**Institutionen för datavetenskap**
Department of Computer and Information Science


Final thesis

# An Evaluation of Clustering and Classification Algorithms in Life-Logging Devices

by


**Anton Amlinger**



LIU-IDA/LITH-EX-A–15/024—SE

2015-06-25



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Supervisor : Johannes Schmidt (Linköping university)
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# Abstract

Using life-logging devices and wearables is a growing trend in today's society. These yield vast amounts of information, data that is not directly overseeable or graspable at a glance due to its size. Gathering a qualitative, comprehensible overview over this quantitative information is essential for life-logging services to serve its purpose.

This thesis provides an overview comparison of CLARANS, DBSCAN and SLINK, representing different branches of clustering algorithm types, as tools for activity detection in geo-spatial data sets. These activities are then classified using a simple model with model parameters learned via Bayesian inference, as a demonstration of a different branch of clustering.

Results are provided using Silhouettes as evaluation for geo-spatial clustering and a user study for the end classification. The results are promising as an outline for a framework of classification and activity detection, and shed lights on various pitfalls that might be encountered during implementation of such service.

# Acknowledgments

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Finally I would like to express sincere gratitude for the support from my family and close friends during the time of this thesis work.

*Linköping, June 2015*
*Anton Amlinger*

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# Chapter 1

# Introduction

People in general are referring to this as the *Information Age*. More and more data is available for each second that comes, and a vast amount of information passes us by every day. Yet, the demand for ways to collect data seem to only be increasing, this embodied in the new wave of life-logging devices.

Our minds have not scaled along with this, so developing filters and making information searchable, shareable and observable is a necessary mean for humans to process this data explosion.

This is where Data Mining comes into the picture, by gathering qualitative information from quantitative data. This master thesis will address Data Mining and Knowledge Discovery in small data sets produced by life-logging devices, first by clustering of spatial data to reduce dimensionality, then to classify these sets of objects by attaching tags or classes to them with semantic relevance.

## 1.1 Motivation

The project and thesis which this report describes has taken place at *Narrative*[1] , a company which develops a life-logging, wearable camera. More general applications are of course of interest as well and will be pondered upon throughout the report, but Narrative will be the primary example and the target for testing various data mining principles, as well as the source of quantitative data.

[1]"Narrative is a young Swedish company with the ambition to give the common man the opportunity of having a photographic memory. Our specially designed camera takes two images per minute and our cloud-based software and apps handles the sorting and managing of the enormous amount of images for the user." - A translation of Narrative's background in their description of the Master Thesis proposal.

### 1.1.1 Narrative

As mentioned above, Narrative produces and sells a life-logging camera named the *Narrative Clip* (hereinafter referred to as the *Clip*) which captures two images per minute along with sensor data from GPS[2], Accelerometer[3] and Magnetometer sensors[4]. The amount of data received by Narrative's cloud-based servers is huge, and hard to overview even for a single user with frequent usage of their device.

Enabling automatic classification of each image series (these specific image series are hereinafter referred to as *Moments*, using Narrative's terminology) taken, makes each Moment more memorable, relateable and most importantly, more searchable for the customer. Narrative as a company can benefit from this as well, being able to answer questions such as *"How many of our users use the Clip at home?"* and similar qualitative analysis questions not being possible to answer without reducing the quantity of the data. This type of answers are beneficial for instance in marketing, product evaluation, and self assessment of the company and the product.

Narrative is currently maintaining applications for different platforms in order to view the Moments stored in their cloud. These platforms currently consist of an Android app, an iOS app as well as a web application.

### 1.1.2 Other Applications

Looking in a broader perspective, this type of approach is of course applicable to similar social or informative services as well, but might also be useful in other areas. Wild animals monitored with tags that use low-frequency updates sensors is susceptible to a similar type of analysis, when for instance wanting to examine the sleeping behavior of a species, anomalies in individuals eating patterns and so on. The same goes for observing a group of team-working microrobots, analyzing if their behaviour is as expected, if some robots are malfunctioning or that the task in general is correctly performed [15].

[2] A *Global Positioning System* sensor is fitted in the Clip, which periodically listens for satellites and registers signal strength when possible. The position is then computed centrally, making the time stamp for the detection an error source, along with some in-accurateness of the GPS signal in urban environments, as well as being completely unavailable indoors.

[3] The accelerometer measures the force pulling the Clip towards the earth or moving it in different directions.

[4] The magnetometer on the Clip measures the magnetic flow around the device, with the intention of providing a bearing of the camera lens, defined by the direction of the cross product of the accelerometer vector along with the magnetometer vector. However, this sensor is to sensitive to other sources of magnetism, often receiving a stronger field from a nearby refrigerator than the magnetic pole, leaving this sensor too unreliable to be used.

