Application of Generative Query Networks for industrial time series

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Abstract

When monitoring a pipeline used to transport different liquids or gases, it is impossible to monitor pressure and other metrics at every point since only a limited number of sensors can be installed. Moreover, some of the installed measurement points can be down due to breakdown or maintenance. The Generative Query Network (GQN) can be used for predicting the measurement in the places where they are not available. Our main aim is, to certain extent, to incorporate the industrial reality into the predictive model.

The model learns different hydraulic states of the pipeline based on pressure time series reflecting common hydraulic events or a given state. During the prediction phase, the model can be requested to generate a state for given presumptions (e.g. time, position, and implicitly the time series from neighboring measurements). Thanks to the generality of the model, we can predict future values as well as determine the exact position of a leak. This approach can be used not only for pressure time series but for many other use-cases where the time dimension plays an important role.

Introduction

Time series recorded at different locations of the pipeline are naturally correlated with each other. This is a manifestation of fundamental physical laws. Within more classical approaches the hydraulic state of the pipeline is determined by a solution of the set of partial differential equations reflecting the conservation laws (mass, energy and momentum). Here, within a data-driven approach, the complex relations between physical quantities are embedded into the predictive models within the trainig process. In particular, the correlation between pressure measurements depends on the physical and time distance between the two points, the nature of the medium within the pipe, the nature of an event and many others. Within the proposed approach we show that all these subtelities can be learned in an empirical manner. Moreover, just by exploiting the generalization potential of statistical model we obtain a deep insight into the hydraulic reality covering the areas unsupported by measurement infrastructure.

Methods

The general idea behind the GQN (Neural scene representation and rendering, Eslami et al., 2018, Science) framework is to train an autoencoder-like model. The representation network, which is an equivalent of the encoder, aims to produce a vector (latent representation) describing the whole scene despite the fact it only sees a very limited number of views. The data introduced into the representation network covers the pictures themselves and the associated parameterization which form the complete set of observations (o_i)

$$o_i = \{\mathbf{x}_i^k, \mathbf{v}_i^k\}_{k=1...K} \qquad (1)$$

These observations are turned into the latent representation which is the final result of the representation network

$$\mathbf{r} = f(o_i). \qquad (2)$$

Then, the generation network (decoder) uses this representation together with a query to produce a view of a scene from the position/orientation given in the query (see Fig 1). The representation network is not aware of the query, thus it must convey a description of the whole scene into the latent representation, that can be later used multiple times by the generation network to generate views of the same scene but from different perspective.

