1143-68-417 **Zachary Charles*** (zcharles@wisc.edu) and **Dimitris Papailiopoulos** (dimitris@ece.wisc.edu). *Stability and generalization of convergent learning algorithms under the Loajasiewicz inequality.*

In machine learning we often want to bound the generalization error of an algorithm. This is a measure of how well a learning algorithm generalizes to new data. While directly quantifying the generalization error of an algorithm can be difficult, prior work has shown that stable algorithms generalize well. Roughly speaking, a learning algorithm is stable if small changes in the training data do not lead to large changes in the output model. Using stability, we derive generalization bounds for algorithms that depend only on the convergence of the algorithm and the geometry of the empirical risk function. We focus on empirical risk functions satisfying a version of the Lojasiewicz inequality from real algebraic geometry. While this condition has a rich history in optimization, we further show that it has strong implications for stability and generalization in machine learning. Our results match or improve many state-of-the-art generalization bounds and easily extend to different learning algorithms. Finally, we show that this condition arises naturally in the theory of neural networks. (Received August 20, 2018)