# On the applicability of Deep Learning Techniques to Time Series Forecasting

David Sauerwein, 7/21/2024, Linkedin article

Many forecasting use cases lack the data volumes to benefit from deep learning. The rise of time series foundation models (TSFMs) is changing this landscape. Here's a summary of the latest approaches and their potential impact.

## The Data Size Challenge

Companies like Amazon, Google, and Zalando rely heavily on deep learning models for forecasting. Yet, practitioners are often disappointed when they try deep learning on their use cases. Use cases with < 10,000 time series never benefit from deep learning scaling laws.

This situation mirrors natural language processing (NLP). Typical NLP use cases can't train effective transformer models because of limited document availability. Instead, they use foundation models trained on massive datasets by selected companies. These models, having learned the general structure of language, can be adapted to specific tasks through few-shot prompting, retrieval-augmented generation (RAG), or fine-tuning.

## Introducing Time Series Foundation Models (TSFMs)

TSFMs follow a similar concept. Companies with extensive compute and data resources develop foundation models with robust generalization capabilities. These models can then be customized for specific use cases. This means benefits of TSFMs are:

1) Even small-scale use cases can benefit from advanced deep learning methods, with the prospect of using multi-modality in the future (see below; comments)
2) TSFMs can deliver impressive accuracy even in scenarios where standard methods (like XGBoost) struggle. An example are cold-start problems.

## Types of TSFMs

There are two primary approaches to TSFMs:

1. Pre-trained Models from Scratch: Built on vast sets of curated time series data. Examples: TimesFM (Google), TimeGPT (Nixla), ForecastPFN, and LagLlama.
2. Bootstrapped from LLMs: Use the hidden structure in sentences that LLMs are trained on, viewing them as time series. Examples: Chronos (Amazon) and TimeLLM.

The choice of approach depends on the specific use case, including the methods for tailoring and explaining the models.

## Looking Ahead

TSFMs hold promise for widespread deep learning adoption in forecasting. Many challenges remain, e.g. the integration of custom covariates, but these will be addressed over time.

Meanwhile, the opportunity is vast, with forecasting being crucial across industries and the options to improve these models further is huge too.

For example, TSFMs could become multi-modal. They could, for example, integrate news articles for more comprehensive demand forecasting.

I'm excited to see TSFMs grow and revolutionize forecasting, making advanced deep learning accessible and effective across a broad range of applications.

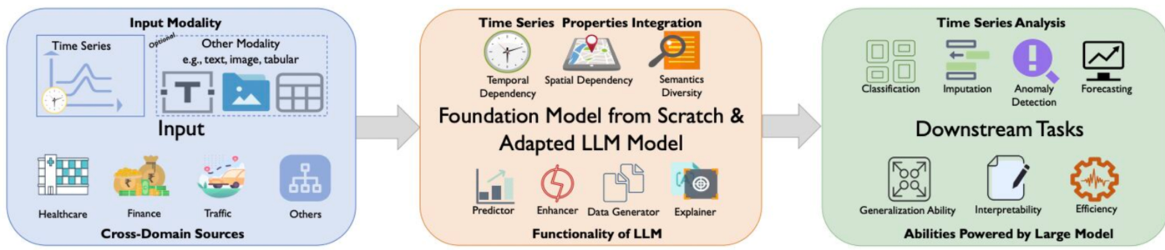


Fig. 1. Foundation models have been employed across various tasks and domains in the context of time series analysis. They have two classes, namely foundation models pre-trained from scratch for time series and adapted large language foundation models (i.e. LLM) for time series. Currently, researches focus on improving the generalization capability of these models by effectively integrating time series properties or fusing multi-modality data. The explainability and efficiency are also concerned topics in this field.

## References

[1] A Survey of Time Series Foundation Models: Generalizing Time Series Representation with Large Language Model, J. Ye et al, Honk Kong U., 2024