Ashish Khetan

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Education

University of Illinois Urbana Champaign ,IL, U.S.A.
PhD in Operations Research - Fall 2014 Onward • Advisor: Professor Sewoong Oh • Cumulative GPA: 3.87/4.00
MS in Computer Science - Fall 2016 Onward • MS in Operations Research: Fall 2012 - Spring 2014

Selected Coursework: Machine Learning Theory · Statistical Learning Theory · Inference in Graphical Models · Algorithms for Inference · Pattern Recognition · Machine Learning · ML in NLP · Convex Optimization · Integer Programming · Linear Programming · Theory of Probability · Real Analysis · Random Processes · Information Theory · Graphs Networks & Algorithms · Advanced Probability & Statistics · Stochastic Processes & Applications

Indian Institute of Technology, Guwahati, India
Bachelor of Technology in Mechanical Eng., Fall 2005 - Spring 2009 • Cumulative GPA: 9.21/10.00 • Rank 1/47 (Silver Medalist)

Internship

Amazon AI - Palo Alto, Summer 2017
Worked under the supervision of Professor Animashree Anandkumar on "Learning from Noisy Labels: Bootstrapping EM". Designed a theoretically provable novel loss function to be used for deep learning when the observed labels are noisy. Empirically verified the approach on large computer vision datasets CIFAR and ImageNet. To be submitted at ICLR 2017.

Publications

Spectrum Estimation from a Few Entries - NIPS 2017 Spotlight (top 3%)
A novel algorithm is given to estimate matrix Schatten norms and thereby estimate singular values of a low rank matrix with missing entries. The algorithm outperforms classical matrix completion algorithms when the number of entries sampled is below the threshold. A minimax lower bound is given that matches with the sample complexity of the proposed algorithm.

Computational and Statistical Tradeoffs in Learning to Rank - NIPS 2016, JMLR
In the application of learning to rank, this work provides a hierarchy of rank-breaking mechanisms ordered by the complexity in the observed data. Theoretical guarantees characterize tradeoff between computational complexity and number of data points needed to achieve a fixed accuracy. It can easily be applied on large scale heterogeneous data.

Achieving Budget-optimality with Adaptive Schemes in Crowdsourcing - NIPS 2016, OR
This work quantifies the gain of adaptive task allocation schemes in crowdsourcing by comparing the tradeoff with the one for non-adaptive schemes. Further, it gives a novel adaptive scheme that matches this fundamental limit.

Data-driven Rank Breaking for Efficient Rank Aggregation - ICML 2016, JMLR 2016
This work gives the optimal (provably) pairwise rank-breaking estimator and characterizes tradeoff between accuracy and complexity under Plackett-Luce model. It is easy to implement using Minorization-Maximization algorithm.

Markov Chain Choice Model from Pairwise Comparisons - Submitted to IEEE Transactions
This work proposes a new approach for learning the Markov chain choice models that only uses pairwise comparisons. Approximation guarantees for mixed multinomial logit model are given for the proposed learning approach.

Working papers

Estimating the Number of Connected Components in a Graph via Subgraph Sampling
A novel algorithm is given to estimate rank of a partially observed graph Laplacian matrix. The algorithm estimates Schatten norms of the Laplacian and exploits approximating a step function with a Chebyshev polynomial to estimate the rank. Theoretical guarantees show that the estimator is minimax optimal.

Temporal Matrix Completion
An alternating minimization algorithm is given to recover all components of a time varying low rank matrix when only a few entries of the matrix are revealed at each time step. Theoretical guarantees show that the number of observed entries across time steps need to be of the order same as when all the entries are revealed at the same time.

Tensor Factorization with Missing Entries
A novel algorithm along is given to recover true singular vectors of a CP decomposable tensor while only a few entries of the tensor are observed. Starting with an initial estimate of singular vectors, alternating minimization is performed to recover the true singular vectors with high probability. Sample complexity for recovering the true tensor is given.

Programming Skills

Python, MATLAB, C++

Work History

iRunway Inc. (Research Associate, Bangalore/Austin, Nov. 2009-July 2012)