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# The Brains behind Brain Scientific Machine Learning

**BY BRAIN SCIENTIFIC**

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**Abstract**

By building large-scale simulations of cortical (brain) computations, we can enable revolutionary progress in artificial intelligence (AI) and machine learning.

Machine learning often works very well; but can be a lot of work to apply, because it requires spending a long time engineering the input representation (or “features”) for each specific problem. This is true for machine learning applications in vision, audio, text/NLP (natural language processing), and other problems.

To address this, we have utilized independent component analysis (ICA) and “deep learning” non-linear algorithms that can automatically learn feature representations from unlabeled data, thus bypassing much of this time-consuming engineering.

Many of these algorithms are developed using simple simulations of cortical (brain) computations and build on ideas of independent component analysis (ICA). By doing so, we are able to exploit large amounts of unlabeled data (which is cheap and easy to obtain) to learn a good feature representation. These methods have surpassed the previous state-of-the-art applications on a number of problems in vision, audio, and text.

**Introduction**

The appealing properties of artificial intelligence (AI) methods are being increasingly acknowledged by the neuroimaging community; as evidenced by the recent surge of brain activity pattern recognition studies, and application of brain-computer interfaces (BCI). Supervised learning and classification, in particular, are appreciated tools for localizing and distinguishing intricate brain response patterns and making predictions about otherwise undetectable neural states.

Our group refines and applies such methods in order to implement sensitive and dynamic tools for characterization of neurophysiological data. Specifically, we employ independent component analysis (ICA) algorithms on electroencephalography (EEG) data. This paper provides a brief overview of our recent advances with Brain Scientific in the development and utilization of AI based analysis as it relates to EEG data.

Machine learning approaches for mining neurophysiological data are rapidly gaining popularity, and justifiably so, as they provide a level of analysis not possible with conventional methods. Commonly used systems for acquiring such brain activity data non-invasively include electroencephalography (EEG), which provides an estimate of electrical currents produced by the brain, and functional magnetic resonance imaging (fMRI), where local blood flow changes are quantified.

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Classically, the analysis of neurophysiological data relies on descriptive statistical measures where average activity changes in single data points are related to an experimental condition and particular data characteristic of interest (e. g. brain regions in fMRI and frequencies in EEG). Artificial intelligence techniques, in contrast, are capable of distinguishing complex and subtle data patterns, distributed across numerous measuring points, on a single-trial basis.

**EEG and Machine Learning**

The benefits of AI were acknowledged early for real-time classification of EEG signals in brain-computer interfaces and more recently for clinical evaluation, as well as a wide range of fMRI analyses. Generally, supervised learning techniques are used: a classifier is trained to recognize and decode subtle intrinsic signal patterns correlated to given brain states, such as the EEG activity produced by a single touch stimulus.

Supervised learning methods not only enable real-time single trial classification (such as brain state tracking or intent decoding), but by virtue of considering information encoded over multiple measuring points they also provide improved condition differentiation sensitivity. In the following sections, we summarize our recent advances in the development and application of such AI-based analysis in EEG studies. In particular, we utilize these methods to characterize human brain activation patterns that are produced.

EEG involves the registration of electrical brain activity at a temporal resolution of milliseconds using electrodes attached to the scalp. The signals are believed to mainly reflect post-synaptic currents in nerve cells and synchronous activity of thousands of cells is required to produce a measurable potential.

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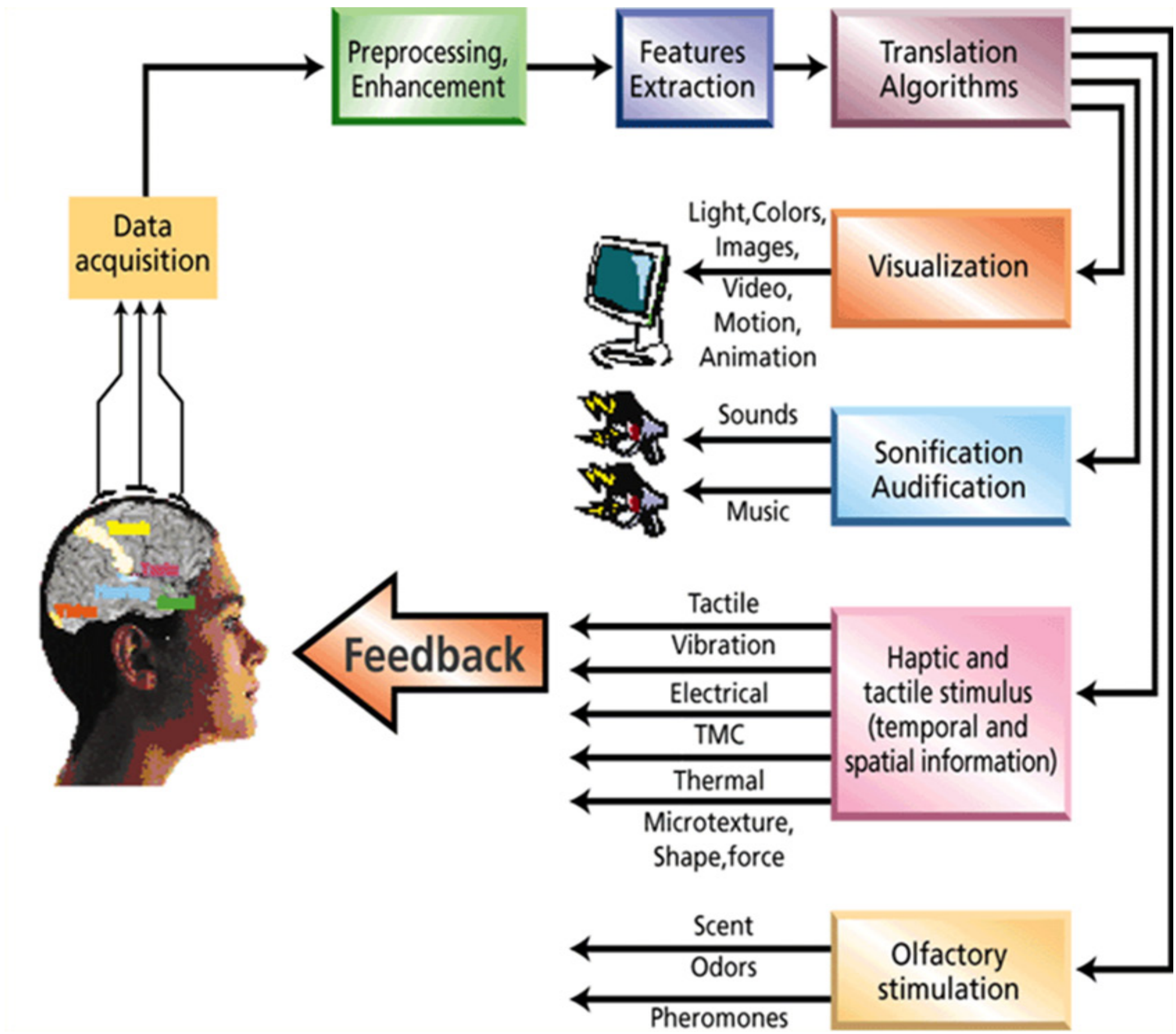


