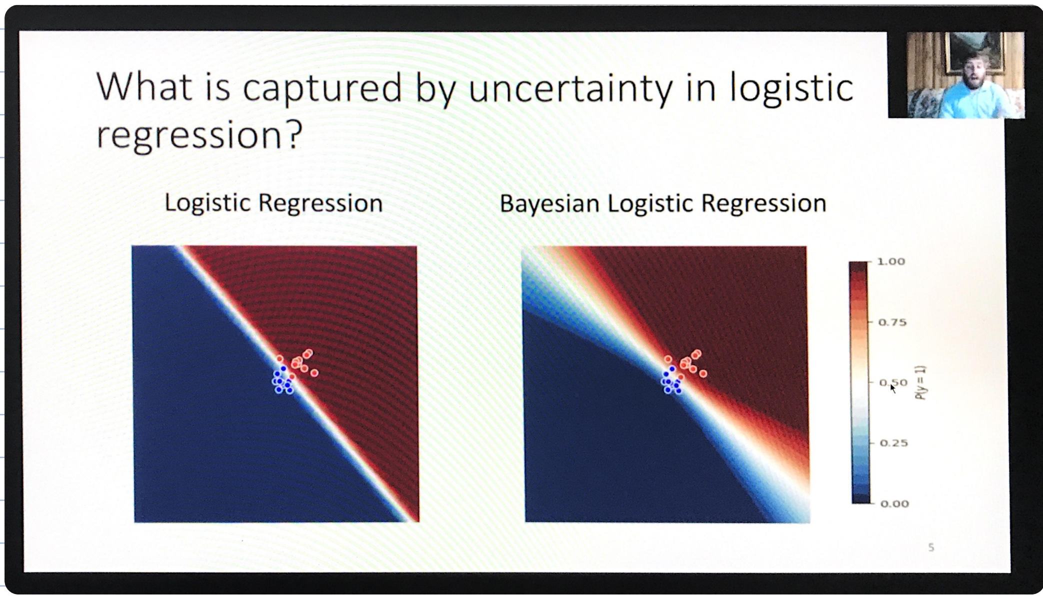
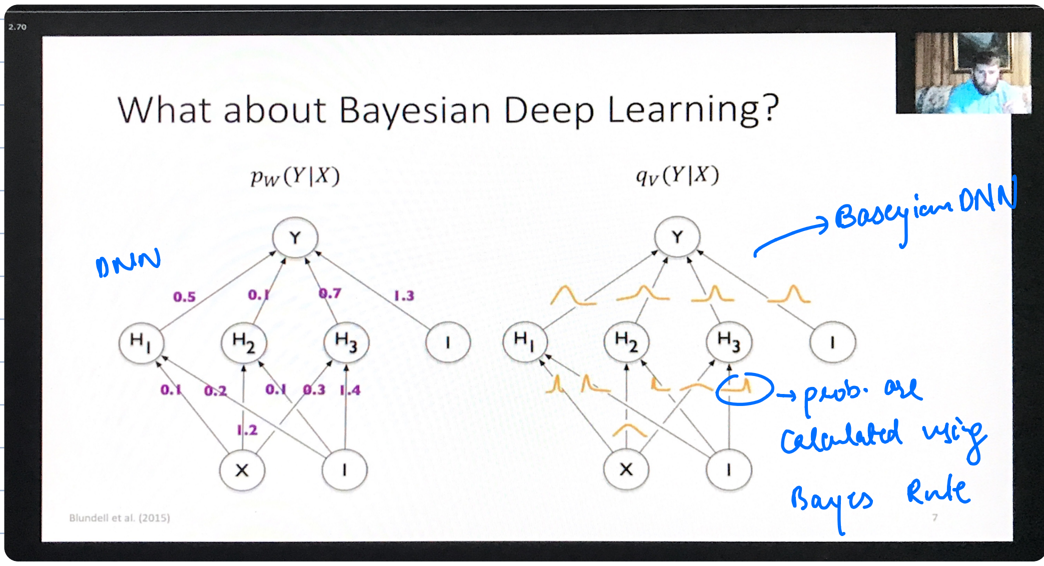
Bayesian DNN





