Deep learning – a promising approach for biomedical signal analysis?

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Signal analysis is important in biomedical engineering, because it provides tools to extract wanted information from 'raw' data. Signal analysis is often deeply connected to mathematics. On the one hand this is demanding, but on the other hand mathematical rigour and clarity are fundamental for the success of these methods. Moreover, they 'guide' the user to apply, modify or even to develop signal analysis tools.

The idea of 'big data' is inherently connected to methods that can handle, process and analyze huge amounts of data. The use of 'big data tools' is frequently expected to be useful for biomedical signal analysis, because the amount of biomedical data is expected to grow significantly, in particular for diagnosis and therapy processes. Many classical signal analysis tools are not well suited to find relations in large data sets. Due to its construction deep learning, which belongs to machine learning, is expected to foster biomedical signal analysis.

Deep learning methods commonly use adaptive elements. These elements can process various input data, e.g. for classification. Learning, which can be supervised, semi-supervised or unsupervised, changes the structure of the system by changing weights/connections between system's information processing elements (artificial neurons). This change is data driven, which is in contrast to task-specific algorithms. In not a few situations deep learning yields astonishing results. Well-known application fields are image processing or playing games.

However, there are many questions concerning deep learning, e.g.: 1) Which method might be useful in biomedical signal analysis? 2) Why do some methods fail, but others not? 3) Can structure and functionality of a successfully trained deep learning system be used to derive new signal processing insights/methods? We'll provide some examples of deep learning methods and want to deepen the scientific discussion towards the extraction of mathematical insights and procedures from deep learning approaches.

Integrating data learning methods and expert models in personal mobile and wearable health marker analytics

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This talk I will illustrate examples of current research in my group on combining data-driven models and expert models to leverage the advantages of both. With a focus on mobile and wearable computing, initially the flexibility of 'datadriven' machine learning and pattern recognition is highlighted and illustrated with examples from behaviour and physiological signal monitoring. In particular, adaptation of classification, regression, and spotting models to sensor data as well as the necessity for personalising pattern models will be discussed. Subsequently, the limitations of purely data-driven approaches are illustrated. Inference architectures for combining data-driven models and expert models will be introduced. The inference architectures examples utilise principles of data fusion and analytical modelling. Application examples of the talk include extracting behavioural markers of sleep and diet, as well as a physiological marker on cardiorespiratory fitness. The talk will conclude with an outlook on the open challenges and long-term goals in creating data-expert model ensembles.

Intensive Care Units

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For deep learning and big data analysis reliable data sources are indispensable. Intensive care unit (ICU) monitors record multiple biosignals (e.g. ecg waves, plethysmography, oxygen saturation, invasive and non-invasive blood pressure etc.) providing important insights into cardiovascular regulations and responses to interventions. Advanced analysis tools such as deep learning and big data analysis might uncover presently unknown information that might lead to better patients' treatment. However, in most centers these data are not systematically stored and accessible for in-depth analysis. In cooperation with Philips Healthcare we implemented a data warehouse system at our intensive and intermediate care units.

The system is capable of storing reliable raw signals recorded directly from the ICU-monitors creating a huge biosignal database. Currently, the system monitors and stores data of 24 ICU beds. The mean data storage consumption is approximately one gigabyte per bed/patient per day. This leads to a total data consumption of 8.5 terabyte per year. The data is stored and archived according to common clinical data protection standards. By customized software algorithms raw signals can be extracted out of the database for further analysis. This allows prospective, retrospective and quasi (several minutes delay) real-time analysis. Together with other clinical datasets (laboratory information, patient health record, PACS system, catheter database) it offers reliable datasets for future big data and deep learning approaches.

A discussion contribution about fail-safe sensor data as input for mHealth applications – requirements and challenges

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In mHealth applications sensor data constitute the source of information for the diagnosis of the patient's health condition. While in metrology it's natural that measurement data are always indicated by a measurement value and the statistical deviation as well as a systematic error, mobile devices typically only display one reading point and in some circumstances a trend over a period of interest. Considering the more adverse situation in mHealth with plenty devices in use, including wearables or implants operating wirelessly or even autonomously with possible security attacks, quantifying the reliability of a sensor reading become inevitable. In life critical applications fail safety is required, going beyond the pure need for reliability.

