# Cloud Infrastructure for Storing and Processing EEG and ERP Experimental Data

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Abstract: Current infrastructures for experimental data, results and computational tools make a shift from locally maintained solutions to remote cloud-based infrastructures. It brings a higher availability, sustainability and performance. However, specifics of different research areas require development of customized solutions for individual research domains. For example, electroencephalography and event-related potentials (EEG/ERP) use specific devices, data formats and machine learning workflows. As a solution, a cloud-based system for the EEG/ERP domain containing a distributed data storage, a signal processing method library and a client GUI is presented. The signal processing method library is used for training of classifiers and classifying the data in the cloud-based system controlled by the GUI. The presented system was tested using a machine learning workflow based on the data stored in the system. In the workflow, various classifiers were trained and their parameters stored into the system. Finally, testing data were classified using previously trained classifiers.

## 1 INTRODUCTION

Laboratories have been using locally maintained databases and tools for experimental data storage and processing. Experimental results have been published and then locally stored or often even supposed as no more needed and discarded. Nowadays because of increasing data storage capacity, fast Internet connectivity, and cheaper hardware equipment, the amount of experimental data is dramatically increasing. With increasing amount of data, requirements to data sustainability (Van Horn and van Pelt, 2008), experiments reproducibility, and publishing also original data not only experimental results (Abelard and Héloise, 2011) are increasing, too. These requirements make locally maintained infrastructures insufficient and obsolete. On one hand the computational performance is cheaper and easily available but on the other hand the increasing number of devices and technologies for data storing and processing require a higher demand on technical knowledge of researchers.

A new view on data storage and management makes a shift from locally maintained infrastructures to remote solutions usually referred to as cloud computing. This approach defines a new delivery model Architecture-as-a-Service (AaaS) that supposes a provider of a remote computational infrastructure who guarantees data integrity, backup and uninterrupted availability. Methods for data processing are also installed in the remote infrastructure which ensures enough performance by scaling tasks over a distributed network of a computational cluster. This approach takes off the responsibilities from researchers who can be focused on the laboratory work instead of maintaining complex infrastructures.

Especially the domain of electroencephalography (EEG) and event-related potentials (ERP) requires various experts from signal processing, database or hardware domains. Moreover, laboratory staff responsible for collecting experiments must be familiar with all the systems in a complex chain of data collecting, storing, processing and finally, presenting results. In the cloud computing approach the responsibilities can be either partly dedicated to a paid service or split out among individual experts not necessarily located in the same laboratory.

We present a complex cloud-based infrastructure for storing and processing experimental data. This infrastructure is validated on an ERP focused use-case study. This infrastructure contains a data storage, a library of signal processing methods, and a simple GUI allowing users to easily control the whole system. Section 2 presents similar concepts and eval-

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uates the approach. Section 3 briefly introduces the ERP domain and introduces a technological stack for the system. Section 4 describes implementation of the system. Finally, Section 5 presents testing of the system and Section 6 concludes the work.

## 2 RELATED WORK

There are some approaches that aim to move traditional desktop-based computing to cloud-based solutions in medicine.

Cloudwave (Sahoo et al., 2013) is a platform that provides paralleled algorithms for computing in a cardiac domain. It supports real-time interaction with large volumes of electrophysiological signals, and features signal visualization and a querying functionality using an ontology-driven web-based interface.

The CARMEN e-science project (Watson et al., 2008) is based on a grid computing concept that integrates heterogeneous resources across virtual organizations represented by registered laboratories. For these laboratories a data/metadata storage, a data analysis service, and a workflow enactment is ensured but laboratories contribute by their own data and data analysis methods.

Electrocardiographic (ECG) signal analysis using Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM) framework is presented in (Varatharajan et al., 2018). This framework provides a data storage for wearable sensors transferred through a 4G network. Once data is transferred to the data storage it is computed by LDA and SVM methods and results are transferred to a doctor's computer where he/she can see reports.

