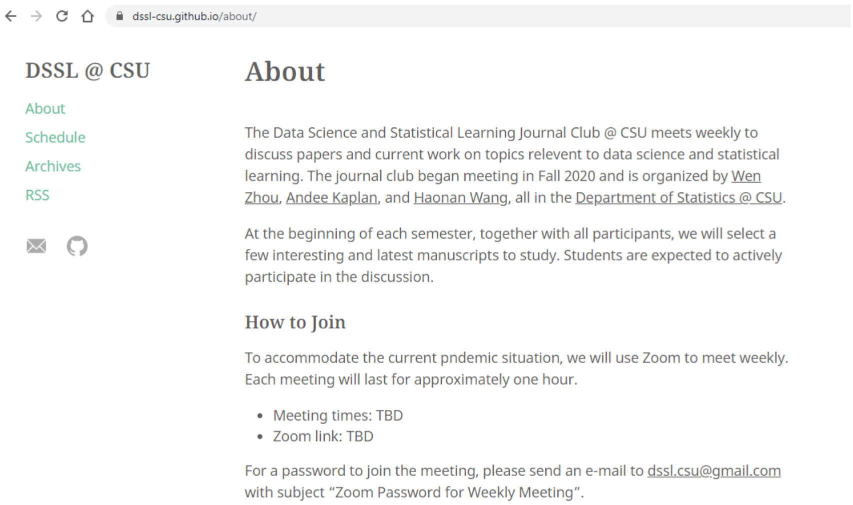
The Data Science and Statistical Learning Journal Club @ CSU: Introduction

DSSL @ CSU Team

Sep, 9th, 2020



About

The Data Science and Statistical Learning Journal Club @ CSU meets weekly to discuss papers and current work on topics relevent to data science and statistical learning. The journal club began meeting in Fall 2020 and is organized by Wen Zhou, Andee Kaplan, and Haonan Wang, all in the Department of Statistics @ CSU.

At the beginning of each semester, together with all participants, we will select a few interesting and latest manuscripts to study. Students are expected to actively participate in the discussion.

How to Join

To accommodate the current pndemic situation, we will use Zoom to meet weekly. Each meeting will last for approximately one hour.

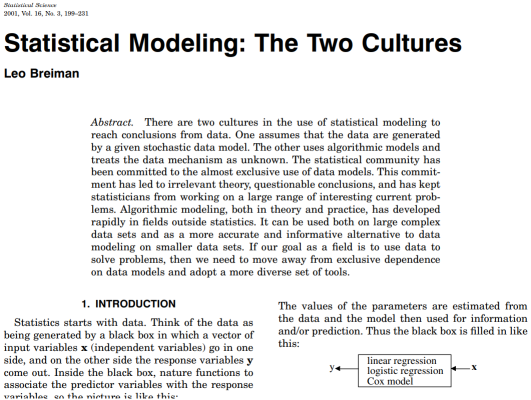
- Meeting times: TBD
- Zoom link: TBD

For a password to join the meeting, please send an e-mail to dssl.csu@gmail.com with subject “Zoom Password for Weekly Meeting”.

DSSL @ CSU

- Weekly meeting on Wednesday 4pm (MST)
- Zoom link: `https://zoom.us/j/93302592479`
- Contact email for DSSL: `dssl@stat.colostate.edu` or `dssl.csu@gmail.com`
- Papers or manuscripts from interesting topics will be picked up by the group, presented by students, and discussed
- Each paper may take 2-3 weeks for presentation and discussion
- Some meetings may have speakers from outside
- Research oriented

“One assumes that the data are generated by a given stochastic data model. The other uses algorithmic models and treats the data mechanism as unknown.”



Statistical Science
2001, Vol. 16, No. 3, 199–231

Statistical Modeling: The Two Cultures

Leo Breiman

Abstract. There are two cultures in the use of statistical modeling to reach conclusions from data. One assumes that the data are generated by a given stochastic data model. The other uses algorithmic models and treats the data mechanism as unknown. The statistical community has been committed to the almost exclusive use of data models. This commitment has led to irrelevant theory, questionable conclusions, and has kept statisticians from working on a large range of interesting current problems. Algorithmic modeling, both in theory and practice, has developed rapidly in fields outside statistics. It can be used both on large complex data sets and as a more accurate and informative alternative to data modeling on smaller data sets. If our goal as a field is to use data to solve problems, then we need to move away from exclusive dependence on data models and adopt a more diverse set of tools.