## 1.2 Questions at Issue

Given the background described above, questions regarding this arise. The focus of the resulting report as well as the project in general will revolve around these questions, and the project will aim for getting an answer to these questions.

*What type of clustering algorithm is most suitable for data mining in small data sets with few clusters?* 1

The described motivation above, yields data sets which do not contain more than hundreds of spatial points. Detection of spatial clusters will enable a base for further knowledge discovery and classification of data series, and the same goes for the ability to detect the absence of clusters.

*How well suited is Bayesian inference for deducting qualitative data classifications in life-logging data sets, such as Narrative's Moments?* 2

Given additional input apart from performed clustering, what else might be deductible, e.g. what classes might we assign a Moment given more stimuli than clustering?

## 1.3 Goal

The goal of this thesis will be to answer the questions above by implementing a proof-of-concept implementation built on Narrative's provided data set.

### 1.3.1 Approach overview

The Method chapter will provide a more in-depth description of the approach and the methodology behind it. This section presents a short and comprehensive introduction to how the questions in the previous sectionwill be answered.

For question 1 the idea is to implement and evaluate representatives from different groups of algorithms on the basis of performance, quality and suitability. These algorithms are chosen from a spectrum of well-known implementations, with different approaches in order of get more diverse clustering approaches. Preferably three algorithms will be compared; one partitioning-based, one hierarchy-based, and one density-based (better explained in Approach). This is also closely related to how storage of the geographical points should be performed, the spatial data representation, which also is considered, as well as storage of detected clusters.

Regarding question 2, Vailaya et al. has quite successfully analyzed images and assigned semantic classifications to said images based on Bayesian analysis. A similar approach should be applicable in this situation, delimited that probabilities and distributions will be assessed by educated guesses [26, 25].

## 1.4 Technical Background

### 1.4.1 Clusters

Mining quantitative data is closely related to the subject of clustering, as discovering clusters in a quantitative data set unravels qualitative information about the distribution of objects. This is a well-studied topic and has been for several decades at the point of writing this.

#### Definition

Estivill-Castro, author of "Why so many clustering algorithms: a position paper", argues that the notation of a cluster cannot be precisely defined, but rather that a cluster exists in the eye of the observer, which is one of the reasons why there are so many clustering algorithms [9]. A task that derives naturally from this is then to find a definition of a cluster that as many people as possible find satisfactory. There is no universal clustering algorithm because there is no universal definition of a cluster.

This of course means that in order to select a suitable clustering algorithm an analysis of what kind of clusters are to be detected needs to be done.

Another consequence of the indefinable concepts of clusters are that clustering algorithms in almost every case need some sort of knowledge about the data set to operate on, as what clustering is expected to be done. This is often represented as the need of input parameters to the clustering algorithm, that defines how the algorithm will perform, and to some extent how a cluster is defined in that instance.

### 1.4.2 Clustering algorithms

As mentioned above, cluster discovery from data is a well-covered scientific topic where algorithms have been improved over the years. This report will focus on comparing different types of algorithms and to evaluate them based on a common evaluation method (later discussed).

Clustering can be done on any type of data, of any dimensionality. The only prerequisite that is needed is a distance measurement that denotes how similar or dissimilar two data points are. In this thesis, only spatial data is considered.

Classically, clustering algorithms are divided into three types:

- Partitioning Clustering Algorithms.
- Hierarchical Clustering Algorithms.
- Density-Based Clustering Algorithms.

all of which revolve around different ways to detect and to represent clusters. Other ways to divide clusters such as representative-based algorithms[5] and model-based algorithms[6] have been proposed as well, which is basically grouping the density-based and hierarchical algorithms together as they generally represent their clusters by models and not by medoids [9].

### Partitioning Clustering Algorithms

As the category name suggests, these algorithms partition the given spatial data in usually a predetermined number of clusters. Thus, traditional algorithms of this type often require knowledge about how many clusters to partition the initial data set into, passed to the algorithm as a cluster parameter.

Partitioning algorithms are usually representative-based, and therefore has difficulties recognizing non-convex clusters, since the COM (Center Of Mass), or other representative, of a cluster might fall outside its bounds.

Examples of partitioning clustering algorithms are:

- *k-means clustering* partitions the input data set with $n$ spatial objects into $k$ clusters, each cluster represented by a mean spatial point. An arbitrary point $p$ belongs to cluster $C$ represented by mean $m \in M$ if and only if $d(p, m) = min_{m' \in M} d(p, m')$. $m \in M$ suggests that the k-means uses the above mentioned COM. The main cause for its success and common use is its implementation simplicity, which is also the reason for the extensive amount of variations to suit more specific needs. Some of these are variations are to accommodate for the original problem's time complexity, as it is NP-hard[7] even for small dimensions $d$ or a pre-determined number of clusters [2]. When $k$ and $d$ is fixed, it can be solved in $\mathcal{O}(n^{dk+1} \log n)$. Relaxations to increase efficiency of this scenario are also common [13].