An IoT-based health-care architecture (Thota et al., 2018) uses a fog computing approach for collecting data from wireless sensors. The fog computing relies on the usage of so-called edge device communicating with wearable devices via a local network. Then this edge-device is connected to the cloud solution via the Internet. Especially in this solution Raspberry Pi is an edge-device that transfers data to the cloud. Data in the cloud is accessible by health-care providers.

## 3 METHODS

### 3.1 ERP Domain

Event-related potentials (ERP) (Sur and Sinha, 2009) can be observed in the electroencephalographic (EEG) signal as small voltages generated by the brain as a reaction to stimuli. Many ERP experiments follow an oddball paradigm (García-Larrea et al., 1992) based on stimulation of tested subjects by two types of auditory or visual stimuli. Oddball experiments consist of a set of common (non-target) stimuli that are infrequently interrupted by rare (target) stimuli. The target stimuli are associated with the P300 waveform. Similar principle can also be applied to brain-computer interfaces (BCIs) as originally proposed with the P300 speller by (Farwell and Donchin, 1988) in which the intended action of a user (such as a row containing the letter that the user wishes to type) represents the target stimuli, and the task is to detect that stimulus by means of machine learning (Hoffmann et al., 2008).

The detection relies on extracting ERPs from the ongoing EEG while minimizing noise. The common procedure is based on epoch extraction and filtering ERP epochs (trials). When aiming at P300 BCI classification, each extracted and processed ERP epoch is evaluated by a binary classifier that is trained to separate between target and non-target trials. Finally, the results of classification or parameters of the classifier itself can be stored for further evaluation. (Hoffmann et al., 2008)

A typical machine learning workflow in the ERP domain can be organized as Fig. 1 depicts, and it can consist of the following steps:

- Data reading. Either from filesystem (a binary file specific for the EEG amplifier or a universal open file format such as EDF (Kemp and Olivan, 2003)), or in real-time from stream such as Lab Streaming Layer (LSL) (Kothe, 2014).
- Pre-processing commonly includes several sub-steps. Subset selection of only relevant EEG channels reduces data dimensionality. Band-pass filtering attenuates undesired frequencies such as line noise at 50 Hz. Epochs extraction splits continuous EEG into ERP epochs using stimuli markers. Each epoch has a pre-stimulus part (a time window before the stimulus onset) and a post-stimulus part (a time window after the stimulus onset). Baseline correction is used to align the ERP epoch around zero e.g. by subtracting average of the pre-stimulus part from the whole ERP epoch. Many other methods can be used, e.g. blind source separation methods such as Independent Component Analysis (Luck, 2014).
- Feature extraction. Most common features to be extracted are time point features and band power features (Lotte et al., 2018). Discrete wavelet transform, matching pursuit (Mallat and Zhang,

