High-dimensional Hessian metric representation on GPGPUs

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Optimization is one of the key problems of machine learning. The propagation graph (or “gradient graph”) of smooth hierarchical models, including neural networks, are based on relations of the compositional function in the tangent bundle. The complexity and the vector space describing the graph and the identified paths and non-trivial connections may result uncorrelated submanifolds while we can achieve efficient representations. Even though current GPGPUs and graph propagation frameworks are not ideal for high-dimensional, sparse representations, we show models achieving higher performance in image classification motivated by constraints of GPGPUs and recent results in graph factorization.