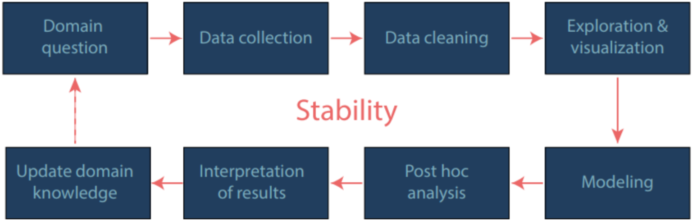
1. INTRODUCTION

Statistics starts with data. Think of the data as being generated by a black box in which a vector of input variables $\mathbf{x}$ (independent variables) go in one side, and on the other side the response variables $\mathbf{y}$ come out. Inside the black box, nature functions to associate the predictor variables with the response variables, so the picture is like this:

The values of the parameters are estimated from the data and the model then used for information and/or prediction. Thus the black box is filled in like this:

y ← linear regression / logistic regression / Cox model ← x

“Three core principles, predictability, computability, and stability (PCS), provide the foundation for such a data driven language and a unified data analysis framework. They serve as minimum requirements for veridical data science.”

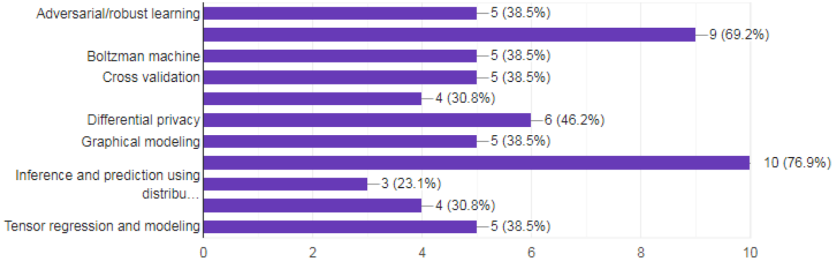


– Prof. B. Yu, PNAS, 2020

Some Topics

- Adversarial/robust learning
- Bayesian network and causal inference
- Boltzman machine
- Cross validation
- Conformal prediction (and/or knock off)
- Differential privacy
- Graphical modeling
- Statistical understanding on neural networks: AMP, double descent, mean field, RF model
- Inference and prediction using distributed optimization
- Topic learning and mining
- Tensor regression and modeling

13 responses



Adversarial/robust learning

Theoretically Principled Trade-off between Robustness and Accuracy

Hongyang Zhang* CMU & TTIC hongyanz@cs.cmu.edu
Yaodong Yu† University of Virginia yy8ms@virginia.edu
Jiantao Jiao UC Berkeley jiantao@eecs.berkeley.edu
Eric P. Xing CMU & Petuum Inc. epxing@cs.cmu.edu
Laurent El Ghaoui UC Berkeley elghaoui@berkeley.edu
Michael I. Jordan UC Berkeley jordan@cs.berkeley.edu

Abstract

We identify a trade-off between robustness and accuracy that serves as a guiding principle in the design of defenses against adversarial examples. Although this problem has been widely studied empirically, much remains unknown concerning the theory underlying this trade-off. In this work, we decompose the prediction error for adversarial examples (robust error) as the sum of the natural (classification) error and boundary error, and provide a differentiable upper bound using the theory of classification-calibrated loss, which is shown to be the tightest possible upper bound uniform over all probability distributions and measurable predictors. Inspired by our theoretical analysis, we also design a new defense method, TRADES, to trade adversarial robustness off against accuracy. Our proposed algorithm performs well experimentally in ' datasets. The methodology is the foundation of our entry to the NeurIPS 2018 Adversarial Vision which we won the 1st place out of ~2,000 submissions, surpassing the runner-up approach by erms of mean ℓ_2 perturbation distance.

ntroduction

sponse to the vulnerability of deep neural networks to small perturbations around input data [SZS+13], rial defenses have been an imperative object of study in machine learning [HPG+17], computer N+18, XWZ+17, MC17], natural language processing [JL17], and many other domains. In machine y of adversarial defenses has led to significant advances in understanding and defending against eat [HWC+17]. In computer vision and natural language processing, adversarial defenses pensable building blocks for a range of security-critical systems and applications, such as ars and speech recognition authorization. The problem of adversarial defenses can be stated as g a classifier with high test accuracy on both natural and *adversarial examples*. The adversarial given labeled data $(\boldsymbol{x}, y)$ is a data point $\boldsymbol{x}'$ that causes a classifier c to output a different label

i] 24 Jun 2019

Certifying Some Distributional Robustness
with Principled Adversarial Training

Aman Sinha*[1] Hongseok Namkoong*[2] Riccardo Volpi[3] John Duchi[1,4]