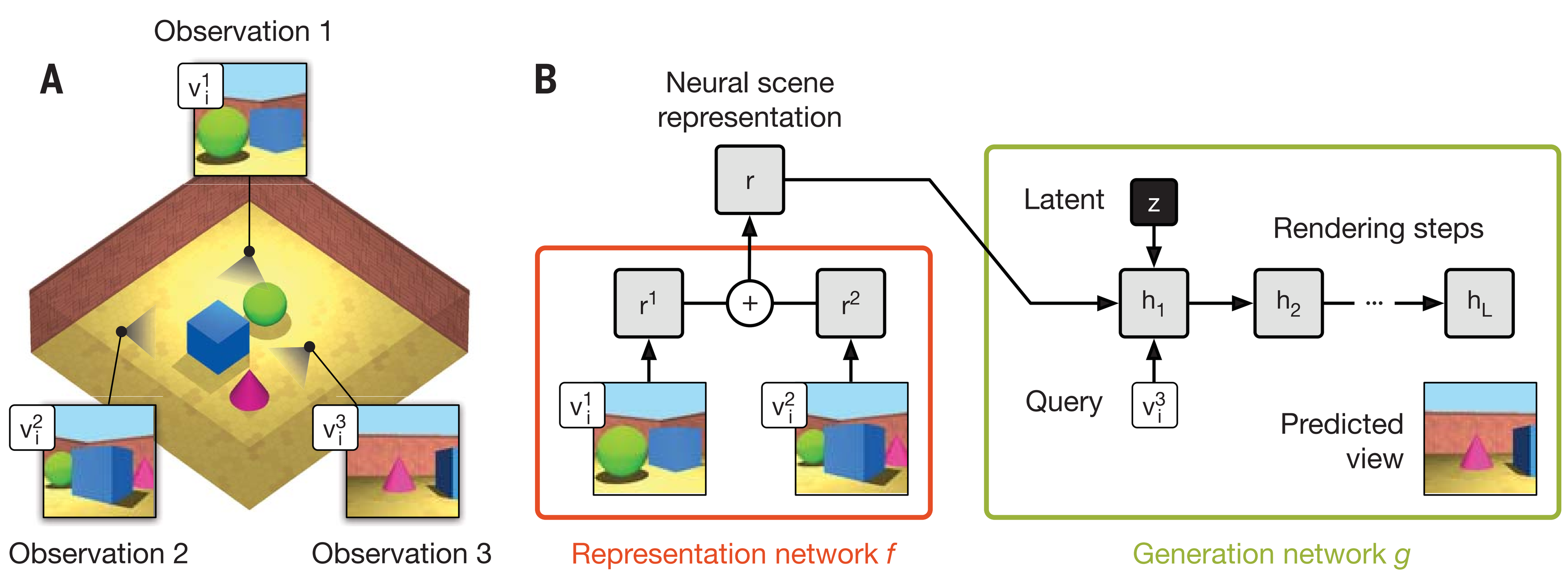

Figure 1: Schematic diagram of the original generative query network framework

In our approach, the model is trained using time series reflecting the pressure at the given position of the pipeline together with the metadata describing the time and the position of the measurement. These static data are combined with the time series by the initialization of the states of the RNN cells (see Efficient Strategies of Static Features Incorporation into the Recurrent Neural Network, Miebs et al., 2020, Neural Processing Letters for further details), see Fig 2. It is worth noting that within this use-case the exposition of the model for the observations formed by a single view does not introduce enough knowledge into the model. In particular the essential information related to the speed with which the pressure wave travels along a pipeline is missing. Therefore we have modified the original approach accordingly and the observation from Eq. 1 contains two pressure curves. The general scheme is presented in Fig 3.