- *k-medoid clustering* essentially operates in the same manner as k-means clustering, with the difference of actual input objects (medoids) representing a cluster, instead of the COM as k-means uses. One of the most common implementations of this is PAM (Partitioning Around Medoids) [16].

- *CLARANS (Clustering Large Applications based on RANdomized Search)* is inspired and motivated by PAM (as well as another algorithm presented by Kaufman & Rousseeuw called CLARA, Clustering LARge Applications [16]). Although both k-means and k-medoids can be

[5] Representative-Based algorithms use a single datum to represent each cluster, such as the Center Of Mass of the cluster or a median representative.

[6] Model-Based Algorithms use some sort of model to represent a cluster, such as a polygon where some spatial objects are in the center, and some in the cluster marginal.

[7] NP-hardness denotes that the worst-case run-time of the algorithm is not in polynomial time. Proof of this is usually done by reduction of the problem to a problem that is known to be in NP.

viewed as graph searches, CLARANS takes it one step further. Necessary input parameters are *numlocal* - the number of local minima to visit and *maxneighbour* - the number of randomly selected neighbours to visit in search of new local minima. As this suggests, the algorithm is not optimal, but usually sufficient, and more effective than CLARA, naive k-means and PAM [19].

### Hierarchical Clustering Algorithms

Hierarchical Algorithms classify, or cluster, objects in an hierarchical manner rather than partitioning these spatial objects straight away, or base it on density-distribution.

These algorithms are usually divided into two sub-groups, *agglomerative* and *divisive* hierarchical clustering algorithms. The first constructs the hierarchical structure of clusters (starting with combining spatial objects) bottom-up, while the latter one divides an all-covering cluster into several new ones. Then divisive flavor has also been seen conjunction with partitioning algorithms, where a distinction between the two sometimes is hard to do.

Hierarchical algorithms thus requires a termination condition to be defined, which determines when the merge or division process should be stopped. The difficulty here lies in deriving appropriate termination conditions, to make the algorithm perform clustering as desired.

Hierarchical algorithms naturally produce a dendrogram[8] of the clustered objects, since it involves either splitting or merging clusters on each step.

Examples of hierarchical clustering algorithms are:

- *SLINK* was meant as an improvement over classical agglomerative clustering, performing in $\mathcal{O}(n^2)$ instead of $\mathcal{O}(n^3)$ as the naïve agglomerative solution. This is due to a different pointer representation, and because of this the algorithm results in a dendrogram but no actual clusters. These have to be found by specifying cutoff conditions to create the clusters [22].

- *Clusterpath* is a convex LP-relaxation of classical hierarchical clustering algorithms, and needs the aid of a solver to perform clustering. A bonus of this relatively new method is that an object tree is obtained, which is cut in order to receive clusters [14].

### Density-Based Clustering Algorithms

As the name suggests, density-based clustering algorithms base their clustering on the density of data, and can recognize clusters of arbitrary shape. Most density-based algorithms are based on a grid and sensitive to the settings of this grid which heavily affects the clustering results. How this grid

[8] A tree structure.

is set up can be viewed as the clustering algorithm input parameters, which as previously mentioned is a necessity for most clustering algorithms.

These algorithms are often model-based, and are therefore applicable to more arbitrarily-shaped clusters. A still remaining problem is the difficulty to detect clusters of various density, since input parameters often control these clustering factors for density-based algorithms.

Examples of density-based clustering algorithms are:

- *DBSCAN (Density Based Spatial Clustering of Applications with Noise)* is an algorithm that is not based on any grid, but instead the notation of the neighbourhood of a point, and the separation of border points and core points of a cluster. The core point criterion (definition A.3.2) is essential when defining which data can be regarded as being core points, and which will be classified as border points of a cluster. This algorithm also disregards noise, if any data diverges too much from the rest of the set [8].

- *OPTICS (Ordering Points To Identify the Clustering Structure)* is not strictly a clustering algorithm per se, since it does not perform any clustering in itself. Motivated by some shortcomings of DBSCAN (regarding difficulties of detecting clusters of varying densities), the input spatial data is sorted in a manner to make clustering afterwards easier, but leaves the clustering to other implementations. OPTICS requires the same input as DBSCAN, but is less sensitive to the parameter values [3].

### 1.4.3 Evaluation

As mentioned above, a cluster only exists in the eyes of the beholder. That means, when it comes to evaluation of an algorithm performance it is not clear how to compute whether the algorithm has produced correct clusters or not, since there is no definition of a correct clustering solution.

