We show that state-of-the-art classification accuracy can be achieved using a fraction of the time required by even these recent, more scalable methods, by transforming time series using random convolutional kernels, and using the transformed features to train a linear classifier. We call this method Rocket (for RandOm Convolutional KErnel Transform).

Convolutional kernels constitute a single mechanism which can capture many of the features which have each previ-ously required their own specialized techniques, and have been shown to be effec-tive in convolutional neural networks for time series classification such as ResNet (Wang et al. 2017; Ismail Fawaz et al. 2019a), and InceptionTime.

In contrast to learned convolutional kernels as used in typical convolutional neural networks, we show that it is effective to generate a large number of random convolutional kernels which, in combination, capture features relevant for time series classification (even though, in isolation, a single random convolutional kernel may only very approximately capture a relevant feature in a given time series).

Rocket is also more scalable for large datasets, with training complexity linear in both time series length and the number of training examples.