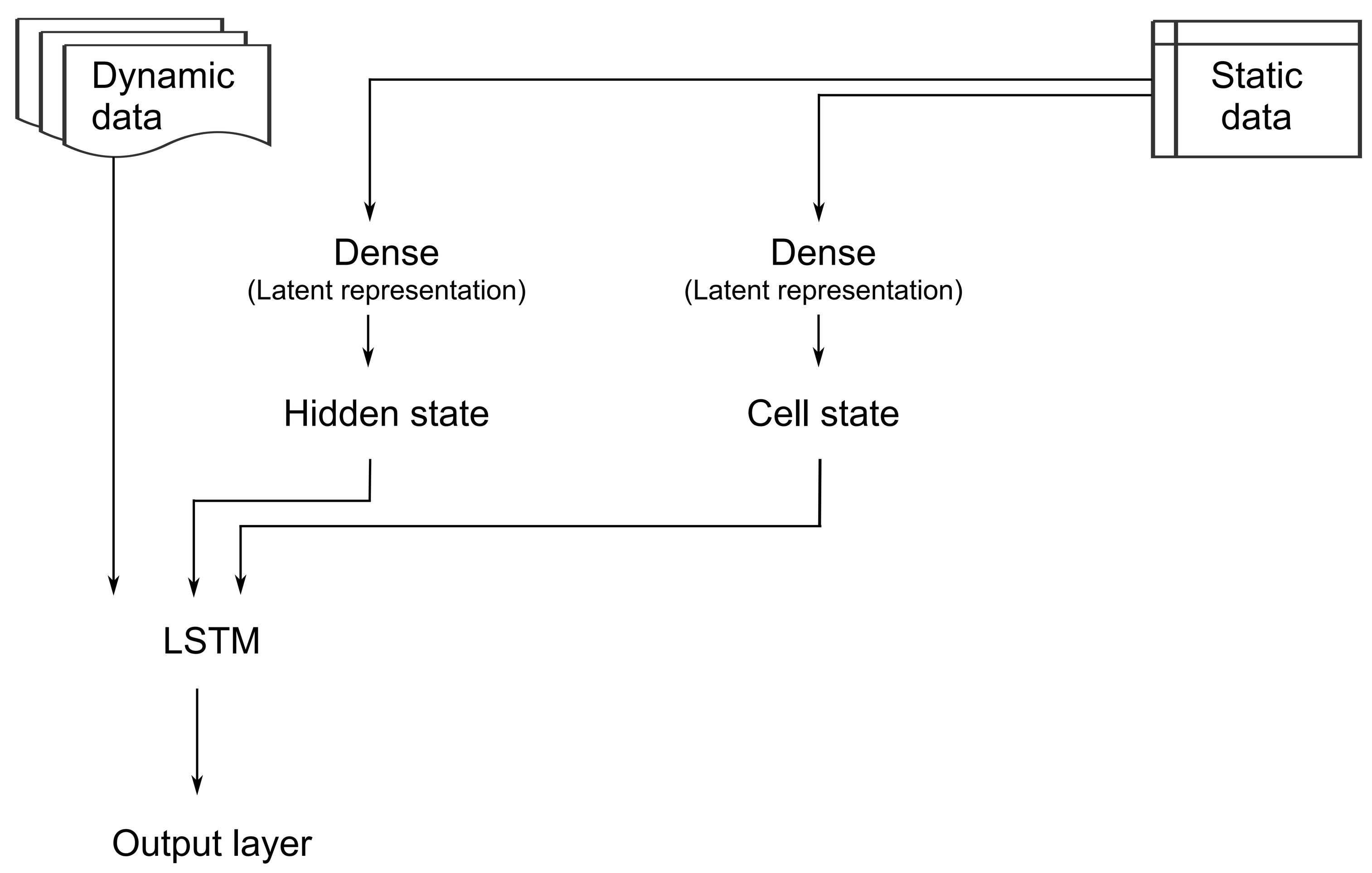

Figure 2: Schematic diagram of neural network which incorporates static features as an initial state of the hidden and cell states of the LSTM layer treated as the latent representation.

It should be clear what is the analogy between the presented use-case and the initial approach (Eslami *et al.*). The pictorial representation of a scene is now replaced by the pressure time series. According to Eq. 1 also the information about the location and time of the pressure signals is provided. This allows for efficient learning process and extracting from the data the relations between the physical quantities measured at different locations.