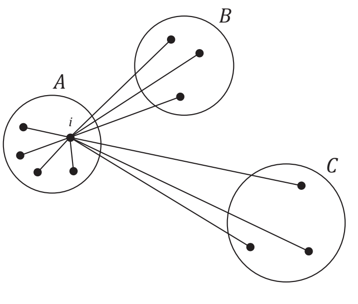



Figure 1.1: Silhouette computation example for a single data point.

| SC | Proposed interpretation |
|---|---|
| 0.71 - 1.00 | A strong structure has been found. |
| 0.51 - 0.70 | A reasonable structure has been found. |
| 0.26 - 0.50 | The structure is weak and could be artificial. |
| $< 0.26$ | No substantial structure has been found. |

Table 1.1: Silhouette Coefficient interpretation.

Therefore Rousseeuw, author of “Silhouettes: a graphical aid to the interpretation and validation of cluster analysis”, speaks of detected clusters as artificial or natural, based on visual inspection, and proceeds to introduce *Silhouettes* as a graphical aid for detecting such artificial fusions of data. The silhouette of a data point is denoted by a numerical value in the interval $[-1, 1]$, denoting how well the particular data point belongs to the cluster it is currently assigned to. A higher value indicates a better assignment.

Silhouettes are, somewhat simplified, defined by dividing the mean distance from the point of concern (in figure 1.1 denoted by $i$) to all other points in the same cluster $A$, with the mean distance from $i$ to all points in the nearest not assigned cluster, $B$. The following equation shows the computation process:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{1.1}$$

where $i$ is the point of concern, $a(i)$ is the average distance from $i$ to all other points in $A$, and $b(i)$ is the average distance from $i$ to all points in $B$.

Silhouettes were suggested to be visualized by a horizontal bar plot, each bar denoting the silhouette value of each point in the cluster the point was assigned to.

Given that, it is desirable to have wide silhouettes describing the clusters, and that the silhouettes should be even edged. A mean silhouette width $\bar{s}$ can also be computed, in order of giving condensed, numerical interpretation of how natural the clustering is of a processed data set [21].

In a later work Kaufman and Rousseeuw suggests using a *Silhouette Coefficient* ($SC$), that is the maximum $\bar{s}(k)$ over various $k$ using a partitioning clustering method

$$SC = \max_{k} \bar{s}(k) \tag{1.2}$$

which suggests how well the data set is suitable for clustering given the particular clustering method being used. Table 1.1 provides a suggested interpretation of the silhouette coefficient, as provided by Kaufman and Rousseeuw [16].

If one considers table 1.1 from a $\bar{s}$ point of view instead of $SC$, this should be applicable for determining the quality of found clusters by an arbitrary algorithm.

It is notable that silhouettes are not meaningful when clustering algorithms produce a single cluster, since the definition of a silhouette describes the relation of points similarity to its assigned cluster and the closest cluster which it is not assigned to, which will not exist given that there is only one cluster. Rousseeuw suggests assigning this sort of silhouette a value of 0 for comparison reasons, as this is the most neutral value.

### 1.4.4 Data Representation

A sound way of representing detected clusters is necessary, in order not to have to re-run the clustering algorithms each time a knowledge discovery is requested. Being able to position clusters and use knowledge about previously recorded clusters is another necessity, to make the algorithm learn based on user corrections (of for instance the name of locations). After all, the sought result is to classify Moments and clusters with *semantically significant* and *meaningful* names, and being corrected by a user on a cluster name should trump everything else, thus being more significant. Detected clusters at the same position as a previous should have the same name, not only for being as correct as possible, but also in order not to be ambiguous in classified cluster names.

Many databases today support geo-spatial queries for both points and polygons[9], and in this case it is the latter that is of interest. Being able to store clusters as areas, and persist these areas represented as polygons enable another level of detection for clusters, where it is possible to detect if it is a cluster that is known previously. Queries asking for overlapping clusters are in general supported by *Spatial Database Management Systems* (SDBMS) using *Dimensionally Extended Nine-Intersection Model* DE-9IM[10]

The support for performing geo-spatial queries on a database and doing this efficiently is usually implemented with some sort of *spatial index*. Common implementations are R-trees and R*-trees, which fits the spatial entities into rectangles of varying sizes in a tree structure, allowing a lookup time of $\mathcal{O}(log(n))$, by balancing the trees [12, 4].

Apart from storing polygons, it is useful during this paper to also persist the spatial points which make the cluster. This is for evaluation purposes, as algorithms examining the quality or naturalness of a cluster in general needs access to all the points in the particular cluster.

