1128-49-73 **Mark Schmidt*** (`schmidtm@cs.ubc.ca`). *Linear Convergence of Gradient and Proximal-Gradient Methods Under the Polyak-Lojasiewicz Condition.*

In 1963, Polyak proposed a simple condition that is sufficient to show a global linear convergence rate for gradient descent. This condition is a special case of the Łojasiewicz inequality proposed in the same year, and it does not require strong convexity (or even convexity). In this work, we show that this much-older Polyak-Łojasiewicz (PL) inequality is actually weaker than the main conditions that have been explored to show linear convergence rates without strong convexity over the last 25 years. We also use the PL inequality to give new analyses of randomized and greedy coordinate descent methods, sign-based gradient descent methods, and stochastic gradient methods in the classic setting (with decreasing or constant step-sizes) as well as the variance-reduced setting. We further propose a generalization that applies to proximal-gradient methods for non-smooth optimization, leading to simple proofs of linear convergence of these methods. Along the way, we give simple convergence results for a wide variety of problems in machine learning: least squares, logistic regression, boosting, resilient backpropagation, L1-regularization, support vector machines, stochastic dual coordinate ascent, and stochastic variance-reduced gradient methods. (Received February 11, 2017)