A Random Matrix Framework For Bigdata Machine Learning And

Intro 19107af510 (relative) Newton method 19107af510 Landing a job at Microsoft Research: Two Fields Medalists are all you need 19107af510 Subtitles and closed captions 19107af510 abc parametrizations (Note: \"a\" is absorbed into \"c\" here): variance and learning rate scalings 19107af510 Technical intro: The Big Picture 19107af510 Whiteboard outline 19107af510 Experiments on real data 19107af510 Law of Large Numbers 19107af510 The non trivial regime 19107af510 Spike models 19107af510 Convolutional sparse coding 19107af510 Takeover message 19107af510 Keyboard shortcuts 19107af510 Concentration Phenomena 19107af510 Wigner's Semicircle Law 19107af510 Randomize 19107af510 Maximum Likelihood Formulation 19107af510 Moment method explicit computations 19107af510 Many large N limits for neural networks 19107af510 Random Matrix Methods for Machine Learning: \"Lossless\" Compression of Large and Deep Neural Networks - Random Matrix Methods for Machine Learning: \"Lossless\" Compression of Large and Deep Neural Networks 1 hour, 34 minutes - Seminar given by Prof. Zhenyu Liao from Huazhong University of Science and Technology (HUST). 19107af510 Random Matrix Advances in Machine Learning - Couillet - Workshop 3 - CEB T1 2019 - Random Matrix Advances in Machine Learning - Couillet - Workshop 3 - CEB T1 2019 45 minutes - Romain Couillet (Université de Grenoble) / 01.04.2019 **Random Matrix**, Advances in **Machine Learning**,. **Machine learning**, ... 19107af510 Geometry of the problem 19107af510 Setup 19107af510 Universality 19107af510 Linear ICA model 19107af510 Machine Learning 19107af510 Statistical Principles of ICA 19107af510 Wrap up 19107af510 (No) feature learning 19107af510 Moment method for RMT 19107af510 Geometric Interpretation of the Covariance Matrix | Unsupervised Learning for Big Data - Geometric Interpretation of the Covariance Matrix | Unsupervised Learning for Big Data 4 minutes, 19 seconds - This is a part of a series of lectures from the Yale class \"Unsupervised **Learning**, for **Big Data**,\", taught by Professor Smita ... 19107af510 Neural network Gaussian Process 19107af510 Correlation traps 19107af510 Biography 19107af510 Universality 19107af510 The matrix theory 19107af510 What are Random Matrices? 19107af510 Corollary: Reproof of RMT results 19107af510 Geometry of space of abc parametrizations 19107af510 TP punchline for RMT 19107af510 Mohamed El Amine Seddik - Random Matrix Theory for Big-Data and Machine Learning - Mohamed El Amine Seddik - Random Matrix Theory for Big-Data and Machine Learning 34 minutes - Talk at **Machine Learning**, Landscape - a workshop at the interface of string theory, **machine learning**, and energy landscapes ... 19107af510 Random Matrix Theory 19107af510 Greg Yang | Large N Limits: Random Matrices \u0026 Neural Networks | The Cartesian Cafe w/ Timothy Nguyen - Greg Yang | Large N Limits: Random Matrices \u0026 Neural Networks | The Cartesian Cafe w/ Timothy Nguyen 3 hours, 1 minute - Greg Yang is a mathematician and AI researcher at Microsoft Research who for the past several years has done incredibly ... 19107af510 Hessian approximations (cont.) 19107af510 Welcome 19107af510 Speed benchmarks 19107af510 Why signal representations? 19107af510 Introduction 19107af510 Supervised Learning 19107af510 Hyperparameter transfer (muP) 19107af510 Motivations 19107af510 Search filters 19107af510 How Large is the Norm of a Random Matrix? - How Large is the Norm of a Random Matrix? 23 minutes - Ramon van Handel, Princeton University Information Theory, **Learning**, and **Big Data**, ... 19107af510 Eigenvalues 19107af510 Linear algebra for data science, chapter 6 exercise 5 (random matrix with arbitrary rank) - Linear algebra for data science, chapter 6 exercise 5 (random matrix with arbitrary rank) 4 minutes, 8 seconds - The videos in this playlist are walk-throughs and explanations of exercises in the book: \"Practical Linear Algebra for **Data**, Science: ... 