#### RethinkDB

RethinkDB will be used in the sought proof-of-concept implementation, as it fulfills the necessary requirements, with support for spatial queries and storage of spatial data both as geographical points, and polygons.

[9]Here, only 2-dimensional data is considered which is the most commonly supported, although support for 3-dimensial data exist in many database solutions.

[10]DE-9IM is a model for representing spatial relationships between polygons and geospatial shapes. This is defined by a matrix specifying Interior, Boundary and Exterior attributes between the different shapes, and varying configuration of the resulting matrix is interpreted as spatial relationships such as *Touches*, *Disjoint*, *Equals* etc [23].

It is an Open Source project hosted on GitHub, and has a growing community at the time of writing providing support when needed. Narrative is currently using RethinkDB as a cache-layer for API requests, making it an even stronger candidate for the proof-of-concept implementation.

## 1.5 Classification

Classification of data is closely related to clustering of data, and the two problems are not even distinguishable in all applications.

### 1.5.1 Bayesian Inference

Bayesian inference is a methodology for updating beliefs about a model when certain evidence is observed, while preserving some level of uncertainty.

The entry point is some *Prior probability* $Pr(\theta)$ that the model we are observing is in world $\theta$. There exist *likelihoods* $Pr(x_i|\theta)$ that some *evidence* $x_i$ will be observed in this $\theta$ world. Given this framework, the target is often to compute a *Posterior probability* containing updated beliefs about the state of the world provided the witnessed evidence.

A model representing Bayesian beliefs can easily be graphically interpreted as a *Bayesian Network*. Bayesian networks are Probability DAG:s (*Directed Acyclic Graphs*), and are used for modeling the probability of certain events when other events are known.

In this report, a Bayesian network is used to model the probability of a series of positions (or more exactly, photographs with positions attached) enhanced with additional sensor data belonging to a certain class.

As this introduction previously established that expected results from clustering algorithm are not precisely defined and lies in the eyes of the beholder. If the results are somewhat fuzzy, and somehow can be computationally evaluated according to some metric, this should prove as a suitable parameter for an automatic decision algorithm, such as one powered by a Bayesian network, which is the idea behind the implementation that is described.

Bayesian networks are the base for Bayesian analysis, which starts with a prior probability $Pr(\theta)$ and a likelihood given $Pr(x_i|\theta)$ in order to compute a posterior probability $Pr(\theta|x_j)$. In the case of this report, $x_i$ represents some input probability while $x_j$ represents some class or end condition.

With each inferred parameter, a dimension is added to the state-space[11]. This makes high-dimensional models hard to observe and analyze by inspection, since modelling more then 3 or perhaps 4-dimensional probability space of various parameters is not possible to visualize.

[11] The state-space is defined as the possible states for a world to be in, and increases with each dimension added.

**Fitting of models**

As models become complex when inferring high dimensionality and observing evidence (thus forcing other probabilities in the model to alter), visualization of the probability of a certain unobserved variable becomes harder. Simply outputting some mathematical formula is not intuitively graspable and computing such a formula is usually hard or impossible when other parameters have been described by sample data.

*Markov Chain Monte Carlo (MCMC)* are a category of algorithms dealing with this particular matter, and instead describes the probability of theses parameters using thousands of samples. The main target is to cover as much of the state-space as possible by randomly drawing samples in a manner that makes the returned collection as close to the true distribution as possible.

When a fitting algorithm is proven to approach the true underlying distribution, when provided with enough steps and enough samples, it is denoted that the algorithm *converges*.

**PyMC**

*PyMC* is the framework used for Bayesian modeling of the classification problems in this report. PyMC:s online user manual states:

> "PyMC is a python module that implements Bayesian statistical models and fitting algorithms, including Markov chain Monte Carlo. Its flexibility and extensibility make it applicable to a large suite of problems. Along with core sampling functionality, PyMC includes methods for summarizing output, plotting, goodness-of-fit and convergence diagnostics." - PyMC User's Manual [10].

PyMC fits the needs of this project well, as it implements the core functionality necessary for Bayesian inference such as a range of probability functions as well as fitting algorithms, mainly MCMC. It is also bundled with algorithms for finding an appropriate starting point for the fitting algorithms to work with, as this affects the rate of convergence for the fitting algorithm.

## 1.6 Limitations

### 1.6.1 Image analysis

Only very simple and limited image analysis is applied in this report, as this could easily have made subject for a thesis of its own (as is the case with other reports) [26, 25].

The purpose of this thesis is not classification of images as such, but of small series of data samples of varying length.

### 1.6.2 Individual classification

Interesting as it might be with performing individual classification of data, in this case images, this is deemed outside of scope for this report, due to time limitations.

The subject considered is, as mentioned above, deducting information about a data set as a whole given attributes in separate data.

