# 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.  
  
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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.  
  
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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.  
  
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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.  
  
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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.

A diagram of a foundation model

Description automatically generated

## 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](https://github.com/dimitarpg13/deep_learning_for_time_series_forecasting/blob/main/literature/articles/A_Survey_of_Time_Serie_Foundation_Models_Generalizing_Time_Series_Representation_with_LLM_Ye_2024.pdf)