DNN

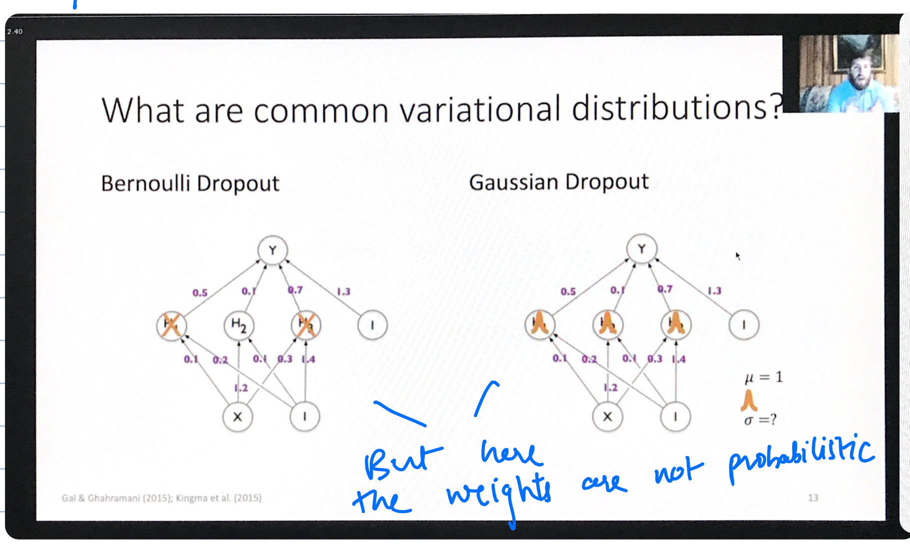
→ Bayesian DNN

→ prob. are calculated using Bayes Rule

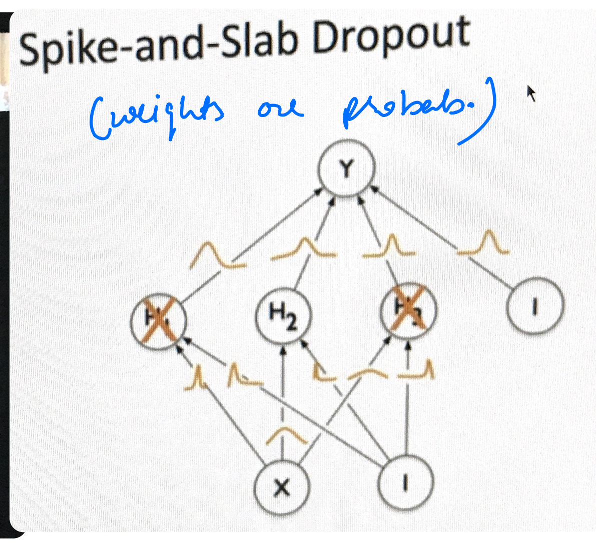
Approximate Bayesian Methods

	Pros	Cons
· Markov chain Monte-Carlo (MCMC)	Asymptotically exact	Not efficient
· Variational Inference	Efficient	Not asymp. exact

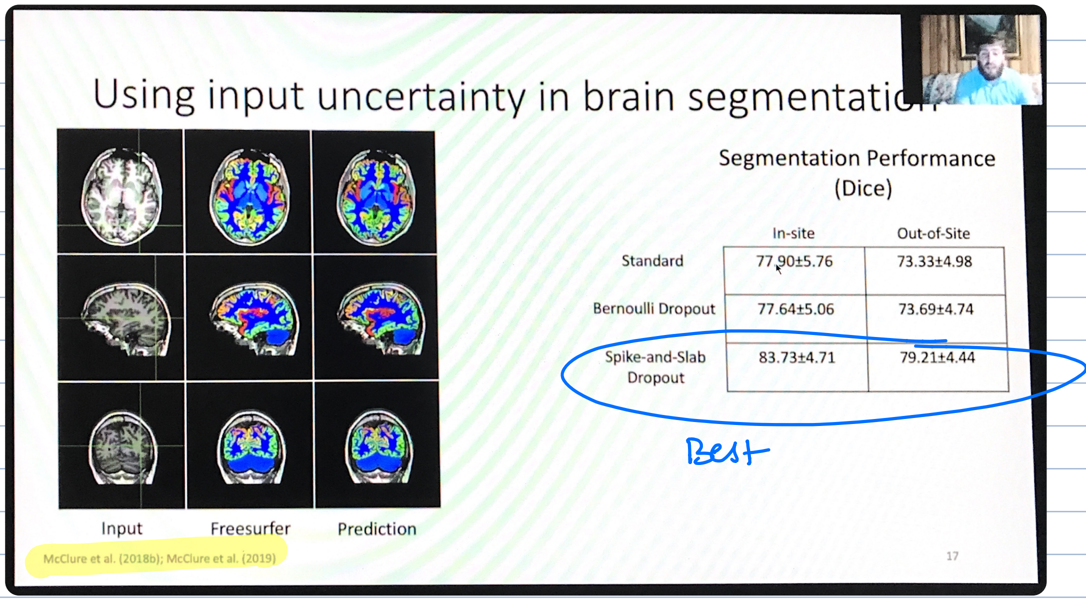
· Dropouts are similar practices



But here the weights are not probabilistic



(weights are probab.)