### 1.6.3 Automatic Learning of Network structure

In machine learning there exist a lot of literature about the subject of automatically determining network structure of a Bayesian network, opposed to let it be specified by an expert. The intent is here to describe the automated process of data set classification, and the initial step such as setting up the decision network is assumed to be done. For simplicity reasons, the second approach is chosen, and extending the work later on by learning the network structure computationally does not interfere with the work of this report.

### 1.6.4 Exact Probabilities

Exact distributions of probabilities of events are hard to come by, and are by its nature virtually impossible to confirm (given that it is probabilities). This report will not focus on determining these optimally, but rather leave the estimated distributions to be decided based on a bit of logical reasoning.

### 1.6.5 Semantic Significance

Choosing labels for derived classes is a problem of its own, and will not to its full extent be discussed in this report. As Vailaya et al., authors of papers “Bayesian framework for semantic classification of outdoor vacation images” and “Content-based hierarchical classification of vacation images”, mentions, search queries often describe more high-level attributes about data sets, or images in this case, such as a search would more likely consist of the word ”sunrise” when looking for an image, than ”predominantly red and orange” [25, 26].

The semantic significance of the label of a class can therefore describe how meaningful that label is, although assessing in full scale how significant the labels are in this report will be left for future research.

### 1.6.6 Only 2-dimensional spatial data is considered

One might consider data of higher dimensionality, encountering other problems than the spatial clustering in this thesis report. This will however not be done here, as this does not seem to have enough relevance for this case.

## 1.7 Related Work

*Finding groups in data: an introduction to cluster analysis* by Kaufman and Rousseeuw is regarded by many as the classic text-book in cluster analysis which provides and introduces several theories that prove the foundation of cluster theory today [16]. Rousseeuw is also the author of the paper [21], that introduces a universal way of evaluating clustering performance under certain conditions, such as that the number of clusters has to be greater than 1. This method is used in this thesis and is discussed itself, based on its suitability to accommodate for different clustering solutions.

Article [9] is a position paper describing ways of looking at clusters and cluster analysis on a broad spectrum, and explains the difficulties as well as why there is no universal solution to clustering.

The papers [8, 3, 19, 11, 22, 14, 13, 16] all describe various clustering algorithms used and were considered as prospects for evaluation in this thesis.

Papers [12, 4] both describe ways of implementing spatial indexes, which are the core of a spatial data base and making spatial queries possible in an efficient manner.

The article "P-DBSCAN: a density based clustering algorithm for exploration and analysis of attractive areas using collections of geo-tagged photos" at first glance seem to be very similar in its aim as this this, but the difference lies in intention. While Kisilevich, Mansmann, and Keim tries to deduct information about attractive areas and places using clustering of photographs, the approach of this paper is to deduct information about a series of photos using areas and places. [18]

The paper [29] introduces learning of detection of probabilities modeled by Gaussian Processes by interpreting the classification as a regression problem. This allows small training sets, which Bayesian numerical techniques for calculating the trace and determinant was not as tolerant of.

Papers [26, 25] use a Bayesian approach for classifying individual images based on their visual attributes, which is fairly closely related to this work. This provides interesting results inspiring this thesis, with the difference of classifying series of images instead of single images, and choosing other attributes to base the classification on.

[6] explains thoroughly how one might regard Bayesian inference and methods from a programming perspective with examples in PyMC, rather than using traditional mathematical notation to address the problems. (Not clear if this is a valid resource, but it sure was helpful). Similarly, [5] provides more in-depth foundation with weight distributed on the theoretical parts of Bayesian analysis.

[27] explains the pitfalls of de Moivres equation by reciting some statistical mishaps throughout history. This explains the care one has to take to not draw premature conclusions from small data sets.

[15] describes discovery moving of spatial clusters, and thus introduces

another dimension into the clustering; time. This is similar to the approach suggested in this thesis, with the difference of observing a lot of spatial points at once.

[31] discusses and compares different methods of evaluation hierarchical clustering algorithms.

[28] is an example of a real-time, big data application using spatial content in the social network Twitter to locate events on a map, similar

Article [30] evaluates the accurateness of mobile units with regard to GPS data, and different techniques that can be used for obtaining this in an urban area. This is useful to keep in mind, as a similar implementation for life-logging devices and the Clip lies close in the future.

## 1.8 Report Structure

This section has presented the motivation and technical foundation for the work done in this paper. More specific implementation details and theory will be addressed in chapter 2. The results of these implementations will be presented with measured test data in chapter 3. These results will later be evaluated and discussed under chapter 4, as well as other factors that might have influenced the results. Finally, a conclusion is drawn in chapter 5 as well as suggestions for further research on the subject.