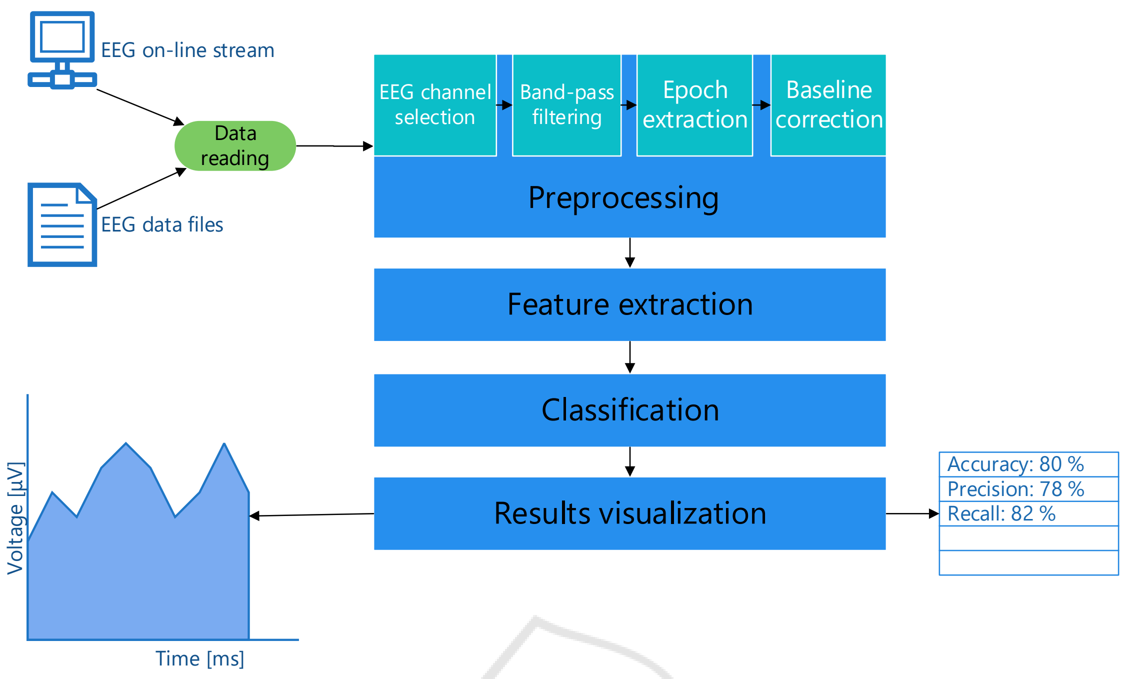


Figure 1: Simple machine learning workflow suitable for the P300 ERP detection.

1993) and other related methods for time frequency analysis can also be applied. Feature selection that usually aims at reducing data dimension by omitting redundant time points or band power features (Lotte et al., 2018).

- Classification. Some methods used in the ERP domains are e.g. Support Vector Machines (SVM) (Subasi and Gursoy, 2010), decision trees (Polat and Güneş, 2007), logistic regression (Subasi and Ercelebi, 2005), random forest (Fraiwan et al., 2012), or neural networks (Güler et al., 2005).
- Results visualization includes charts, tables or single values.

## 3.2 System Requirements

The experimental workflow outlined in Section 3.1 defines requirements for the developed system. Data must be collected in a robust and secured data storage. Processing of data is a sequence of mostly linearly executed operations but e.g. classification that uses deep learning methods is required to be paralleled. A cloud-based solution is suitable for classifier training because it is usually the most time consuming part of the workflow. However, the data is usually collected on a local laboratory notebook connected either to the Internet or at least to a local laboratory network. Hence a secured data transfer from the laboratory notebook to the cloud solution must be ensured. Data must be anonymized and the server located inside a protected network secured by firewalls.

## 3.3 Apache Hadoop and Spark

Commonly used open source technologies for data storing and data processing in distributed environment include Apache Hadoop and Apache Spark. Apache Hadoop (Apache Software Foundation, 2009) is designed for performing massive, parallel jobs and is de facto supposed as a place where data and computational resources are shared and accessed. It is an ecosystem of several technologies (Ishwarappa and Anuradha, 2015). We used a Hadoop Distributed File System (HDFS) that provides high-throughput access to data stored in a distributed environment.

Hadoop provides a map-reduce implementation for processing big data in the distributed environment (Ekanayake et al., 2008). However, Apache Spark (Zaharia et al., 2016) reports significantly better performance than the map-reduce implementation (Gopalani and Arora, 2015). Moreover, an open-source distributed machine learning library (MLlib) (Meng et al., 2016) available for Apache Spark provides an implementation of various methods suitable for training classifiers in the ERP domain.

## 4 RESULTS

### 4.1 Server

The server operates HDFS for experimental data, a data analysis package described in Section 4.2, and a Spring boot (Webb et al., 2013) application that operates a REST API described in Section 4.3.

Once a processing of data is required, a job on the server is created. The server handles all jobs in a job manager. Once a job is done, a flag FINISHED is set up and results are stored on the server. This approach does not require to wait for every single job but allows users to run any number of jobs in a row and see the results once they are available.

ERP experiments (see Section: 3.1) require training of classifiers reusable for similar kinds of experiments. Typically, same experiment is repeated with various tested subjects. The server allows users to either train a classifier on selected data or test a classifier already trained and saved on the server.

The server is controlled by a GUI via the REST API described in Section 4.4.