With recent advances in the complex problem of localizing signal sources within the brain, EEG has emerged as an excellent tool for both characterizing temporal dynamics and localizing cognitive processing. Standard EEG analysis involves averaging over numerous events to produce event-related potentials (ERPs) which are subsequently analyzed based on the latency and amplitude of characteristic deflections.

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**Machine Learning as an EEG Analysis Tool**

The averaging procedure; however, may mask or even eliminate relevant information potentially concealed in complex signal patterns. We therefore explored an EEG analysis approach based on independent component analysis (ICA) combined with supervised learning. ICA blindly decomposes multi-channel EEG data into maximally independent component processes (ICs) that typically express either particular brain generated EEG activities, or some type of non-brain artifacts (e. g. line noise or muscle activity).

We used this approach to identify and characterize differential temporal patterns in the EEG responses to stimulation of the finger pad with surfaces of varying roughness. Our classifier (independent-component analysis) was successfully trained to differentiate between the temporal patterns evoked by the two different textures in some ICs but not in others. For example, an EEG component generated in the contralateral somatosensory cortex with activation peaks at 100 ms after onset (P100) of stimulation significantly differentiated the textures.

**Potential Uses of Machine Learning and EEG**

Exploring the possibilities and patient benefits that lie within the domain of AI and Brain-Computer Interfaces, using Brain Scientific technology is immense. The field of Brain-Computer Interfaces (BCI) is a driving force for utilizing electroencephalography technology (EEG), which is the process of recording brain activity from the scalp using electrodes (see figure above).

In the past, the main focus have been about developing applications in a medical context, helping paralyzed or disabled patients to interact with the external world, by mapping brain signals to human cognitive and/or sensorimotor functions. However, BCI development is no longer constrained to just patients or for treatment because there is a shift of focus towards people with ordinary health.

Training (athletic, military, occupational, consumer engagement, or entertainment) is becoming a target group that would likely to be adaptive to use EEG as a new modality; giving them advantages or new experiences in that particular space. It is not just treatment in mind, but immersive interaction also.

This shift could inherently benefit patients, because when EEG technology becomes more available and the powerful "training" industry gets involved. They can become the driver for improvements for all silicon-based technology: needing, and thus getting, faster processors and graphic engines so they can create better outcomes and experiences.

By taking BCI that level, the motivation for making more user-friendly, faster, cheaper and publicly available systems will be totally different and become of a much

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higher priority. The targeted group of users are not forced to utilize BCI systems, and thus need better reasons to do so, other than it is cool to be able to control your computer with the mind.

Current systems and our competitors do not meet such standards. The motivating thought is that approaching this issue from such a point of view could help getting AI and BCIs to such standards faster.

**Artificial Intelligence and Brain-Computer Interfaces**

AI and BCI-based approaches for analyzing brain activity provide a highly appealing complement to conventional statistical methods, enable a deeper understanding of brain function, and promote the development of novel medical techniques. Whereas we primarily use AI for the characterization of brain activation patterns, other brain signal decoding applications include brain-computer interfaces (BCIs), biofeedback, real-time signal analysis, disease diagnosis, enabling prosthesis control, and opening communication channels with locked-in patients.

**Conclusion**

The integration of BCI and application of AI/machine-learning concepts in EEG data-mining; and neuroimaging, is rapidly expanding at Brain Scientific to further refine these algorithms and better understand how to achieve better population and patient health outcomes.