- Graph Convolution Networks (GCN) → Read More

In 2D conv, we have a defined neigh. for each node ⇒ we can use same filter size

In graph conv. ⇒ we can see neighb. are unorderder & different size
⇒ one way is to take avg. of all the neighb. for a node

(other lectures were basic for me so didn't watch)

Deep Learning for Human Brain Mapping

Ariel Rokem Co Organizer
The University of Washington eScience Institute
eScience Institute
Seattle, WA
United States

Andrew Doyle Organizer
McGill University
Montreal, Quebec
Canada

Deep learning is a powerful method for learning non-linear function approximations in a data-driven manner. Many parallels have been drawn between biological brains and artificial neural networks, and this exciting new tool offers several avenues to study the brain: both as a tool to analyze brain data and as a way to model biological neural networks. In this course, we aim for participants to: write Python code that implements a deep convolutional neural network; apply deep learning at different scales in time and space; explore new ways to model and learn structure in neuroimaging data; learn creative ways to apply deep learning with little or noisy data; model dynamic neural systems.

A diverse set of world experts, from a variety of academic backgrounds, research fields and career stages, from both academia and industry, will teach learners how artificial neural networks are constructed and trained. We provide hands-on examples of applications where deep learning is used for mapping the human brain, across a variety of imaging methods and scales. Participants are asked to bring laptops and actively engage with the materials, which will be posted in the weeks before the course.

Course website: https://brainhack101.github.io/IntroDL/

Objective

1) Write Python code that implements a deep convolutional neural network
2) Apply deep learning at different scales in time and space
3) Learn creative ways to apply deep learning with little or noisy data

Target Audience

Researchers across a variety of fields that can benefit from the use of deep learning methods, and who would like to understand deep learning methods and apply them to brain mapping problems. The course is designed to provide a gentle introduction to the topic, leading up to more advanced lectures, so no prior knowledge is assumed, but practitioners with prior knowledge will still find interest in many of the lectures.

Presentations

Deep Learning: from computer vision to brain mapping

Deep learning uses a combination of methods and concepts from computer vision, statistics, and optimization. This presentation will set the stage for the other lectures in the course, by introducing the fundamental concepts behind deep learning: convolutions, back-propagation, gradient descent, stochastic gradient descent, etc. The lecture will be accompanied by detailed code examples using the TensorFlow/Keras libraries that are used in many applications of deep learning to brain mapping data. At the end of this presentation, learners should be ready to implement their own deep neural network to learn to classify brain images and should be prepared for the other lectures in this course.

Presenter

Ariel Rokem, The University of Washington eScience Institute
eScience Institute
Seattle, WA
United States

Introduction to Bayesian Deep Neural Networks

Deep neural networks (DNNs) are being applied to an increasing number of diverse areas, including neuroimaging. One area of active research is improving the estimation of DNN uncertainty. Better uncertainty estimation leads to better performance for a variety of problems, including transfer learning, distributed learning, and anomaly detection. These issues are particularly common for neuroimaging. Bayesian DNNs have been proposed as a principled solution for improving DNN uncertainty estimation by learning distributions of DNNs. In this talk, we will briefly introduce Bayesian DNNs and discuss multiple uses of uncertainty. We will then demonstrate the usefulness of Bayesian DNNs in neuroimaging, using structural magnetic resonance imaging (sMRI) brain segmentation as a case study.

Presenter

Patrick McClure, National Institute for Mental Health Bethesda, MD
United States

Weakly supervised learning for quantitative analysis of biomedical images

High throughput quantitative analysis of biomedical images is very challenging, since it generally requires experts to identify, decode and precisely locate the biological structures of interest. Traditional approaches involve the manual classification and segmentation of the patterns in the field of view, which is a tedious and time consuming task. It was recently demonstrated that deep convolutional neural networks (DCNN) are excellent feature extractors and can successfully be applied to the classification and segmentation of various biological structures. To alleviate the labeling process, weakly supervised deep learning methods using whole image or bounding boxes labelling were introduced and applied to biomedical image analysis where there is a lack of fully annotated ore precisely labeled datasets. In this lecture, we will introduce weakly supervised learning and demonstrate how it can be applied to different tasks related to biomedical image analysis.