19107af510 Optimization strategy 19107af510 Wigner semicircle law 19107af510 Harvard hiatus 1: Becoming a DJ 19107af510 History of Random Matrices 19107af510 Kernel regime 19107af510 The Master Theorem (the key result of TP) 19107af510 ICA vs Dictionary Learning 19107af510 Can we reuse the Hessian approx. idea? 19107af510 Intro 19107af510 General definition of a tensor program 19107af510 ICA on fMRI data 19107af510 Harvard math applicants and culture 19107af510 Random Matrices: 1. Introduction - Random Matrices: 1. Introduction 1 hour, 29 minutes - The lecture notes for the course can be found at https://rolandspeicher.com/wp-content/uploads/2020/05/rm-notes-speicher-v2.pdf ... 19107af510 Electroencephalography (EEG) 19107af510 On EEG 19107af510 Correlation Flow 19107af510 Picard relies on L-BFGS algorithm 19107af510 Friendship with Shing-Tung Yau 19107af510 Romain Couillet -- Mini course: Why Random Matrices can Change the Future of Research in AI? - Romain Couillet -- Mini course: Why Random Matrices can Change the Future of Research in AI? 1 hour, 38 minutes - Abstract: **Machine learning**, and AI algorithms are becoming increasingly more powerful but also increasingly more complex, ... 19107af510 Principle Component Analysis 19107af510 Some Histograms of Eigenvalues 19107af510 Spherical Videos 19107af510 Source imaging with magnetoencephalography (MEG) 19107af510 Feed forward neural network (3 layers) example 19107af510 Gérard Ben Arous - 1/4 Random Matrices and Dynamics of Optimization in Very High Dimensions - Gérard Ben Arous - 1/4 Random Matrices and Dynamics of Optimization in Very High Dimensions 2 hours, 3 minutes - Machine learning, and **Data**, science algorithms involve in their last stage the need for optimization of complex **random**, functions in ... 19107af510 I really want to make AGI happen (back in 2012) 19107af510 Charles Martin - Self-

Regularization in Deep Neural Networks: Evidence from Random Matrix Theory - Charles Martin - Self-Regularization in Deep Neural Networks: Evidence from Random Matrix Theory 32 minutes - We present a semiempirical theory of **Deep Learning**, which explains the remarkable generalization performance of state-of-the-art ... 19107af510 ICA, EM and quadratic majorant 19107af510 Proof of CLT: Moment method 19107af510 L-BFGS algorithm with Hessian approx. 19107af510 The problem of clustering 19107af510 Multivariate CSC 19107af510 Eigenvectors 19107af510 Framework of Random Matrix Theory for Power System Data Mining in a Non Gaussian Environment - Framework of Random Matrix Theory for Power System Data Mining in a Non Gaussian Environment 40 seconds - Framework, of **Random Matrix**, Theory for Power System **Data**, Mining in a Non Gaussian Environment https://okokprojects.com/ ... 19107af510 Central Limit Theorem 19107af510 Random Matrix Theory Approach to Deep Learning Optimization and Generalization - Random Matrix Theory Approach to Deep Learning Optimization and Generalization 1 hour, 22 minutes - Slides: https://github.com/bayesgroup/bayesgroup.github.io/blob/master/bmml_sem/2022/Granziol_DNNs%20from%20Theory%20to%20SoTA ... 19107af510 Harvard hiatus 2: Math autodidact 19107af510 Maximal feature learning 19107af510 Segue using RMT 19107af510 Prof. Jon Keating | Lecture 1: A Primer in Random Matrix Theory - Prof. Jon Keating | Lecture 1: A Primer in Random Matrix Theory 57 minutes - Title: Lecture 1: A Primer in **Random Matrix**, Theory Speaker: Professor Jon Keating (University of Oxford) Date: 4th Sep 2013 ... 19107af510 Neural tangent kernel 19107af510 Eigenvalues of Random Matrices 19107af510 General 19107af510 Tensor Programs Preview 19107af510 Example using astrophysics 19107af510 Relative gradient / Hessian 19107af510 Average Alpha 19107af510 Playback 19107af510 Current problems with deep learning 19107af510 From Histograms to Moments 19107af510