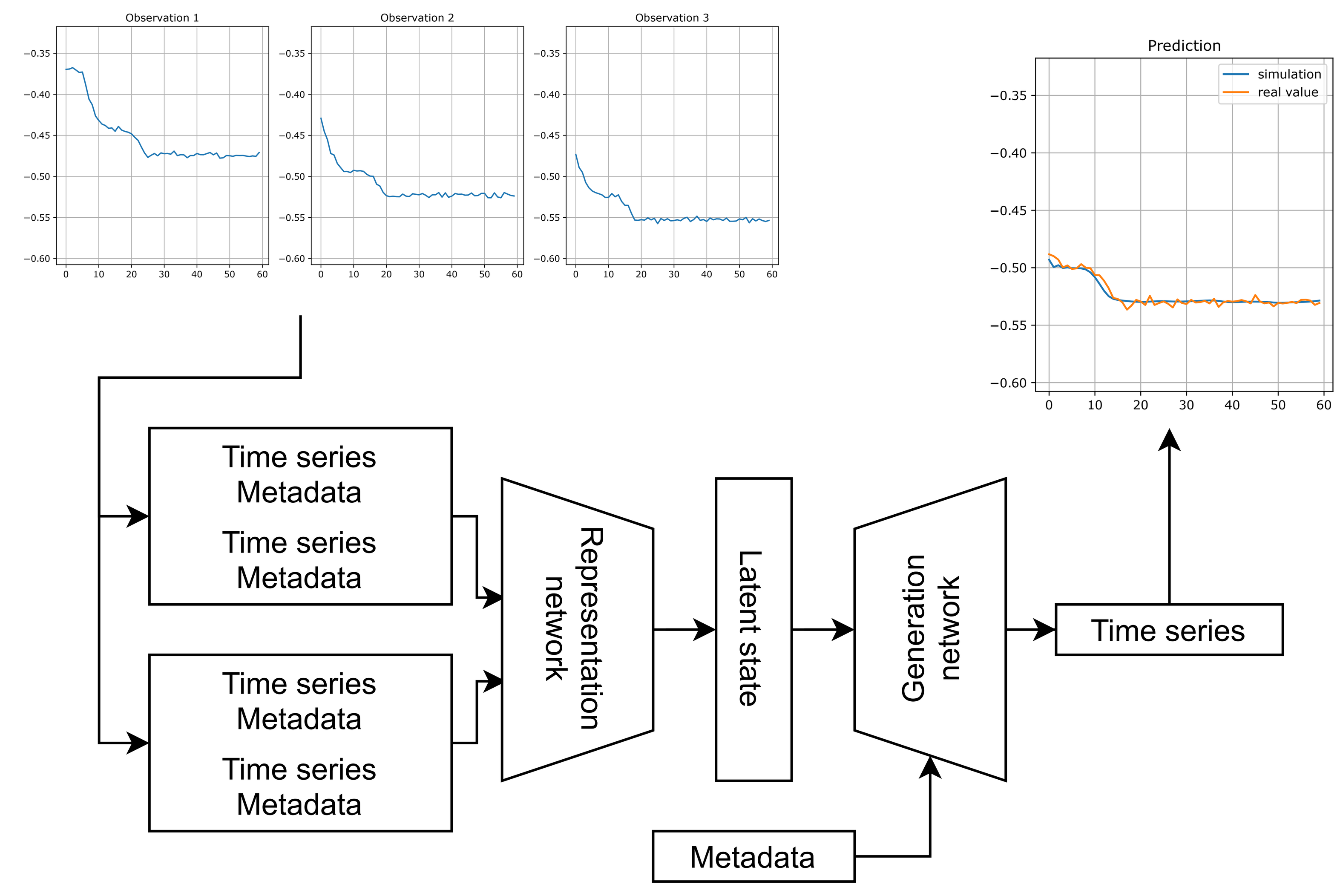

Figure 3: Architecture of the model used to produce time series

Data and business context

The presented use-case aims to show how the hydraulic reality of the pipeline can be incorporated into the statistical model. Therefore the data used within this study reflect the pressure at given locations of the pipeline. The fundamental laws governing the hydraulic state of the pipeline are rather complicated and in a general case take into account multiple factors influencing the pipeline state. The complexity of the description becomes critical in the case of so-called unsteady states which are associated with rapid pressure changes caused by pump switches of valve operations. The mathematical modelling of high transient states is particularly challenging and the proposed approach can be considered as a supportive tool providing additional data for running hydraulic simulation. The other potential application is providing the missing measurement in case of breakdown or maintanence. The properly trained model is capable of recovering missing measurement based on the neighboring ones. In the case of critical applications, like Leak Detection and Localization systems, this missing information can be of key importance for the reliable estimation of the pipeline state.

Results

The model has learned how to predict the pressure in the unknown position based on the time series from other points. The more views provided to the model the better the results, however, there should be a relation between the input and expected output. Ideally, they should reflect the same hydraulic event just at different locations. The model was able to reflect all variability present in the data including varying speed of the medium, different base pressure, changes in the pressure coming from the pipeline topology, and different patterns reflecting different hydraulic events.

