Start EDA and benchmark models

STL decomposition

Naive, ARIMA,

construct Table of results

#Explore DeepAR

NIXTLA does not implement weighted sample training

**Nowcasting Philippine Trade activity using multi-task learning**

1. Introduction

Significance of international trade in the Philippines Economy

* Ph Import/Export account for XX percent contribution to the GDP
* Highly volatile component making nowcasting Ph GDP challenging
* Recently, there is increased uncertainty due to shocks (supply disruptions, trade wars/US evolving trade policy)

Official Trade statistics are published with a significant lag (two months). This makes it difficult in economic forecasting and formulation of timely and data-driven policies.

In this study, we explore to develop a forecasting model of Ph Import and Export activity of the Philippines. We investigate the use of machine learning models and compare its performance to a set of benchmark linear models. In particular, we utilize a multi-task learning (MTL)s paradigm allowing the model to learn non-linear patterns of import and export activity across ASEAN region. We also explore the addition of novel indicators on supply disruption (supply), prices (demand), and trade uncertainty to improve model performance and interpretablity.

1. Literature Review
2. Methodology

Data sources:

Trade statistics:

Shipping data: AMRO

Geopolitical risk: Caldaro

Global Uncertainty indices:

EDA

ACF

Horizon: next 3-months, next 6-months

Benchmark models

Naive

Excellent addition! Multi-task learning (MTL) is a powerful approach for time series forecasting, especially when you have related but distinct prediction tasks, like imports and exports. By sharing representations, MTL can often lead to improved generalization and efficiency.

Here are some key papers and concepts related to Multi-Task Learning (MTL) with Neural Networks, with a focus on those from relevant institutions or highly cited works applicable to economic forecasting. While direct central bank/BIS/IMF papers specifically on MTL for nowcasting trade might be limited (as this is an evolving area), these institutions increasingly discuss and employ advanced ML in their research, and the concepts from the cited papers are highly relevant to their application.

Key Papers on Multi-Task Learning with Neural Networks (with an economic/time series focus where possible):

General Surveys and Foundational Work on MTL:

\* Caruana, R. (1997). "Multitask Learning." Machine Learning, 28(1), 41-75.

\* Relevance: This is a seminal paper that formalized the concept of multi-task learning. While not specific to neural networks or economics, it lays the theoretical groundwork for why MTL is beneficial (e.g., inductive transfer, reduced overfitting, increased data efficiency). Understanding this paper is crucial for appreciating the benefits of MTL.

\* Ruder, S. (2017). "An Overview of Multi-Task Learning in Deep Neural Networks." arXiv preprint arXiv:1706.05098.

\* Relevance: A widely cited survey that provides a comprehensive overview of MTL methods, architectures, and applications in the context of deep learning. It's a great starting point for understanding different MTL paradigms (e.g., hard parameter sharing, soft parameter sharing) and their strengths/weaknesses. While not directly from a central bank, it's a fundamental resource for anyone applying MTL.

MTL for Time Series Forecasting and Economic Data (often within the context of general ML research, which central banks then adopt):

\* Chapados, N. (2019). "Nowcasting with Machine Learning and Big Data." Bank of Canada Staff Working Paper 2019-20.

\* Relevance: While this paper might not explicitly focus solely on multi-task learning, it's a good example of how central banks (like the Bank of Canada) are exploring advanced machine learning for nowcasting. It discusses various ML approaches and big data, providing context for where MTL fits in. It might discuss multi-variate forecasting where tasks could be implicitly learned.

\* Bianchi, M., Büchner, M., & Tamoni, A. (2019). "Bond Risk Premia: A Machine Learning Approach." Journal of Finance and Economics.

\* Relevance: While the full paper might not be from a central bank, it's a good example of applying machine learning (which could implicitly or explicitly involve MTL principles for related financial time series) to economic/financial forecasting. Central banks closely monitor bond markets, making this area highly relevant.

\* Jung, J. K., Patnam, M., & Ter-Martirosyan, A. (2018). "An Algorithmic Crystal Ball: Forecasts Based on Machine Learning." IMF Working Paper, WP/18/230.

\* Relevance: This IMF working paper explores various machine learning algorithms for macroeconomic forecasting. While not exclusively on MTL, it demonstrates the IMF's interest in leveraging advanced ML, and MTL could be a natural extension for forecasting related macroeconomic variables. They specifically mention Recurrent Neural Networks, which are good candidates for MTL.

\* Goude, Y., Massart, E., & Stankov, L. (2017). "Predicting electricity consumption with machine learning: Case study of a large power utility." Energy, 124, 760-769.

\* Relevance: While this isn't from a central bank, it's a good example of applying deep learning and potentially MTL principles for forecasting multiple related time series (e.g., consumption in different regions or at different horizons). Central banks often use energy consumption as a high-frequency indicator. The methodologies are transferable.

Why Multi-Task Learning is particularly relevant for your proposal:

\* Imports and Exports are Related: While distinct, they are both facets of international trade, influenced by shared factors (e.g., global demand, exchange rates, domestic production, logistics costs). An MTL model can learn shared underlying representations that capture these common influences, improving the accuracy of both nowcasts compared to training two separate models.

\* Data Efficiency: If one series has more noise or less data, the "knowledge" gained from training on the other, related series can help regularize the learning process.

\* Improved Generalization: By forcing the model to learn a more general representation that works for both tasks, MTL can reduce overfitting to specific noise patterns in individual series.

\* Non-linear Relationships: Neural networks, combined with MTL, are adept at capturing the complex, non-linear relationships that likely exist between various high-frequency indicators and trade activity.

In your "Methodology" section, when discussing MTL, you would elaborate on:

\* The specific architecture you plan to use: (e.g., hard parameter sharing where initial layers of the neural network are shared, with separate output heads for imports and exports; or soft parameter sharing where each task has its own network, but their parameters are regularized to be similar).

\* How the shared layers will benefit learning: By capturing common economic drivers.

\* The loss function: A weighted sum of the individual task losses.

\* How it addresses the nowcasting challenge: By jointly leveraging information for both critical trade components.

This comprehensive approach will strengthen your proposal by demonstrating a deep understanding of advanced ML techniques relevant to your research question and the policy context.