The appendices contain further implementation details beyond what is described in the report. These should not be necessary to grasp the main outlines of the report, but prove interesting for a full understanding of how algorithms have been implemented in this work.

# Chapter 2

# Method

## 2.1 Classification

The classification is the main target for the proof-of-concept implementation, described below.

The main targets for the classification algorithm is determined by some spatial clustering algorithm. This data set might either be entire Moments if no cluster is found, or if the entire data set is regarded to be a cluster. If several clusters are found, these will be classified individually. Moments or clusters sent to the classification algorithm will below be referenced to as an activity (not to be confused with the later mentioned class *activity*, representing the amount of physical activity).

### 2.1.1 Input Beliefs - Evidence

In order to establish a prior belief in the data to model, it is necessary to model the estimated prior distribution of the input data to model the prior belief in class assignment. This is later updated based on observations of the data, and beliefs are reinforced or skewed based on these observations into *posterior beliefs*.

#### Accelerometer

The accelerometer provides 3 values for each sample taken by the sensor, one for each direction in the three dimensional coordinate system. As the Clip can be mounted on the user in different ways, as well as being tilted, these acceleration vectors are not bound to some specific orientation in relation with the earths coordinate system.

Most commonly the Clip is either fitted on the user with the buckle facing down, or horizontally (either left or right). This makes the x-axis and y-axis interchangeable.

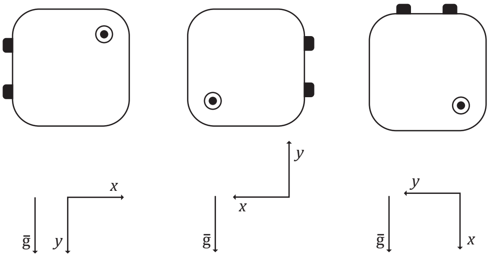



Figure 2.1: An illustration of the most plausible orientations of The Clip as worn by the user.

Given the uncertainty of which direction the sample was recorded in, the solution would be to use the magnitude of the vectors combined, and ignore the direction of the resulting vector[1]. Chances that the combined vectors should sum up to the original, stationary vector when moving seem slim.

An accelerometer measures *proper acceleration*[2] and will therefore usually have a constant approximated value corresponding to $g \approx 9.8m/s^2$ when stationary, and somewhere around that value when a user is in motion.

The most feasible application of the accelerometer seems to be determining the level of activity in the Moment. When a user is active (such as being out for a run or sporting), it is probable that the acceleration is varying, partly because of the actual movement, and partly because the Clip jiggles around when in movement.

Given the above, the most feasible distribution of the samples observed seem to be around $g$, with decreasing probability around this point as the acceleration diverges more and more from $g$. Such a distribution could be described using a *Normal distribution* with the following *probability density function*:

**Definition 2.1.1 (Normal Distribution Probability Density Function)**

$$PDF_{Norm}(x, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

We denote a stochastic variable that is Normally distributed by

[1]If the Clips orientation was of interest, or there was a specific need to know each composant of the accelerometer vector, it could be assumed that the composant being closest to $g \approx 9.8m/s^2$ in magnitude was the direction facing downward. The user is not likely to change the orientation of the Clip between each photo, so detecting the orientation based on multiple photos seems more robust and feasible.

[2]Proper acceleration is the physical acceleration that is experienced by an object, including gravitational force.

**Definition 2.1.2 (Normally distributed variable)**

$$X_i \sim Norm(\mu, \sigma)$$

where $\mu$ is the expected mean value (which we expect to be $g \approx 9.8m/s^2$ or equivalent), and $\sigma$ the standard deviation.

In order to measure how the acceleration varies, the *auto-correlation* (or serial correlation) of the samples can be used. The auto-correlation is defined as the cross-correlation of a series of samples with itself. This is generally used in statistics as a measurement of the predictability of a series of samples from a distribution, and predicts how much a value is likely to change given two consecutive measurements.

This is another reason to use the magnitude of the accelerometer vector, as values close to 0 (as the y- and z-axis tend to be while stationary) show very little auto-correlation, due to small changes in small values.

### Area

The area size of an activity. When there are no spatial data points available for an activity, this is for simplicity reasons assumed to be 0, indicating that a user is in such a small area that it can be neglected.

**Definition 2.1.3 (Area distribution)**

$$X_{area} \sim Norm(\mu_{area}, \sigma_{area})$$

where $\mu_{area}$ is found by using the mean area value in a subset of all currently sampled activities, and $\sigma$ is the variance in the same data set.

### Face Detection

Narrative runs a face detection algorithm on the set of their images, determining whether any face is present or not in a photo. The ratio between images with faces and without are of particular interest, as we can see below, and is deduced for each activity in the classification algorithm. The faces/photos distribution is modelled as

**Definition 2.1.4 (Faces/Photos distribution)**

$$X_{faces} \sim Norm(\mu_{faces}, \sigma_{faces})$$

where $\mu$ is found by using the mean value in a subset of all currently stored activities, and $\sigma$ is the variance in the same data set.

