	doc_1	doc_2	decision	id
cases			DUPLICATES	321

doc_1

authors	• Dennis Forster • JÃ¶rg LÃ¼cke
title	Truncated Variational EM for Semi-Supervised Neural Simpletrons
publication_date	2017-02-07 13:16:05+00:00
source	SupportedSources.ARXIV
journal	None
volume	
doi	
urls	• http://arxiv.org/pdf/1702.01997v1 • http://arxiv.org/abs/1702.01997v1 • http://arxiv.org/pdf/1702.01997v1
id	id-2398243997809190053
abstract	Inference and learning for probabilistic generative networks is often very challenging and typically prevents scalability to as large networks as used for deep discriminative approaches. To obtain efficiently trainable, large-scale and well performing generative networks for semi-supervised learning, we here combine two recent developments: a neural network reformulation of hierarchical Poisson mixtures (Neural Simpletrons), and a novel truncated variational EM approach (TV-EM). TV-EM provides theoretical guarantees for learning in generative networks, and its application to Neural Simpletrons results in particularly compact, yet approximately optimal, modifications of learning equations. If applied to standard benchmarks, we empirically find, that learning converges in fewer EM iterations, that the complexity per EM iteration is reduced, and that final likelihood values are higher on average. For the task of classification on data sets with few labels, learning improvements result in consistently lower error rates if compared to applications without truncation. Experiments on the MNIST data set herein allow for comparison to standard and state-of-the-art models in the semi-supervised setting. Further experiments on the NIST SD19 data set show the scalability of the approach when a manifold of additional unlabeled data is available.
versions	

doc_2

authors	• D. Forster • JÃ¶rg LÃ¼cke
title	Truncated variational EM for semi-supervised neural simpletrons
publication_date	2017-02-07 00:00:00
source	SupportedSources.SEMANTIC_SCHOLAR
journal	
volume	
doi	10.1109/IJCNN.2017.7966331
urls	• https://www.semanticscholar.org/paper/664fca9d9a310a4150128c3f2345a18f8fcce804
id	id-6019090030384174748
abstract	Inference and learning for probabilistic generative networks is often very challenging and typically prevents scalability to as large networks as used for deep discriminative approaches. To obtain efficiently trainable, large-scale and well performing generative networks for semi-supervised learning, we here combine two recent developments: a neural network reformulation of hierarchical Poisson mixtures (Neural Simpletrons), and a novel truncated variational EM approach (TV-EM). TV-EM provides theoretical guarantees for learning in generative networks, and its application to Neural Simpletrons results in particularly compact, yet approximately optimal, modifications of learning equations. If applied to standard benchmarks, we empirically find: that learning converges in fewer EM iterations, that the complexity per EM iteration is reduced, and that final likelihood values are higher on average. For the task of classification on data sets with few labels, learning improvements result in consistently lower error rates if compared to applications without truncation. Experiments on the MNIST data set herein allow for comparison to standard and state-of-the-art models in the semi-supervised setting. Further experiments on the NIST SD19 data set show the scalability of the approach when a very large amount of additional unlabeled data is available.
versions	