Departments of [1]Electrical Engineering, [2]Management Science & Engineering,
[3]Pattern Analysis & Computer Vision, and [4]Statistics
[1,2,4]Stanford University, [3]Istituto Italiano di Tecnologia

{amans,hnamk,jduchi}@stanford.edu, riccardo.volpi@iit.it

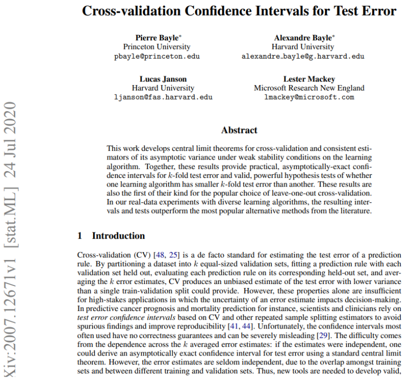
Abstract

Neural networks are vulnerable to adversarial examples and researchers have proposed many heuristic attack and defense mechanisms. We address this problem through the principled lens of distributionally robust optimization, which guarantees performance under adversarial input perturbations. By considering a Lagrangian penalty formulation of perturbing the underlying data distribution in a Wasserstein ball, we provide a training procedure that augments model parameter updates with worst-case perturbations of training data. For smooth losses, our procedure provably achieves moderate levels of robustness with little computational or statistical cost relative to empirical risk minimization. Furthermore, our statistical guarantees allow us to efficiently certify robustness for the population loss. For imperceptible perturbations, our method matches or outperforms heuristic approaches.

1 Introduction

Consider the classical stochastic optimization problem, in which we minimize an expected loss $\mathbb{E}_{P_0}[\ell(\theta; Z)]$ over a parameter $\theta \in \Theta$, where $Z \sim P_0$, P_0 is a distribution on a space $\mathcal{Z}$, and ℓ is a loss function. In many systems, robustness to changes in the data-generating distribution P_0 is desirable, whether they be from covariate shifts, changes in the underlying domain [3], or adversarial attacks [28, 38]. As deep networks become prevalent in modern performance-critical systems—prominent examples include perception systems for self-driving cars, and automated detection of

Cross validation



Xiv:2007.12671v1 [stat.ML] 24 Jul 2020

Cross-validation Confidence Intervals for Test Error

Pierre Bayle[*]
Princeton University
pbayle@princeton.edu

Alexandre Bayle[*]
Harvard University
alexandre_bayle@g.harvard.edu

Lucas Janson
Harvard University
ljanson@fas.harvard.edu

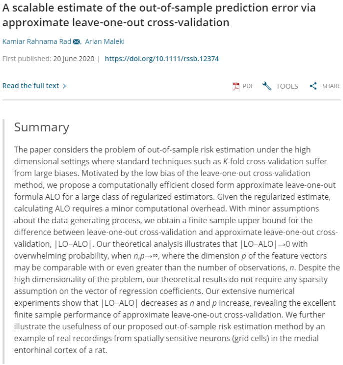
Lester Mackey
Microsoft Research New England
lmackey@microsoft.com

Abstract

This work develops central limit theorems for cross-validation and consistent estimators of its asymptotic variance under weak stability conditions on the learning algorithm. Together, these results provide practical, asymptotically-exact confidence intervals for k-fold test error and valid, powerful hypothesis tests of whether one learning algorithm has smaller k-fold test error than another. These results are also the first of their kind for the popular choice of leave-one-out cross-validation. In our real-data experiments with diverse learning algorithms, the resulting intervals and tests outperform the most popular alternative methods from the literature.