Because installing a server with all needed tools is a difficult task and the server is supposed to be easily transferred to other environments, we used Docker (Merkel, 2014). There are several Hadoop Docker images (e. g. (Vohra, 2015)). We used Cloudera Quickstart (Taylor, 2010) that we extended by the tools we implemented (described later in Sections 4.2 and 4.3).

A complete architecture is shown in Figure 2.

### 4.2 Methods Library

An aim of the methods library is providing the signal processing tools needed for training and classifying the ERP signal. We implemented three packages of tools for (1) data reading and transformation, (2) features extraction and (3) classification. The Apache Spark API enables parallelism of the processes over available nodes. This feature is useful especially for deep learning methods. The methods library also contains a pipeline builder responsible for running methods in a workflow as described in Section 3.1. The Apache Spark distributes data and computational load over nodes connected in the HDFS cluster and collects results. Figure 3 shows all methods currently implemented in the library.

### 4.3 REST API

The Apache Spark job is a single process configured by Spark properties[1]. We provided a REST API for controlling individual Spark jobs from a client computer. The REST API methods are designed to allow users to run any number of jobs they need, check their status, and once they are finished, download results.

Available methods are:

- /jobs/submit/(id)?(qp) - to submit a job with an id. Gp is a configuration via the Spark properties.
- /jobs/check/(id) - to check the status of a job with an id
- /jobs/result/(id) - to get the result of a job with an id
- /jobs/log/(id) - to get the log of a job with an id
- /jobs/cancel/id - to cancel a job with an id
- /jobs/configuration/(id) to get the configuration of a job with an id
- /classifiers/list - to list all the saved classifiers

### 4.4 Client GUI

The graphical user interface is only a tool supposed to be installed locally on a laboratory notebook. The GUI implements a wizard through which the user can upload a file or a complete folder, or delete existing files or folders on the server. Once the data is uploaded the user can choose data for classifier training or testing. In the next step, the user lists available methods on the server, selects one and configures its parameters. Finally, the REST API method is called, data from the HDFS storage is submitted to the Spark, and a Spark job is created and executed. A print-screen of the GUI is in Figure 4. A complete sequence of steps from storing data to obtaining results is in a sequence diagram in Figure 5. Communication between the client and the server is secured by Kerberos (Neuman and Ts'o, 1994).

### 4.5 System Security

The server itself operates a daily updated Debian Linux distribution. It is located on a secured university network protected by the firewall. Communication with the server is secured by Kerberos and the SSL channel. Moreover, all datasets are anonymized before uploading. The datasets were anonymized by using identification numbers and neither potential attackers nor experimenters themselves would be able to assign them to any real person. Since the server itself is secured and datasets are anonymized, raw EEG data encryption was not necessary.

[1]https://spark.apache.org/docs/latest/configuration.html

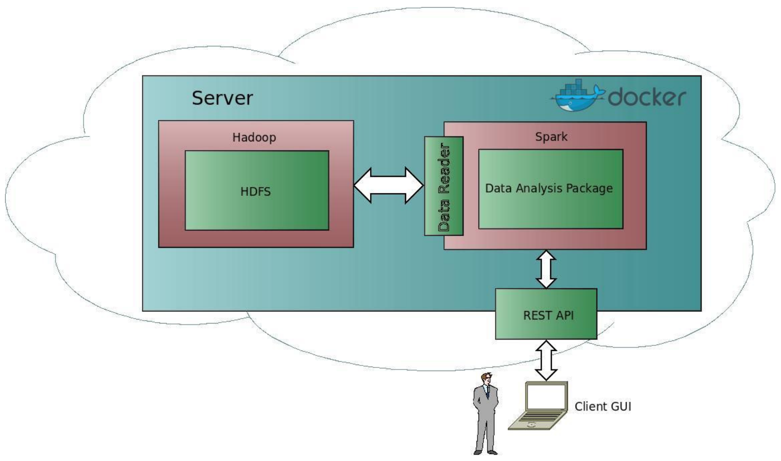


Figure 2: Architecture of the system. A cloud part of the architecture is a docker image containing on the left side: A Hadoop distributed file system (HDFS) implemented in the Cloudera platform. On the right side: The remote server operating the data analysis package. The server accesses data via a data reader and communicates with the client GUI program via the REST API.

