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<tr><th>authors</th><td>Mansura Habiba
Barak A. Pearlmutter</td></tr>
<tr><th>title</th><td>Neural ODEs for Informative Missingness in Multivariate Time Series</td></tr>
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<tr><th>abstract</th><td>Informative missingness is unavoidable in the digital processing of continuous time series, where the value for one or more observations at different time points are missing. Such missing observations are one of the major limitations of time series processing using deep learning. Practical applications, e.g., sensor data, healthcare, weather, generates data that is in truth continuous in time, and informative missingness is a common phenomenon in these datasets. These datasets often consist of multiple variables, and often there are missing values for one or many of these variables. This characteristic makes time series prediction more challenging, and the impact of missing input observations on the accuracy of the final output can be significant. A recent novel deep learning model called GRU-D is one early attempt to address informative missingness in time series data. On the other hand, a new family of neural networks called Neural ODEs (Ordinary Differential Equations) are natural and efficient for processing time series data which is continuous in time. In this paper, a deep learning model is proposed that leverages the effective imputation of GRU-D, and the temporal continuity of Neural ODEs. A time series classification task performed on the PhysioNet dataset demonstrates the performance of this architecture.</td></tr>
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Barak A. Pearlmutter</td></tr>
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<tr><th>publication_date</th><td>2020-05-20 01:02:29+00:00</td></tr>
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<tr><th>abstract</th><td>Neural differential equations are a promising new member in the neural network family. They show the potential of differential equations for time series data analysis. In this paper, the strength of the ordinary differential equation (ODE) is explored with a new extension. The main goal of this work is to answer the following questions: (i)~can ODE be used to redefine the existing neural network model? (ii)~can Neural ODEs solve the irregular sampling rate challenge of existing neural network models for a continuous time series, i.e., length and dynamic nature, (iii)~how to reduce the training and evaluation time of existing Neural ODE systems? This work leverages the mathematical foundation of ODEs to redesign traditional RNNs such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). The main contribution of this paper is to illustrate the design of two new ODE-based RNN models (GRU-ODE model and LSTM-ODE) which can compute the hidden state and cell state at any point of time using an ODE solver. These models reduce the computation overhead of hidden state and cell state by a vast amount. The performance evaluation of these two new models for learning continuous time series with irregular sampling rate is then demonstrated. Experiments show that these new ODE based RNN models require less training time than Latent ODEs and conventional Neural ODEs. They can achieve higher accuracy quickly, and the design of the neural network is simpler than, previous neural ODE systems.</td></tr>
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