1 Introduction

Cross-validation (CV) [48, 25] is a de facto standard for estimating the test error of a prediction rule. By partitioning a dataset into k equal-sized validation sets, fitting a prediction rule with each validation set held out, evaluating each prediction rule on its corresponding held-out set, and averaging the k error estimates, CV produces an unbiased estimate of the test error with lower variance than a single train-validation split could provide. However, these properties alone are insufficient for high-stakes applications in which the uncertainty of an error estimate impacts decision-making. In predictive cancer prognosis and mortality prediction for instance, scientists and clinicians rely on *test error confidence intervals* based on CV and other repeated sample splitting estimators to avoid spurious findings and improve reproducibility [41, 44]. Unfortunately, the confidence intervals most often used have no correctness guarantees and can be severely misleading [29]. The difficulty comes from the dependence across the k averaged error estimates: if the estimates were independent, one could derive an asymptotically exact confidence interval for test error using a standard central limit theorem. However, the error estimates are seldom independent, due to the overlap amongst training sets and between different training and validation sets. Thus, new tools are needed to develop valid,



A scalable estimate of the out-of-sample prediction error via approximate leave-one-out cross-validation

Kamiar Rahnama Rad ✉, Arian Maleki

First published: 20 June 2020 | https://doi.org/10.1111/rssb.12374

Summary

The paper considers the problem of out-of-sample risk estimation under the high dimensional settings where standard techniques such as K-fold cross-validation suffer from large biases. Motivated by the low bias of the leave-one-out cross-validation method, we propose a computationally efficient closed form approximate leave-one-out formula ALO for a large class of regularized estimators. Given the regularized estimate, calculating ALO requires a minor computational overhead. With minor assumptions about the data-generating process, we obtain a finite sample upper bound for the difference between leave-one-out cross-validation and approximate leave-one-out cross-validation, |LO−ALO|. Our theoretical analysis illustrates that |LO−ALO|→0 with overwhelming probability, when $n,p\to\infty$, where the dimension p of the feature vectors may be comparable with or even greater than the number of observations, n. Despite the high dimensionality of the problem, our theoretical results do not require any sparsity assumption on the vector of regression coefficients. Our extensive numerical experiments show that |LO−ALO| decreases as n and p increase, revealing the excellent finite sample performance of approximate leave-one-out cross-validation. We further illustrate the usefulness of our proposed out-of-sample risk estimation method by an example of real recordings from spatially sensitive neurons (grid cells) in the medial entorhinal cortex of a rat.

Conformal prediction

Journal

Journal of the American Statistical Association ›

Volume 113, 2018 - Issue 523

Enter keywords, authors, DOI,

3,409

Views

25

CrossRef citations to date

12

Altmetric

Theory and Methods

Distribution-Free Predictive Inference for Regression

Jing Lei, Max G'Sell, Alessandro Rinaldo, Ryan J. Tibshirani & Larry Wasserman

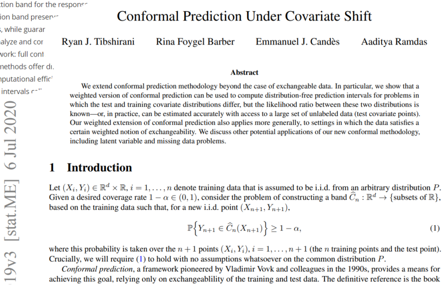
Pages 1094-1111 | Received 21 Apr 2016, Accepted author version posted online: 03 Apr 2017, Published online: 08 Jun 2018

Download citation https://doi.org/10.1080/01621459.2017.1307116 Check for updates

Full Article | Figures & data | References | Supplemental | Citations | Metrics | Reprints & Permissions

ABSTRACT

We develop a general framework for distribution-free predictive inference in regression, using conformal inference. The proposed methodology allows for the construction of a prediction band for the respons variable using any estimator of the regression function. The resulting prediction band preser consistency properties of the original estimator under standard assumptions, while guarar sample marginal coverage even when these assumptions do not hold. We analyze and cor empirically and theoretically, the two major variants of our conformal framework: full cont and split conformal inference, along with a related jackknife method. These methods offer di between statistical accuracy (length of resulting prediction intervals) and computational effic extensions, we develop a method for constructing valid in-sample prediction intervals c conformal inference, which has essentially the same computational efficier We also describe an extension of our procedures for producing prediction to adapt to heteroscedasticity in the data. Finally, we propose a model-fre



19v3 [stat.ME] 6 Jul 2020

Conformal Prediction Under Covariate Shift

Ryan J. Tibshirani Rina Foygel Barber Emmanuel J. Candès Aaditya Ramdas

Abstract

We extend conformal prediction methodology beyond the case of exchangeable data. In particular, we show that a weighted version of conformal prediction can be used to compute distribution-free prediction intervals for problems in which the test and training covariate distributions differ, but the likelihood ratio between these two distributions is known—or, in practice, can be estimated accurately with access to a large set of unlabeled data (test covariate points). Our weighted extension of conformal prediction also applies more generally, to settings in which the data satisfies a certain weighted notion of exchangeability. We discuss other potential applications of our new conformal methodology, including latent variable and missing data problems.