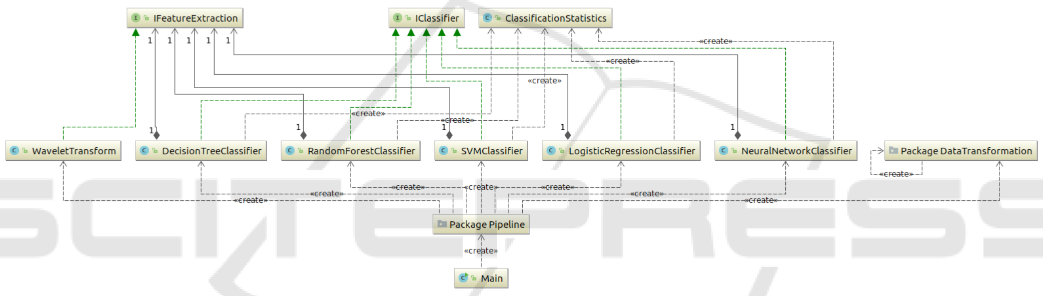
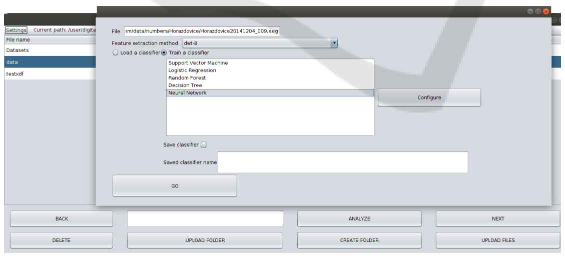


Figure 3: UML Diagram. Wavelet transformation implements the IFeatureExtraction interface. The IClassifier interface is implemented by several classifiers including random forest, SVM, logistic regression and neural networks. A flow of the data through the code is controlled by the Pipeline package.


Settings Current path: /user/digita

File name

Datasets

data

testxdf

File :m/data/numbers/Horazdovice/Horazdovice20141204_009.eeg

Feature extraction method dwt-8

Load a classifier [✓ Train a classifier]

Support Vector Machine

Logistic Regression

Random Forest

Decision Tree

Neural Network

Save classifier ☐

Saved classifier name

Figure 4: Graphical User Interface.

## 5 DISCUSSION

We have been collecting ERP experiments in a neuroinformatics laboratory at our department, in a hospital university and also outside using portable devices. Between autumn 2014 and spring 2015 we measured experiments at primary and secondary schools for a science popularization event. Ten times during that period, we attended various schools and measured about 20 to 40 tested subjects per day. Later in 2018, we attended the University hospital in Pilsen about 10 times where we measured 2-3 tested subjects per visit. The laboratory experiments from the same time period consist of about 10 days of experiments with about 20 tested experimental sessions per day.

The typical experiment we performed at schools is a 'Guess the number' experiment. The tested subject is asked to choose a number from a range 1-9 (the target stimulus). He/she is then visually stimulated with a monitor with randomly presented numbers from the

