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Poszter szekció

On Applying Artificial Intelligence Techniques in Water Treatment: an Overview

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Abstract

Artificial intelligence is a subfield of computer science that was created in the 1960s. It comprises a collection of problems and methods related to making computers behave intelligently and solve complex problems. This paper provides an overview on artificial intelligence methods addressing some key problems in water treatment services.

Introduction

Artificial intelligence (AI) is a subfield of computer science that was created in the 1960s. It comprises a collection of problems and methods related to making computers behave intelligently and solve complex problems. The field AI can be classified as general and narrow. Strong or artificial general intelligence (AGI) would be a system that can do anything a human can, and can raised to intelligence levels that match human beings. Such a system has not yet been developed, AGI machines have remained in science fiction movies.

What we can do falls into the category of narrow or weak AI. In contrast to strong AI, narrow AI does not attempt to perform the full range of human cognitive abilities. Narrow AI based systems are able to perform specific tasks better than human can. Approaches that have evolved to achieve narrow artificial intelligence include but are not limited to the following techniques: machine learning, artificial neural networks, deep machine learning.

This paper presents artificial intelligence techniques and work with influence on water treatment industry. The goal of this overview is to collect and present some papers that can provide an answer to the question: what is artificial intelligence good for in water treatment?

Machine Learning

Machine learning (ML) is an approach to achieve artificial intelligence 0. It includes statistical techniques that enable machines to improve at tasks with experience. ML uses algorithms to parse data, learn from it, and then make a determination or prediction about something in the world. ML uses data-driven modelling methods that estimates unknown dependency between a system's inputs and its outputs from the available data 0. As soon a dependency is discovered, it can be used to predict the future system's outputs from the known input values. Given an AI problem that can be described in discrete terms, then the machine can be trained using large amounts of data and algorithms that give the ability to learn how to perform the task. To draw a distinction with AI, if a clever program is written that has human-like behaviour, it can be AI, but unless its parameters are automatically learned from data, it's not machine learning. Algorithmic ML approaches may include decision tree learning, inductive logic programming, clustering, reinforcement learning, and Bayesian networks 0.

There are many papers on data driven methods and on their application in the water sector. Some examples are presented here. In 0 decision trees are used in classifying surge water levels in the coastal zone depending on the hydro meteorological data. In 0 of hydrologically homogeneous regions were classified. Generalizing hydrological variables, such as the quantiles of the frequency distributions of floods and low flows, are collectively referred to as regionalization methods. An important feature of these methods is the demarcation of hydrologically .homogeneous regions. The paper showed that classes may be defined by Representative Regional Catchments (RRCs), whose characteristics are hydrologically more appealing than those imparted merely by geographical proximity. The techniques employed were Kohonen networks and fuzzy c-means.

Another ML approach, actually a nonparametric Bayesian model is described in 0. Non-parametric models assume that the data distribution cannot be defined in terms of finite set of parameters. In these models the amount of information that can be captured about the data can grow as the amount of data grows. The goal of this paper is to improve risk management of water distribution systems. The authors used hierarchical beta process approach to predict water pipe failures throughout the city of Sydney Australia. They were able to find pipes at high risk of failure before they fail and result in significant service disruption to the community.

Artificial Neural Networks

Artificial Neural Networks (ANN) are composed of artificial neurons or nodes. The goal of neural network is to try to simulate the way the human brain works and learn. ANNs are built and trained to help solve artificial intelligence problems. Artificial neurons are programming constructs that try to mimic the properties of biological neurons and connected via directed graph connections. The structure of an ANN is presented in Figure 1 0.