Conventional approaches using data mining of centrally stored data sets that can subsequently be analysed are questionable. New approaches to extract knowledge from multiple, distributed data streams have to consider the limited resources of computing and storage in sensor networks, communication, and human factors. Data may be lost or corrupted during sensing and transmission. Missing synchronisation can generate mistake in time series from various devices. Redundancy helps to reduce risk. This can include over-sampling using extra sensors or different types of sensors for the same measurand improving confidence in the correctness of data. Online model checking might enable realtime check of data plausibility, built-in self-test and self-calibration enhance the reliability of the device. Multi-parameter sensors are required for the detection of the target parameter as well as for the monitoring of operating condition, e.g. power supply of the device or quality of the communication channel. Last but not least, sensor readings have to constitute of measurement data and error estimation. Developing devices and architecture being able to provide these quality information and algorithms to process these data give opportunities and pose challenges for the implementation of fail-safe mHealth applications.

Vital Sign Sensors for Artificial Intelligence and Deep Learning

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Up to now vital data of patients are mostly acquired during clinical or ambulant examination. Here, the sensors are carefully placed by trained personal and movements of the patient are well controlled, e.g. during exercise ECG on a recumbent ergometer. In this way, misplacement of the sensors as well as motion artifacts are avoided and physical load is well defined, such that high quality data is ensured that can be used for diagnostic purposes.

Such a clinical or ambulant examination, however, captures only a short moment in time and is not representative for daily life. More preferable from the perspective of the treating physician would be data collected on a regular basis from daily routine work of the subjects. In such a situation, however, sensors may not be placed properly by the patient and movements are not well controlled anymore, so data quality can be compromised.

Hence, the validity of the sensor data has to be assessed and taken into account during data analysis in order to derive reasonable conclusions. Therefore, a wearable sensor system for daily life must be multimodal to allow machine learning algorithms to clean the acquired sensor data from artefacts. Artificial intelligence and deep learning system can then identify corrupt data segments, substract artefact patterns and by that clean up sensor data.

The talk will highlight the trade-off between usability and integratability of a sensor system into daily life versus the validity of data obtained. This challenge will be illustrated by a multimodal sensor platform for elderly and dementia care that was developed during the course of the Medical Valley excellence cluster funded by German Federal Ministry of Education and Research (BMBF).

Another example discussed in the talk are ECG circuit concepts that make the sensor more robust and compatible with daily life. Special focus will be put on capacitive ECG. Here, movement artefacts can be cleaned up if the movement during ECG acquisition is known, which can be done, e.g., by EMG or acceleration/gyroscopic sensors. Apart from that, these sensors allow to interpret the captured ECG data with respect to the current load to the body and thus provide context information.

In conclusion, a combination of advancements in both sensor hardware/circuitry and multimodal sensor processing by artificial intelligence is needed to make the sketched vision real.

Addressing challenges in bringing Artificial Intelligence and Deep Learning into clinical routine

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Artifical intelligence (AI) and deep learning currently show a hugh potential to provide valuable insights in healthcare to improve patient outcomes. Great examples are presented in this focus sessions. Others can be seen throughout the world. However, there are key questions like acceptance, patient safety and regulatory implications, which need to be addressed early to allow a smooth translation of these ideas into clinical routine. To give an example: Classical medical device certification relies on validation processes, in which specific input paramaters lead to defined output varibales. Also a design specification needs to be provided against which the verification and validation is performed. These approaches pose a challenge for AI and Deep Learning systems as it is the nature of theses systems that they are not fully defined and change with growing data sets. Statistical methods may help to overcome these challenges. Another example is the increasing use of speech recognition systems which is also entering the medical device arena. While speech recognition shows an high level of ease of use to control devices it also comes with challenges regarding validatitation and certification to ensure the require reliability. These challenges need to be addressed to come up with the required new methods. The goal is to start a discussion around these topics to ensure a smooth translation of ideas on AI and deep learning into daily clinical routine. First answers to these challenges can be found in adjacent areas as well as internationally.