1 Introduction

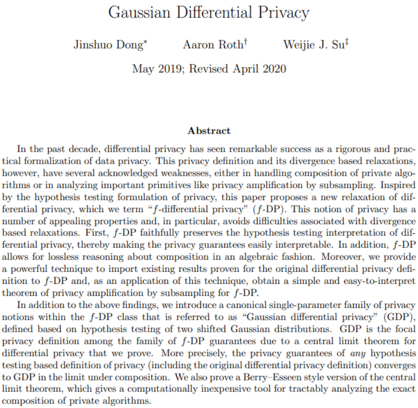
Let $(X_i, Y_i) \in \mathbb{R}^d \times \mathbb{R}$, $i = 1, \dots, n$ denote training data that is assumed to be i.i.d. from an arbitrary distribution P. Given a desired coverage rate $1 - \alpha \in (0, 1)$, consider the problem of constructing a band $\widehat{C}_n : \mathbb{R}^d \to \{\text{subsets of } \mathbb{R}\}$, based on the training data such that, for a new i.i.d. point (X_{n+1}, Y_{n+1}),

$$\mathbb{P}\Big\{Y_{n+1} \in \widehat{C}_n(X_{n+1})\Big\} \geq 1 - \alpha, \qquad (1)$$

where this probability is taken over the $n + 1$ points (X_i, Y_i), $i = 1, \dots, n + 1$ (the n training points and the test point). Crucially, we will require (1) to hold with no assumptions whatsoever on the common distribution P.

Conformal prediction, a framework pioneered by Vladimir Vovk and colleagues in the 1990s, provides a means for achieving this goal, relying only on exchangeablity of the training and test data. The definitive reference is the book

Differential privacy



Gaussian Differential Privacy

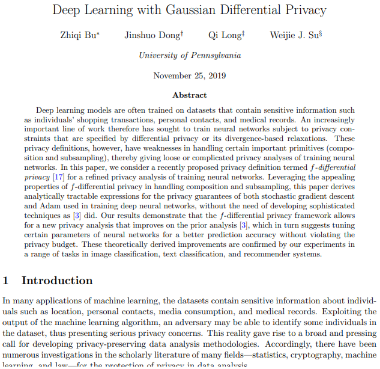
Jinshuo Dong[*] Aaron Roth[†] Weijie J. Su[‡]

May 2019; Revised April 2020

Abstract

In the past decade, differential privacy has seen remarkable success as a rigorous and practical formalization of data privacy. This privacy definition and its divergence based relaxations, however, have several acknowledged weaknesses, either in handling composition of private algorithms or in analyzing important primitives like privacy amplification by subsampling. Inspired by the hypothesis testing formulation of privacy, this paper proposes a new relaxation of differential privacy, which we term "f-differential privacy" (f-DP). This notion of privacy has a number of appealing properties and, in particular, avoids difficulties associated with divergence based relaxations. First, f-DP faithfully preserves the hypothesis testing interpretation of differential privacy, thereby making the privacy guarantees easily interpretable. In addition, f-DP allows for lossless reasoning about composition in an algebraic fashion. Moreover, we provide a powerful technique to import existing results proven for the original differential privacy definition to f-DP and, as an application of this technique, obtain a simple and easy-to-interpret theorem of privacy amplification by subsampling for f-DP.

In addition to the above findings, we introduce a canonical single-parameter family of privacy notions within the f-DP class that is referred to as "Gaussian differential privacy" (GDP), defined based on hypothesis testing of two shifted Gaussian distributions. GDP is the focal privacy definition among the family of f-DP guarantees due to a central limit theorem for differential privacy that we prove. More precisely, the privacy guarantees of *any* hypothesis testing based definition of privacy (including the original differential privacy definition) converges to GDP in the limit under composition. We also prove a Berry–Esseen style version of the central limit theorem, which gives a computationally inexpensive tool for tractably analyzing the exact composition of private algorithms.



