Transfer Learning for Data-efficient analysis of similar IoT devices

The Internet of Things (IoT) is expected to scale to a large number of devices in the coming years, resulting in a large amount of data in need of analysis. Several common analytics tasks, e.g. forecasting and anomaly detection, require a long history of data to allow training good models. This is especially true for measurements with strong seasonalities where one or more seasonal effects have a long periodicity, e.g. a yearly periodicity. Such long lead times before analytics results become available is a detractor for any analytics feature.

In this project, we aim to explore if and how information can be shared across similar sensors to reduce the lead time for analytics results to become available. It is safe to assume that it will be common for users of an IoT platform to deploy many identical IoT devices (or at least IoT devices that measure the same physical quantities) in different environments, rather than all IoT devices owned by a user being a unique make and model measuring different physical quantities. Consequently, information or learnings from previously installed sensors may be useful in building analytics for a newly installed sensor.

A possible way to tackle these issues is consider Transfer Learning (TL) for improving the forecasting task. TL refers to a set of Machine Learning methods where a trained model for one task is reused as a starting point for another similar task [1]. TL differs from traditional ML because it involves a pre-trained model as a bootstrap to learn a secondary task. This approach mimics the way humans apply knowledge acquired for one task to solve related ones. In real-world scenarios, TL gives one way of addressing the adaptability of AI and ML methods to systematic changes in the data, as for example a new sensor displacement. This technique has been successfully used for example in image classification domain [2] and less in the time series domain. In particular a common problem when doing forecasting for time series is that there is not enough data to learn the task at hand. We may, however, have access to many related time series, and it should be possible to use the information in these related time series to improve learning. Examples of wanted outcomes are: 1) to be able to forecast values earlier, making it possible to make good decisions earlier, 2) to lend information across many time series, which makes model- ling more robust and makes it possible to incorporate prior information in a systematic manner, and 3) to share some dynamics of interest across many time series to learn new highly non- stationary time series dynamics.

Data

European air quality measurements have been identified as a suitable data set, containing about 10 sensor types, with over 1500 sensors or more of each type, spread across Europe. Data has been recorded hourly for most sensors. The measurement period varies between sensors, being 6 years long at most. Other open datasets can also be considered.

The task

The task will be to build forecasting models that exploit similarities between sensors to share information and learning across sensors. Describe approach (if needed)

Tasks:

- Review relevant literature on both Time Series Forecasting, Deep Learning for Time Series Analysis and Transfer Learning Techniques
- Establish a baseline for forecasts on the dataset (using classical methods and/or ML methods)
- Explore the feasibility of Transfer Learning techniques and adapt them in the Time Series Domain for the task of forecasting, by using Deep Neural Network based techniques

Thesis information

The proposed topic is seen as challenging, and it therefore preferable to do both an MSc project (fall 2020) and MSc thesis (spring 2021) on the topic.
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References

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