



Editorial

Machine Learning and Neuroimaging

Nezih OKTAR¹, Yigit OKTAR²

¹*Editor-in-chief, J Neurol Sci Turk* ²*MSE in Robotics*

Summary

Machine learning usage in the neurosciences has been explosively increased for the past three years. Besides strengths and also the inherent misuse of machine learning in neurosciences, the results obtained from these studies suggest that machine learning methods may extensively be used for the clinical diagnosis and for the investigation of different brain diseases.

Key words: Machine Learning, Neuroimaging, NeuralNetwork, Dynamic Logic, Neurological Disease

Makine Öğrenimi ve Sinirbilim Görüntüleme

Özet

Sinirbilim görüntüleme makine öğrenimi kullanımı son 3 yılda inanılmaz ölçüde artış gösterdi. Güçlü yanları yanı sıra doğasında olan kötü kullanımı dahil makine öğreniminin sinirbilimlerinde uygulanımı sonuçlarına bakılacak olursa çok değişik sinir sistemi hastalıklarının klinik tanısı ve araştırmalarında kullanılabileceği önerilir.

Anahtar Kelimeler: Makine öğrenimi, Sinirbilim görüntüleme, Yapay Sinir Ağları, Dinamik Mantık, Sinir Hastalıkları

Machine learning usage in the neurosciences has been explosively increased for the past three years. Besides strengths and also the inherent misuse of machine learning in neurosciences, the results obtained from these studies suggest that machine learning methods may extensively be used for the clinical diagnosis and for the investigation of different brain diseases.

Brains learn much better than computers. This has been discussed in a number of reviews on artificial intelligence, pattern recognitions, and neural networks⁽³⁴⁾. Our conscious understanding is an end state of

many rational, sometimes irrational feelings, deliberate thoughts, or even unconscious dynamic logic processes. Although computers are described to be complex, it is still an open question whether they can match the complexity of human brain. On the contrary, recent advancements in the field of machine learning suggest that machines may in fact undergo 'learning' as nearly good as humans do.

Machine learning is a study of algorithms to learn from observed data, in any form, to deduce a model that describes the data accurately. An algorithm is a recipe for machine to be executed step by step. Note

that, as opposed to hard-coded (static) algorithms, machine learning algorithms have a goal of fitting models to data observed. This provides an abstraction layer between the data and the machine much like human learning process, perhaps rather cruder. There are various categories of such algorithms, but the main goal is to learn a model in order to predict outcomes for input never-seen-before. And the accuracy of model is tested that way.

A popular machine learning approach is statistical learning theory⁽⁴²⁾, in which learning process is based on statistical inferences from the data. Unlike dynamic logic, it is not related to the cognitive mechanisms of the brain-mind. In other words, it tries to formalize the observations solely by statistics where there is little room for improvisation that may be needed in the learning process. Rather complex formalizations can still be achieved which show its similarity to dynamic logic in that aspect. Statistical and other rigorous math-based approaches turned out to be too rigid to formalize a complex process like learning. It is really hard to grasp the high-level abstraction present in such complex data in one shot. The current trend in machine learning tends toward learning hierarchical representations to break this complexity into multiple levels of abstractions, so that hopefully each such layer will make more sense to us. Artificial neural networks are very well suited for such architecture and have received a considerable attention recently. The beauty of model based learning is that: these methods can be applied to any form of data once the way to properly feed input into the algorithm is figured out.

Machine learning and pattern recognition algorithms have in the past years developed to become a working horse in brain imaging and the computational neurosciences, as they are instrumental for mining vast amounts of data, are discriminative against high noise levels,

and benefit from increased measurement precision. Machine learning usage in the neurosciences has been explosively increased for the past three years. Started with using for MRI-based classification of brain neoplasms⁽⁴⁶⁾, Alzheimer's Disease^(1,5,9,10,11,13,16,28,31), radiology^(26,45), to classify childhood onset schizophrenia⁽¹⁹⁾ and then other psychiatric disorders especially on schizophrenia^(4,20,24,37,44). Studies have been continued on epileptic seizure detection in EEGs^(6,39), major depressive disorder⁽²¹⁾, obsessive-compulsive disorder⁽²²⁾, aging⁽²⁹⁾, ADHD⁽³³⁾, neonatal encephalopathy⁽⁴⁷⁾, pain⁽³⁶⁾, spinal cord injuries⁽⁴¹⁾, epilepsy^(2,25), preoperative glioma MRI and brain tumors^(14,15), MS lesions⁽⁴⁰⁾, genetics^(8,18), stroke^(3,35), smoking⁽³²⁾, Parkinson's disease⁽²³⁾, psychological trauma⁽⁷⁾, dyslexia⁽¹⁷⁾, myelin damage⁽³⁰⁾, cognitive neuroimaging and fMRI data analysis^(38,43).

Besides strengths and also the inherent misuse of machine learning in neurosciences⁽²⁷⁾, the results obtained from these studies suggest that machine learning methods may extensively be used for the clinical diagnosis and for the investigation of different brain diseases.

Best regards
Prof. Nezh OKTAR MD
editor@jns.dergisi.org

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