Deep Learning with Gaussian Differential Privacy

Zhiqi Bu[*] Jinshuo Dong[†] Qi Long[‡] Weijie J. Su[§]

University of Pennsylvania

November 25, 2019

Abstract

Deep learning models are often trained on datasets that contain sensitive information such as individuals' shopping transactions, personal contacts, and medical records. An increasingly important line of work therefore has sought to train neural networks subject to privacy constraints that are specified by differential privacy or its divergence-based relaxations. These privacy definitions, however, have weaknesses in handling certain important primitives (composition and subsampling), thereby giving loose or complicated privacy analyses of training neural networks. In this paper, we consider a recently proposed privacy definition termed *f-differential privacy* [17] for a refined privacy analysis of training neural networks. Leveraging the appealing properties of f-differential privacy in handling composition and subsampling, this paper derives analytically tractable expressions for the privacy guarantees of both stochastic gradient descent and Adam used in training deep neural networks, without the need of developing sophisticated techniques as [3] did. Our results demonstrate that the f-differential privacy framework allows for a new privacy analysis that improves on the prior analysis [3], which in turn suggests tuning certain parameters of neural networks for a better prediction accuracy without violating the privacy budget. These theoretically derived improvements are confirmed by our experiments in a range of tasks in image classification, text classification, and recommender systems.

1 Introduction

In many applications of machine learning, the datasets contain sensitive information about individuals such as location, personal contacts, media consumption, and medical records. Exploiting the output of the machine learning algorithm, an adversary may be able to identify some individuals in the dataset, thus presenting serious privacy concerns. This reality gave rise to a broad and pressing call for developing privacy-preserving data analysis methodologies. Accordingly, there have been numerous investigations in the scholarly literature of many fields—statistics, cryptography, machine learning, and law—for the protection of privacy in data analysis

Statistical understanding on neural networks

RESEARCH ARTICLE

A mean field view of the landscape of two-layer neural networks

Song Mei, Andrea Montanari, and Phan-Minh Nguyen

PNAS August 14, 2018 115 (33) E7665-E7671; first published July 27, 2018 https://doi.org/10.1073/pnas.1806579115

Edited by Peter J. Bickel, University of California, Berkeley, CA, and approved June 21, 2018 (received for review April 16, 2018)

Article | Figures & SI | Info & Metrics | PDF

Significance

Multilayer neural networks have proven extremely succ
image classification to robotics. However, the reasons f
precise domain of applicability are unknown. Learning a
solving a complex optimization problem with millions of
stochastic gradient descent (SGD) algorithms. We study
and derive a compact description of the
differential equation. Among other c
become more complex when the

08.05355v3 [math.ST] 22 Oct 2019

The generalization error of random features regression: Precise asymptotics and double descent curve

Song Mei* and Andrea Montanari†

October 23, 2019

Abstract

Deep learning methods operate in regimes that defy the traditional statistical mindset. Neural
work architectures often contain more parameters than training samples, and are so rich that they
interpolate the observed labels, even if the latter are replaced by pure noise. Despite their huge co
plexity, the same architectures achieve small generalization error on real data.

This phenomenon has been rationalized in terms of a so-called 'double descent' curve. As the mo
complexity increases, the test error follows the usual U-shaped curve at the beginning, first decrea
and then peaking around the interpolation threshold (when the model achieves vanishing training err
However, it descends again as model complexity exceeds this threshold. The global minimum of
test error is found above the interpolation threshold, often in the extreme overparametrization regim
which the number of parameters is much larger than the number of samples. Far from being a pecu
property of deep neural networks, elements of this behavior have been demonstrated in much simpler settings, including linear regression with random covariates.

In this paper we consider the problem of learning an unknown function over the d-dimensional sphere $\mathbb{S}^{d-1}$, from n i.i.d. samples $(\boldsymbol{x}_i, y_i) \in \mathbb{S}^{d-1} \times \mathbb{R}$, $i \le n$. We perform ridge regression on N random features of the form $\sigma(\boldsymbol{w}_a^{\mathsf{T}}\boldsymbol{x})$, $a \le N$. This can be equivalently described as a two-layers neural network with random first-layer weights. We compute the precise asymptotics of the test error, in the limit $N, n, d \to \infty$ with N/d and n/d fixed. This provides the first analytically tractable model that captures all the features of the double descent phenomenon without assuming ad hoc misspecification structures. In particular, above a critical value of the signal-to-noise ratio, minimum test error is achieved by extremely overparametrized interpolators, i.e., networks that have a number of parameters much larger than the sample size, and vanishing training error.