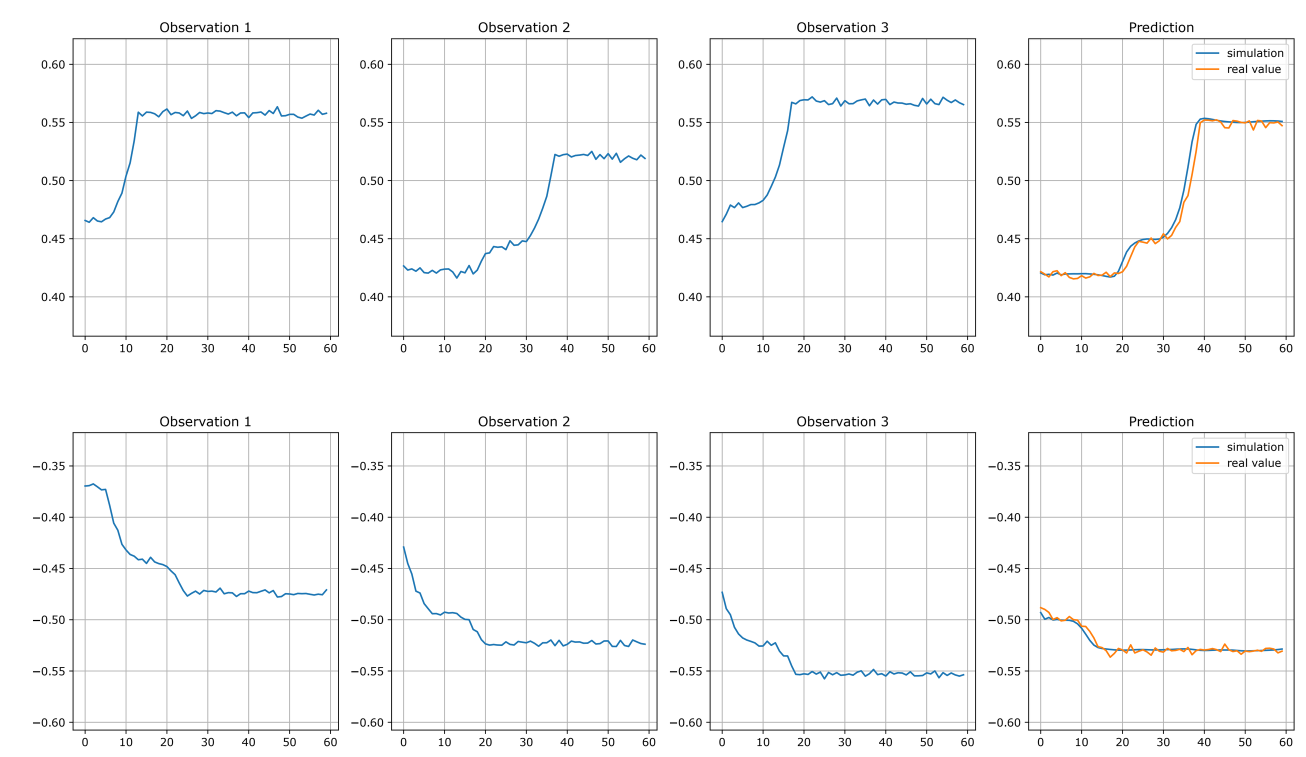

Figure 4: Observations provided to the model and comparison of prediction and ground truth.

Conclusions

- A representation network can produce a latent vector that efficently stores the information about the given quantity (e.g. pressure)
- The model can generate pressure time series at the locations which were not provided during the training
- Initialization of hidden states is a proper way to incorporate static features during dynamic component processing
- The presented approach can be combined with the LDS systems by providing a supportive information

Bibliography

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