Presenter

Flavie Lavoie-Cardinal, Université Laval Québec, Quebec
Canada

Making more data out of little data: data augmentation techniques for enabling deep learning with small labeled datasets

Deep learning has been shown to be a powerful tool for tasks such as face detection and object recognition. However, the use of deep neural networks for medical imaging is often limited by the amount of labeled data available. Data augmentation – the application of transformations such as rotations, scaling and warping – is often used to expand small datasets. I will discuss some data augmentation techniques for brain MRI data, including commonly used hand-engineered methods, as well as recent advances in learning transformations for data augmentation. We will examine the use of these learned transformations for synthesizing realistic examples for MRI segmentation.

Presenter

Amy Zhao, MIT Cambridge, MA
United States

Making the most out of little data - Ways to provide more informative training signals in deep learning for neuroimaging

This talk deals with the problem that training deep artificial neural networks usually requires substantial amounts of data – much more than what can often be provided with reasonable effort when working with brain activity recordings of any kind. In order to still leverage the power of deep learning techniques with limited available data, special care needs to be taken when designing the learning task, defining the structure of the deep model, and choosing the training method. I will discuss several strategies that are specifically applicable for neuroimaging data.

Presenter

Sebastian Stober, Otto von Guericke University Magdeburg Magdeburg, Saxony-Anhalt
Germany

Deep Neural Network-based Generative Models for EEG Signals

Generative models, i.e., models that learn the underlying probability distribution from a given set of input examples, have recently been used in fascinating applications in domains such as speech recognition, computer vision or chemical drug design. Deep neural network-based generative models can also be used in EEG-based brain-signal decoding, for example to ... generate synthetic signals ... perform semi-supervised classification ... detect if a signal distribution as changed over time … perform anomaly detection ... learn more about hidden features of the signal itself Training these deep neural network-based generative models has many practical challenges. In this tutorial, we will introduce some common generative models and train them on EEG signals, be learning both about their potential applications as well as their challenges and pitfalls.

Presenter

Robin Schirrmeister, University Freiburg Freiburg, Baden-Württemberg
Germany

Graph Laplacian and Graph Neural Networks: A unified framework to analyze brain activity

Brain graphs provide a simple way of modeling human brain connectome. Based on this architecture, a non-linear embedding tool, called graph Laplacian, can be used to project the high dimensional brain activities onto subspaces of the graph Laplacian eigenbasis. This method has gained more and more attention in neuroscience studies, for instance identifying functional areas and networks, generating connectivity gradients and harmonics, and predicting atrophy patterns of dementia. Recently, graph convolutional networks (GCN) was proposed, which combines the graph Laplacian theory with deep learning architectures. This approach has shown promising findings in neuroscience applications. I will introduce several applications of graph Laplacian and GCN for neuroimaging data, and specifically focus on our recent project of decoding human cognitive functions using a short series of fMRI volumes.

Presenter

Yu Zhang, University de Montreal / CRIUGM Montréal, QC

Canada

Attention mechanisms and their potential applications

Attention mechanisms have become almost a de facto standard in sequence-based tasks such as image captioning (image to sequence of words), sentiment classification (sequence of words to label) or machine translation (sequence-to-sequence). One of the benefits of attention mechanisms is that they allow for dealing with variable sized inputs, focusing on the most relevant parts of the input to make decisions. In this presentation, we will introduce attention in the context of natural language processing, and will move towards a broader range of application domains where attention-based models have been leveraged to address the shortcomings of prior methods. In particular, we will focus on improving graph convolutional networks by exploiting (self-)attention, and set prediction if time allows.

Presenter

Adriana Romero, Facebook AI Research Montreal, Quebec
Canada

Inductive biases in recurrent neural networks: lessons from computational neuroscience

Networks of neurons —either biological or artificial— are called recurrent if their connections are distributed and contain feedback loops. Such networks can perform remarkably complex computations on temporally structured inputs, as evidenced by their ubiquity throughout the brain and ever-increasing use in machine learning. They are, however, notoriously hard to control and their dynamics are generally poorly understood, especially in the presence of external forcing. This is why training artificial recurrent networks is a difficult problem. In this lecture, I will present lessons learned from the brain and discuss how biologically-inspired inductive biases help design improved artificial networks.

Presenter

Guillaume Lajoie, Montreal Institute for Learning Algorithms Montreal, Quebec
Canada