.ML] 19 Feb 2020

Implicit Regularization of Random Feature Models

Arthur Jacot*[1] Berfin Şimşek*[1 2] Francesco Spadaro[1] Clément Hongler[1] Franck Gabriel[1]

Abstract

Random Feature (RF) models are used as efficient parametric approximations of kernel methods. We investigate, by means of random matrix theory, the connection between Gaussian RF models and Kernel Ridge Regression (KRR). For a Gaussian RF model with P features, N data points, and a ridge λ, we show that the average (i.e. expected) RF predictor is close to a KRR predictor with an *effective ridge* $\tilde{\lambda}$. We show that $\tilde{\lambda} > \lambda$ and $\tilde{\lambda} \searrow \lambda$ monotonically as P grows, thus revealing the *implicit regularization effect* of finite RF sampling. We then compare the risk (i.e. test error) of the $\tilde{\lambda}$-KRR predictor with the average risk of the λ-RF predictor and obtain a precise and explicit bound

due to the random initialization of the parameters an
to the stochasticity of the training algorithm; for ran
forests, to the random branching; for random feature mo
to the sampling of random features. The somehow sur
ing generalization behavior of these models has rece
been the subject of increasing attention. In general, the
(i.e. test error) is a random variable with two sources of
domness: the usual one due to the sampling of the trai
set, and the second one due to the randomness of the m
itself.

We consider the Random Feature (RF) model (Rahin
Recht, 2008) with features sampled from a Gaussian Pro
(GP) and study the RF predictor $\hat{f}$ minimizing the reg
ized least squares error, isolating the randomness of
model by considering fixed training data points. RF r

Boltzmann machines

COGNITIVE SCIENCE 9, 147-169 (1985)

A Learning Algorithm for Boltzmann Machines*

DAVID H. ACKLEY
GEOFFREY E. HINTON
Computer Science Department
Carnegie-Mellon University
TERRENCE J. SEJNOWSKI
Biophysics Department
The Johns Hopkins University

The computational power of massively parallel networks of simple processing elements resides in the communication bandwidth provided by the hardware connections between elements. These connections can allow a significant fraction of the knowledge of the system to be applied to an instance of a problem in a very short time. One kind of computation for which massively parallel
networks appear to be well suited is large constraint s
but to use the connections efficiently two conditions r
search technique that is suitable for parallel networks m
there must be some way of choosing internal representa
preexisting hardware connections to be used efficiently
straints in the domain being searched. We describe a ge
method, based on statistical mechanics, and we show h
eral learning rule for modifying the connection strength
knowledge about a task domain in an efficient way. We
examples in which the learning algorithm creates inte
that are demonstrably the most efficient way of using th
tivity structure.

1. INTRODUCTION

Evidence about the architecture of the brain and th
VLSI technology have led to a resurgence of interest

* The research reported here was supported by grants fr
Foundation. We thank Peter Brown, Francis Crick, Mark Der
Feldman, Stuart Geman, Gail Gong, John Hopfield, Jay McC
Harry Printz, Dave Rumelhart, Tim Shallice, Paul Smolensky, F
man Venkatasubramanian for helpful discussions.
Reprint requests should be addressed to David Ackley, Co
Carnegie-Mellon University, Pittsburgh, PA 15213.

ARTICLE Communicated by Guido Montufar

An Infinite Restricted Boltzmann Machine

Marc-Alexandre Côté
marc-alexandre.cote@usherbrooke.ca
Hugo Larochelle
hugo.larochelle@usherbrooke.ca
Department of Computer Science, Université de Sherbrooke,
Sherbrooke, QC J1K 2R1, Canada

We present a mathematical construction for the restricted Boltzmann machine (RBM) that does not require specifying the number of hidden units. In fact, the hidden layer size is adaptive and can grow during training. This is obtained by first extending the RBM to be sensitive to the ordering
of its hidden units. Then, with a carefully chosen definition of the energy
nfinitely many hidden units is well
naximum likelihood training can be
that naturally and adaptively adds
. We empirically study the behavior
performance is competitive to that
tuning of a hidden layer size.

Cogn Comput (2016) 8:1064–1073
DOI 10.1007/s12559-016-9429-1

CrossMark

Weight Uncertainty in Boltzmann Machine

Jian Zhang[1,2] · Shifei Ding[1,2] · Nan Zhang[1,2] · Yu Xue[3]

Received: 14 November 2015 / Accepted: 19 August 2016 / Published online: 31 August 2016

