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TENNISBALL: An Empirical Approach to Gradient Descent

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Abstract

As Machine Learning is used in an ever-increasing number of applications, a variety of gradient-descent methods have been developed for a variety of situations. We present TENNISBALL, a new empirical technique founded in physical theory. Our system finds accurate local minima with minimal computational time and physical guarantees of correctness. Our results significantly outperform state-of-the-art techniques on each task we examine.

Keywords: Gradient Descent, Optimization, Efficiency, Efficientness, Efficacy, Concision

1. Introduction

We present TENNISBALL (**T**ype-safe **E**mpirical (**N**eural **N**et Compat**i**ble) **S**earching-for-**B**owls **A**lgorithm with **L**ess **L**atency), an Empirical method for gradient descent that utilizes physical constraints to solve optimization problems. We achieve state of the art results.

2. Related Work

Prior techniques for gradient descent include Stochastic Gradient DescentBottou (2010), ADAGRAD Duchi et al. (2011), and ADADELTA Zeiler (2012). However, none of these techniques directly utilize physical constraints. To the best of our knowledge, our work is the first to eschew expensive computational techniques for empirical ones.

3. Method

3.1 TENNISBALL

TENNISBALL utilizes physical constraints to discover exact local extrema. See Figure 1 for an illustration of the technique.

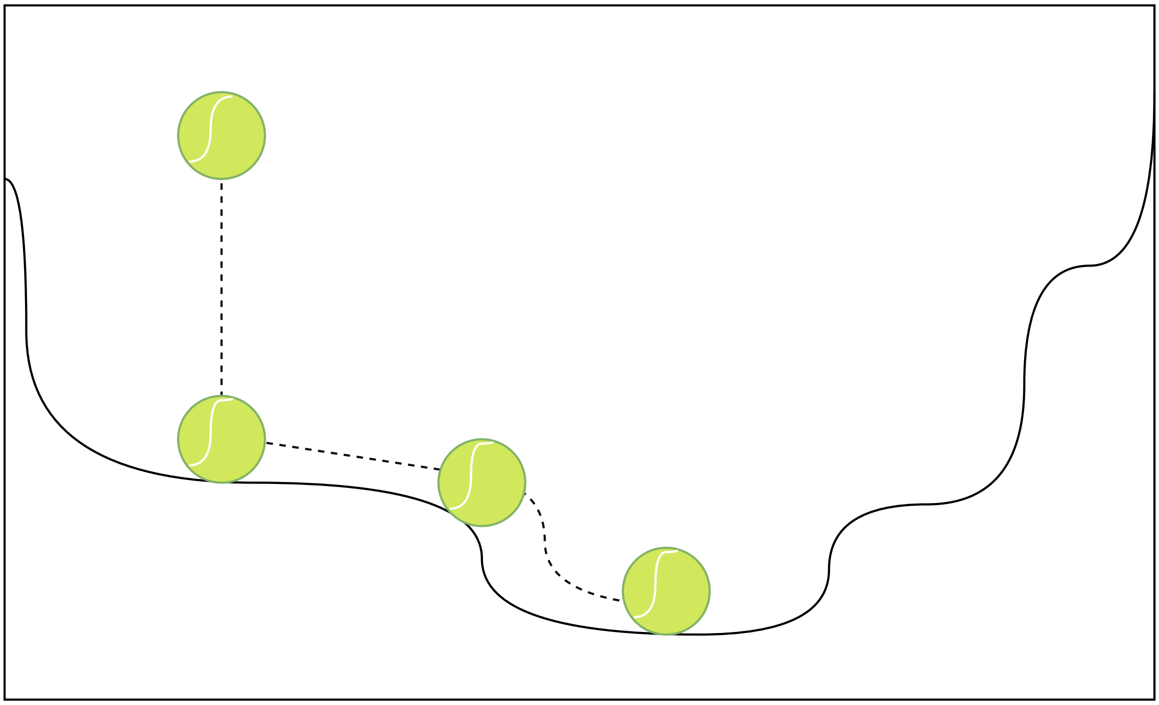

Figure 1: Illustration of the TENNISBALL technique.

3.2 Snow Sculpting

If natural hillscape cannot properly model the function to examine, one only needs to wait for snow accumulation. Then, the proper function shape can be formed using *Snow Sculpting*, allowing analysis of extrema for more unusual functions.

4. Data

We collected data by hand around Cornell's Ithaca campus.

5. Results

Our method is great: it avoids issues in flat areas (a problem with Newton's method), it can model arbitrary functions with snow sculpting, it avoids the curse of dimensionality by limiting optimization to 1- or 2-dimensional problems. It uses far less computational time than prior gradient descent algorithms.
It can face pitfalls like local minima, gorges and pitfalls, but avoiding these is up to the user.

6. Conclusion

Our TENNISBALL Technique is basically perfect and way better than everything else. We've revolutionized the field and nothing will ever be the same.

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