Testing and Tuning SkinnyDip: Noise-Robust Clustering

Grant King
kinggra1@msu.edu

1. PROBLEM DESCRIPTION

It is not uncommon for some real-world data sets to feature an abundance of noise. Depending on the severity of this noise, classical clustering methods may fail due to due to dependence on clean data or confusion from increasingly excessive noise. SkinnyDip is an algorithm proposed by Maurus et al.[1] designed to handle clustering data in highly noisy environments. SkinnyDip is based on the statistical concept of the *dip* [2].

The dip views the structure of the Empirical Cumulative Distribution Function(ECDF) of a set of single dimensional data to determine whether it is unimodal or multimodal. This test is expanded to a multidimensional, recursive heuristic in order to isolate the various modes of each feature of a set of data. This results in a deterministic, parameter-free, unsupervised method of finding clusters that are based on the modes of multivariate distributions.

A visual example of the purpose of SkinnyDip is demonstrated in the running example from [1] (See Figure 1) which shows the extraction of distinct shapes from a two-dimensional data field that consists of 80% static noise. A variety of similar clustering methods were shown to perform poorly on this data set, both through the inclusion of the evenly-distributed, static noise in clusters, and through excessive segmentation of the actual classes.

My goal is to implement the SkinnyDip algorithm and perform additional tests to demonstrate its usefulness on noisy, real-world data sets, with a final goal of reducing the extraneous information introduced by SkinnyDip's hypercubic boundaries through extension with a second clustering method.

2. RELATED WORK

Data clustering is a fundamental problem in Machine Learning, and has been approached in a variety of ways, resulting in a plethora of tools and methods [3], many of which are sensitive to noise and other outliers. Additionally, many common techniques, such as k-means clustering, operate as closed set clustering methods and are unable to reject noise at all.

[4] is a density-based technique for finding clusters in environments that may contain noise. However, it has the disadvantages of being a parameterized method, and still continues to find extraneous clusters in increasingly noisy data when compared to SkinnyDip.

A single other existing method for clustering using the statistical dip test was found, a technique called DipMeans[5]. This method, however, takes a different approach to the test, and performs the dip test on a collection of distance measurements as opposed to the raw data values themselves. SkinnyDip, however, requires no distance measurements and is both functionally and computationally distinct from the DipMeans technique.

3. PROJECT MILESTONES

Projected Project Milestones are given in Figure 2. It appears that most of the work will be in creating an actual implementation of the SkinnyDip algorithm itself in MATLAB. This may be mitigated by using an existing code base implemented in R and focusing more on the testing and extension vs. the algorithm itself, though this would require the extra learning curve of an entirely new language and tool set.

In order to obtain a solid understanding of the algorithm itself, I am inclined to perform a migration of the code, which may also help determine where future extensions should be worked in. For an additional level of understanding, I plan on spending some time before the intermediate milestone testing the dip-based clustering method on synthetic data sets to determine what kinds of data may cause issues.

Beyond this, the work that will largely be reported for this project will involve working with some real-world data (currently considering star data and galaxy clustering) as well as testing methods to improve the accuracy of SkinnyDip under higher-dimensional data sets.

4. REFERENCES

[1] Samuel Maurus and Claudia Plant. Skinny-dip: Clustering in a sea of noise. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1055–1064, 2016.

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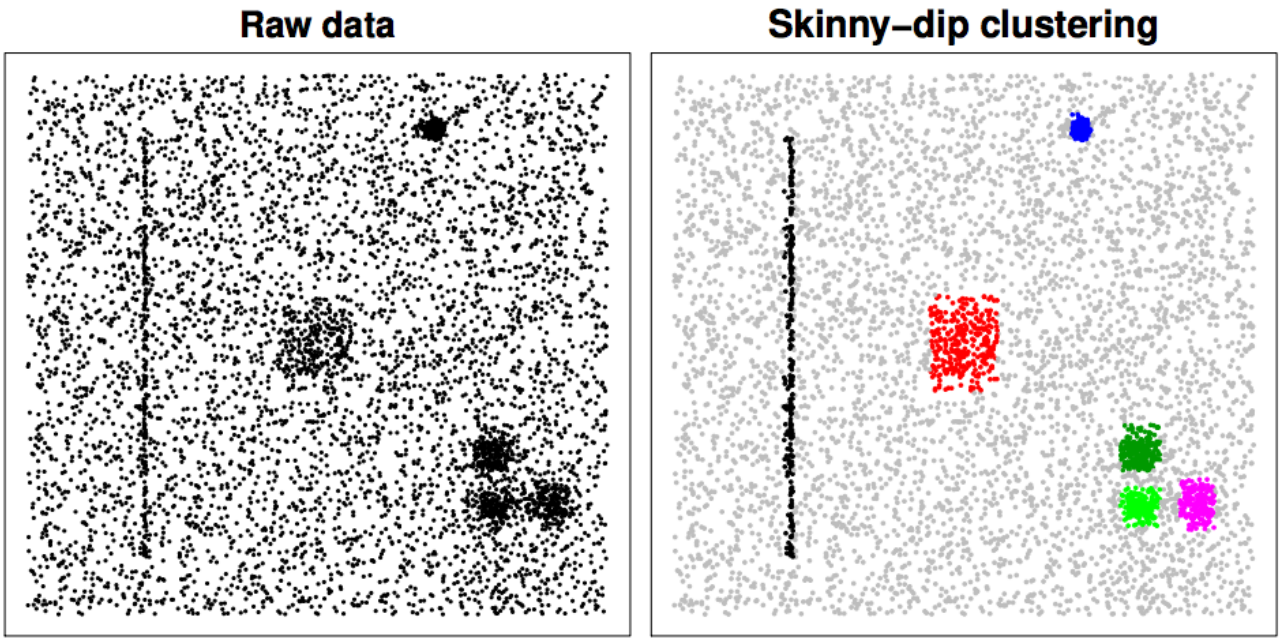

Figure 1: The running example used by Maurus, et al. throughout [1]

2/17/2017	Proposal Due
2/24/2017	Finalize Project Goals
3/3/2017	Working Code for UniDip
3/10/2017	Testing on Synthetic Data with UniDip
3/17/2017	Intermediate Report Due
3/24/2017	Find Noisy Real-World Data Sets
3/31/2017	Expand to SkinnyDip
4/7/2017	Expand to SkinnyDip
4/14/2017	Try Fine Tuning Clustering Results (e.g. Density Based Methods)
4/21/2017	Finalize Report

Figure 2: Tentative Project Milestones