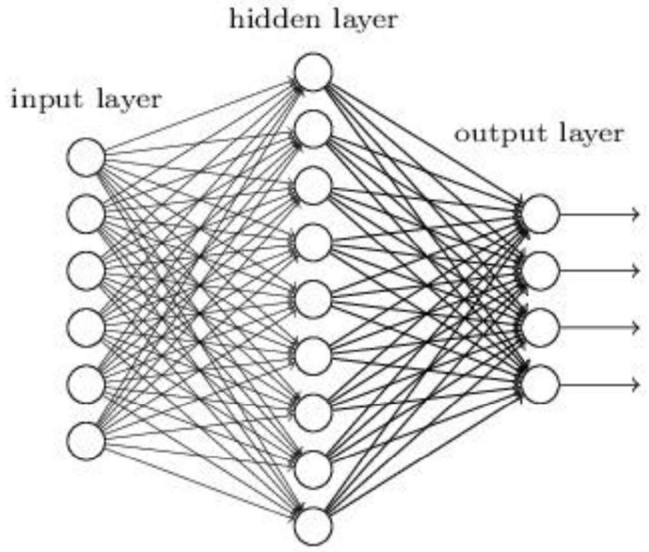

Figure 1. Artificial neural network

Neural networks are typically organized in layers. Layers are made up of a number of interconnected nodes which contain an activation function. These artificial neurons are connected by links and they interact with each other. The nodes can take input data and perform simple operations on the data. Patterns are presented to the network via the input layer, which communicates to one or more hidden layers where the actual processing is done via a system of weighted connections. The result of these operations is passed to other neurons. The output at each node is called its activation or node value. The hidden layers link to an output layer where the answer is output. Each link is associated with weight. ANNs are capable of learning, which takes place by altering weight values, however they need to be trained. The training algorithm, called back propagation learns by example. It changes the network’s weights so that it can produce desired output for a particular input on finishing the training. Once a neural network is trained to a satisfactory level it may be used as an analytical tool on other data.

In 0 a neural network based method of wastewater treatment is presented. The paper suggests that the estimation and control of an activated sludge process (ASP) at a wastewater treatment plant using neural networks can improve the plant performance in terms of reduced operation costs and improved effluent quality. In this paper, a neural-network-based soft sensor is developed for the on-line prediction of effluent concentrations in an ASP in terms of primary hard-to-measure variables, such as chemical oxygen demand, total nitrogen content and total suspended solids, starting from secondary on-line easy to-measure variables, such as oxygen and nitrogen compound concentrations in biological tanks, input flow rate and alkalinity, among others. The network structure selected for the neural composition estimator was a three-layer multilayer perceptron, and the net has been trained using the Levenberg–Marquardt algorithm. The prediction results obtained show that the proposed method results in adequate performance and it is simpler in comparison than other heuristic-based prediction methods such as fuzzy sets or expert system reasoning,

A recurrent neural network (RNN) is a class of artificial neural network. The fundamental feature of an RNN is that the network contains at least one feed-back connection, so the activations can flow round in a loop. RNNs are called recurrent because they perform the same task for every element of a sequence, with the output being dependent on the previous computations. In 0 an RNN based method is used to forecasting the quality of water diversion. Water diversion has been widely applied to irrigation, flood control, water supply, power generation etc. Without careful modelling, forecasting, and analysis, even the most acceptable conceptual and physically-based models are too difficult to arrive the end results during the period of water diversion. A conceptual and physically-based model requires a lot of data and parameters that are often unknown, while data-driven techniques may provide an effective solution. RNN models are such data-driven models. In this paper, Elman's RNN was used for modelling. The goal was to predict and forecast total nitrogen, total phosphorus and dissolved oxygen in water resource of Lake Taihu during the period of water diversion. The results suggests that a neural network is an effective tool for the computation of transfer water quality and can be used to improve the understanding of water quality change during the period of water diversion. The Elman RNN can be used as a powerful predictive alternative to traditional modelling techniques

Conventional machine learning techniques are limited in their ability to process natural data in their raw form. Constructing such a machine learning system requires careful engineering and considerable domain expertise to design a feature extractor that transforms the raw data into a suitable internal representation or feature vector from which the learning subsystem, often a classifier, could detect or classify patterns in the input. Representation learning is a set of methods that allows a machine to be fed with raw data and to automatically discover the representations needed for detection or classification. Deep learning methods, described in the next section are representation learning methods.

Deep Learning

Deep learning is a subset of machine learning composed of algorithms that permit the software to train itself to perform tasks by using multi layered neural networks to huge amount of data represented with multiple levels of abstraction 0. The structure of a deep neural network is presented in Figure 2 0.