Abstract
Background Based on restricted Boltzmann machine (RBM), the deep learning models can be roughly divided into deep belief networks (DBNs) and deep Boltzmann machine (DBM). However, the overfitting problems commonly exist in neural networks and RBM models. In order to alleviate the overfitting problem, lots of research has been done. This paper alleviated the overfitting problem in RBM and proposed the weight uncertainty semi-restricted Boltzmann machine (WSRBM) to improve the ability of image recognition and image reconstruction.
Methods First, this paper built weight uncertainty RBM model based on maximum likelihood estimation. And in the experimental section, this paper verified the effectiveness of the weight uncertainty deep belief network and the weight uncertainty deep Boltzmann machine. Second, in order to obtain better reconstructed images, this paper used the semi-restricted Boltzmann machine (SRBM) as the feature extractor and built the WSRBM. Lastly, this paper

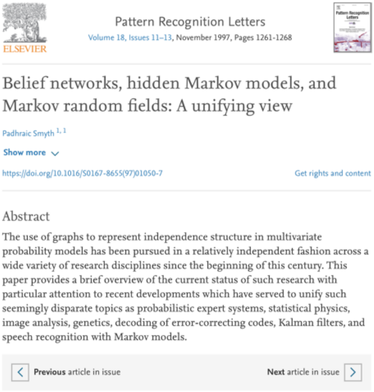
uncertainty DBM were effective compared with the dropout method. And the WSDBM model performed well in image recognition and image reconstruction as well.
Conclusions This paper introduced the weight uncertainty method to RBM, and proposed a WSDBM model, which was effective in image recognition and image reconstruction.

Keywords RBM · DBM · DBN · Weight uncertainty

Introduction

In the viewpoint of supervised learning, deep neural networks can be regarded as multilayer perceptrons. The position that the network converged in the error curved surface depended on the initialized weights. However, the error curved surface of the multilayer perceptron is complex. And the network may converge to different local

Bayesian networks



Pattern Recognition Letters

Volume 18, Issues 11–13, November 1997, Pages 1261-1268

Belief networks, hidden Markov models, and Markov random fields: A unifying view

Padhraic Smyth [1, 1]

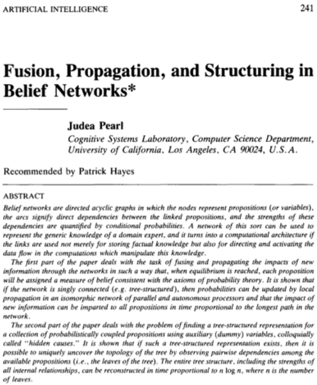
Show more

https://doi.org/10.1016/S0167-8655(97)01050-7

Get rights and content

Abstract

The use of graphs to represent independence structure in multivariate probability models has been pursued in a relatively independent fashion across a wide variety of research disciplines since the beginning of this century. This paper provides a brief overview of the current status of such research with particular attention to recent developments which have served to unify such seemingly disparate topics as probabilistic expert systems, statistical physics, image analysis, genetics, decoding of error-correcting codes, Kalman filters, and speech recognition with Markov models.



ARTIFICIAL INTELLIGENCE 241

Fusion, Propagation, and Structuring in Belief Networks*

Judea Pearl

Cognitive Systems Laboratory, Computer Science Department, University of California, Los Angeles, CA 90024, U.S.A.

Recommended by Patrick Hayes

ABSTRACT

Belief networks are directed acyclic graphs in which the nodes represent propositions (or variables), the arcs signify direct dependencies between the linked propositions, and the strengths of these dependencies are quantified by conditional probabilities. A network of this sort can be used to represent the generic knowledge of a domain expert, and it turns into a computational architecture if the links are used not merely for storing factual knowledge but also for directing and activating the data flow in the computations which manipulate this knowledge.

The first part of the paper deals with the task of fusing and propagating the impacts of new information through the networks in such a way that, when equilibrium is reached, each proposition will be assigned a measure of belief consistent with the axioms of probability theory. It is shown that if the network is singly connected (e.g. tree-structured), then probabilities can be updated by local propagation in an isomorphic network of parallel and autonomous processors and that the impact of new information can be imparted to all propositions in time proportional to the longest path in the network.

The second part of the paper deals with the problem of finding a tree-structured representation for a collection of probabilistically coupled propositions using auxiliary (dummy) variables, colloquially called "hidden causes." It is shown that if such a tree-structured representation exists, then it is possible to uniquely uncover the topology of the tree by observing pairwise dependencies among the available propositions (i.e., the leaves of the tree). The entire tree structure, including the strengths of all internal relationships, can be reconstructed in time proportional to n log n, where n is the number of leaves.

To-Do

- Pick up your topics
- Pick up/select your paper to be presented
- Make our presenting schedule
- “Scribed notes” or slides?
- Your Comments?