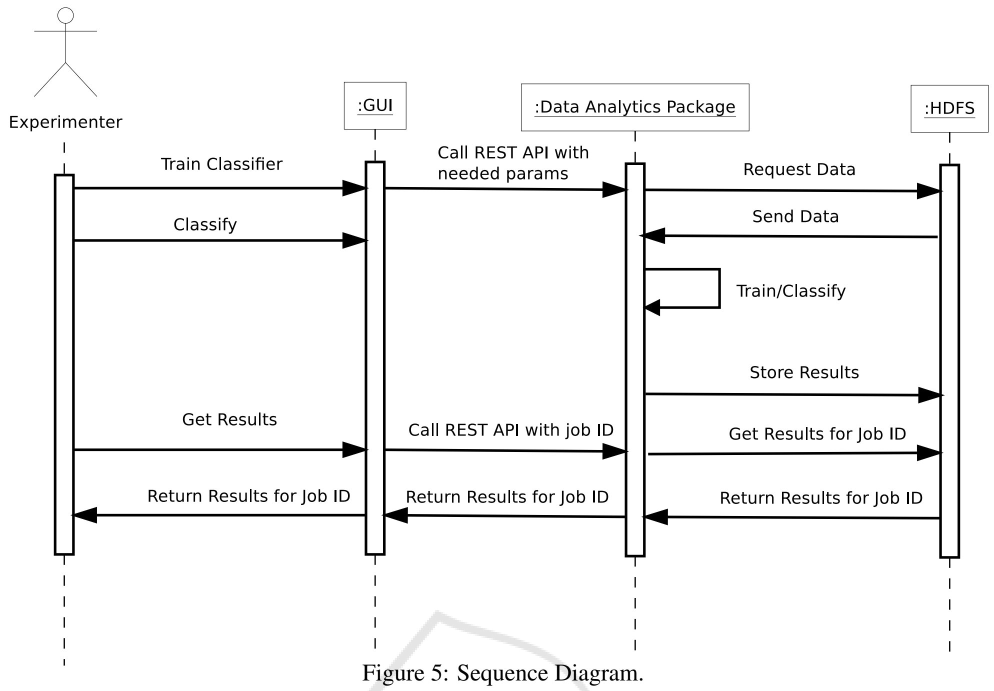


Figure 5: Sequence Diagram.

same range. The goal of the experimenter is to guess the number based on observing the averaged waveforms. The P300 waveform is supposed to appear following the target stimulus. Finally, we also asked the participants to reveal the number thought and that number was recorded as a part of metadata so that the labels for classifier training were available. Details about the 'Guess the number' experiment as well as the experimental data are described in (Moucek et al., 2017).

We uploaded the datasets to the cloud infrastructure by the developed GUI. More than 400 experiments have been stored (tens of gigabytes). Then we prepared a bash script calling the REST API for obtaining the datasets and running a simple machine learning workflow. A part of the data was used for training and another part for testing. For testing data, classification accuracy was between 60-70 %. However, achieving high classification accuracy was not the main aim of this paper. Classification accuracy is strongly dependent on how the classifiers are configured, how the testing/training data are selected, and also on the quality of datasets themselves. The most important was validation of the complete infrastructure. We validated that the system is suitably integrated, the data is incorruptibly stored, and classification gives reasonable results in reasonable time even when tested on a single cluster. If more performance is needed, a new node to the infrastructure can be added without changing the presented system.

## 6 CONCLUSIONS

Increasing performance and availability of cloud solutions open new possibilities for storing, processing and visualization of experimental data. Cloud computing concepts allow users to be more focused on laboratory work without being worried about maintaining complex data infrastructures. The usage of cloud based approaches also relies on the researchers willingness to entrust sensitive data to third-party providers. The cloud solutions must be secured, reliable and easy-to-use to be accepted by researchers. There are some existing cloud solution providers such as Microsoft Azure, IBM Cloud or iCloud but they do not provide sufficient means to satisfy specific needs of the electrophysiology domain. Some existing solutions were presented in Section 2. However, they are not focused on the ERP domain and they are intended to be used mainly in hospitals or in a clinician practice. However, there has been no solution for research in laboratories.

We presented a system based on open source concepts using Apache Hadoop and Spark. We used HDFS for data storing and we implemented the methods for signal processing in the Spark context. The methods are controlled by the REST API. We tested this infrastructure by storing more than 400 datasets into the distributed file system and by running simple workflows aiming at training and testing classifiers.

The presented GUI provides a functionality for data management and for controlling the available methods. Moreover if a laboratory notebook operates some open source tool for collecting data such as e.g. Neurolab or LabRecorder it can be integrated with the system using the REST API.

Our future work includes e.g. an implementation of a workflow designer that is supposed to be a comfortable graphical tool for designing signal processing workflows (as described in Section 3.1). Data running through these workflows could be processed in the presented system, too. There also exist micro devices such as smart phones, smart watches or other wearable devices as heart belts, insulin pumps etc. Storing data from these micro devices in the presented system could be finally helpful in building complete Internet of Things (IoT) infrastructures. Our future goal is also extending the methods library to provide a larger collection of methods.

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