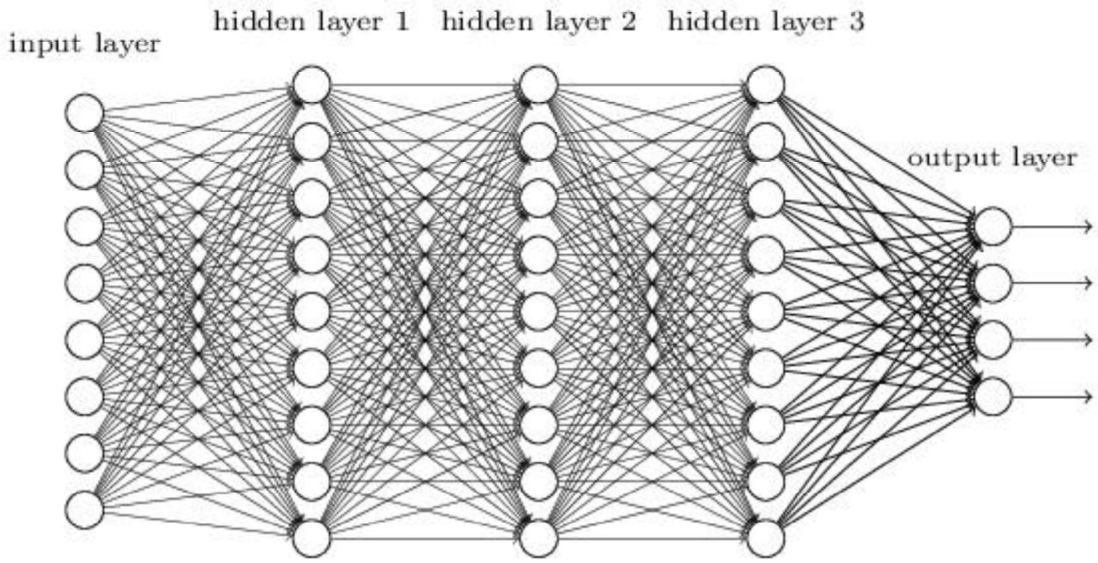

Figure 2. Deep neural network

Deep learning neural network architectures differ from classical neural networks in the way that they have more hidden layers. Deep learning discovers complex structure in large data sets by using the backpropagation algorithm to indicate how a machine should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer. The key aspect of deep learning is that these layers of features are not designed by human engineers, but they are learned from data using a general purpose learning procedure.

An application of deep learning for smart water networks is presented in 0. Sufficient water quantity and water quality is one of the key challenges, which the cities around the world are facing in sustaining economic growth. The features of a smart water network include monitoring / sensing with instrumentation, data management, data analytics for useful / actionable information retrieve or extraction, systematic analytics including simulation and optimization modelling for decision making, and finally the automation control for triggering / communicating the instruments in the field. In this paper preliminary investigation of deep learning for efficiently and effectively extracting the intelligence from data, with potential of wide applications in simulation and prediction analysis is presented. The elaborated deep learning framework is with potential applications of e.g. detection of abnormal events from the recorded time series data (pressures, flows and consumptions etc.), water usage prediction, and acceleration of the solution search for smart water distribution management, which aims at improving operation efficiency, reducing carbon footprint, and exceling customers' expectation.

Another application of deep learning in 0 is used to achieve predictive analysis of water quality parameters, especially for lakes and reservoirs. The authors used data collected from Chaskaman River located near Nasik, Maharashtra, India. The data received by monitoring the quality of the water can be useful to make predictions about the quality a few steps ahead in order to get better water management.

Deep learning methods are widely used for image recognition. In 0 a stacked sparse autoencoder method is used to extract water body from Landsat imagery. Water body recognition is crucial to many applications e.g. environmental monitoring, flood assessment and drought detection. Satellite based remote sensing technology provides continuous snapshots of Earth's surface over long periods, and can be used for water body extraction. Numerous threshold based methods have been proposed to abstract water bodies from satellite images so far. However, these methods have many limitations. Deep learning has a good capacity of hierarchical feature learning from unlabelled data. Stacked sparse autoencoder (SSAE), one deep learning method, is widely investigated for image recognition. In 0, a new water body extraction model based on SSAE is established. Three study areas in China with different water body types were chosen to evaluate the robustness of the proposed method. The experiment results showed that the proposed model has outstanding capability of feature learning. Because of unsupervised feature learning, the proposed model provides a lead for using limited number or few training samples and getting higher accuracy.

Another deep neural network based solution was developed to monitor changes in surface water reserves by a startup called Orbital Insight 00. Orbital Insight is able to track the water levels of key bodies around the world. This provides valuable data for a wide range of organizations, such as industrial companies attempting to forecast input prices relating to water, financial firms investing in water resources, and governments attempting to negotiate and monitor water treaties. Orbital Insight classifies water using low resolution, high coverage satellites to map bodies of water, analysing each pixel to determine a probability of it being water or land to catalogue surface water. The company trained its neural network on billions of pixels contained in thousands of USGS[1] satellite images. NVIDIA GPUs hosted in the Amazon Web Services cloud accelerated the training process. Orbital Insight isn't the first to measure Earth's water levels, but its deep learning-based architecture results in higher accuracy than many conventional techniques, which often mistake shadows of clouds or mountains for water 0.

Conclusion

In this paper artificial intelligence techniques i.e. machine learning, neural networks and deep neural networks and their application in water treatment industry were presented. This brief overview was written with the aim to show what artificial intelligence is good for in water treatment. It can be seen from the examples presented, that artificial intelligence may be useful in solving problems like risk management of water distribution systems, wastewater treatment, forecasting the quality of water diversion, predictive analysis of water quality parameters and water body recognition.

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