

[3, 20, 12, 10, 5] – which model the deterministic or stochastic evolution of hidden states, and naturally handle continuous time forecasts. However, improvements have mainly been demonstrated using simulated data, which make it difficult to assess the performance of Neural ODEs/SDEs on real-world time series datasets. In addition to benchmarking and extensions to state-of-the-art time series architectures, we also recommend investigations into hybrid continuous-time models – which would allow for direct comparisons to traditional methods in applications where they are most beneficial.

**Multivariate Time Series:** The majority of previous work (see Section 2) has focused on the development of univariate forecasting models – i.e. assuming that targets are driven only by inputs for a given entity, and are independent of each other. In this manner, deep neural networks are trained to capture temporal relationships that are generally applicable across all entities, without taking into account cross-sectional relationships between them. While this allows networks to be trained with a larger pool of data – as mini-batches are sampled across entities and time – there are instances where multivariate forecast can be beneficial, particularly in non-stationary datasets. For instance, in portfolio management, market breakdowns can cause a general decline of all stocks and result in short-time increases in asset correlations. In retail forecasting, unforeseen events, such as natural disasters, can also lead to spikes in the joint demand for specific categories of goods. As such, multivariate models can help improve performance in datasets where common driving factors exist across entities – motivating the need for extensions to existing univariate architectures.