### Time

The starting time of a Moment is probably more likely to occur mid-day or during the evening, when more special activities occur and the users decide to clip it on. This timely information is used to detect where users are spending their time, and if their activity is work-related or recreational, on their spare time. The probability of observing such a timestamp is therefor estimated using a *Binomial Distribution*, with the following *probability mass function*[3]:

**Definition 2.1.5 (Binomial Distribution Probability Mass Function)**

$$PMF_{Bin}(k; n, p) = \Pr(X = k) = \binom{n}{k} p^k (1-p)^{n-k}$$

We denote a stochastic variable that is Binomially distributed by

**Definition 2.1.6 (Binomially distributed variable)**

$$X_i \sim Bin(n, p)$$

where $n$ is the number of trials attempted and $p$ is the expected number of successes.

### 2.1.2 Output Beliefs

The target is to classify a received data set into a finite set of classes. According to Bayesian methodology, it is necessary to model an experts belief in the distribution of assigned classes. First of all, assume that an input data set can never partly be assigned a class but always fully. The assignment is either done, or not. This model was described by the Swiss mathematician Jakob Bernoulli, who coined the *Bernoulli distribution* with the following probability mass function:

**Definition 2.1.7 (Bernoulli Probability Mass Function)**

$$PMF_{Bernoulli}(k, p) = \begin{cases} p & \text{if } k = 1 \\ 1 - p & \text{if } k = 0 \end{cases}$$

This describes the probability $p$ of a class being assigned to the data set received. We denote a stochastic variable that is Bernoulli distributed, the prior probability of a class $i$ being assigned, by

**Definition 2.1.8 (Bernoulli distributed variable)**

$$X_i \sim Ber(p_i)$$

This prior probability is modelled by one or several threshold values, which determine the probability of which class is used.

The inferred classes that we will attempt to predict are the following:

[3]This is denoted *probability mass function* instead of the previously mentioned *probability density function*. This is essentially the same thing, with the difference of the first being a continuous distribution while the latter is discrete.

- *Social* - Whether the user is engaging in a social activity or not. This is believed to be effected by the amount of faces in the photos in a series.
- *Working* - The users working status during a Moment. This is believed to be affected by the starting point of the series of images, as well as the area size of the detected clusters.
- *Indoors* - Whether the user is indoors or not. This is believed to be affected by the area size of an activity.
- *Movement* - How much physical activity the user is undergoing during an activity. This is believed to be affected by the auto-correlations mean value of an activity.

These classes can take on two discrete values; either they are assigned or not (this is somewhat simplified with the labels for the classes - with friends or not alone, for *Social*, working or off hours for *Working* and indoors or outdoors for *Indoors*). Thus, these are Bernoulli distributed as mentioned above:

$$\begin{aligned} X_{social} &\sim Ber(p_{social}) \\ X_{indoors} &\sim Ber(p_{indoors}) \\ X_{working} &\sim Ber(p_{working}) \end{aligned} \tag{2.1}$$

where $p_i$ depends on the parent values (see figure 2.2 on page 21).

The exception here is $X_{activity}$ which is *Categorically distributed*, a generalization of the Bernoulli distribution:

**Definition 2.1.9 (Categorical Probability Mass Function)**

$$PMF_{Categorical}(k, p) = p_i$$

where $p_i$ represents the probability case $i$ to be true. We denote a stochastic variable that is Categorically distributed, the prior probability of a class $i$ being assigned, by

**Definition 2.1.10 (Categorically distributed variable)**

$$X_i \sim Cat(p_1, ..., p_i)$$

It is worth reminding here that it is the concept of using Bayesian Inference as a classification tool for life-logging environments that is up for testing, and not necessarily the model for each implementation. As mentioned among the limitations, the structure of the network is assumed to be fixed from the start and automated learning of the structure is not applicable. Because of this, it seems more suitable to infer a rather simple and shallow model to test the concept. Using several classes that only depend on a few parameters allow some error and redundancy to sneak in due to model construction errors, which will be discussed later in this thesis.

### 2.1.3 Model Parameters

All parameters mentioned above can be observed by inspecting data, and are thus the evidence $E$ that can be observed when the model is in certain world state. Modelling these correctly is nevertheless important anyway, in the case of missing values.

The classification depends on a series of model parameters, such as thresholds for when different classes should be inferred.

These breakpoints are be denoted as model parameters, and are of interest for learning how classification can be done. While approximating these with a well-formed probability function is a cause for faster convergence and faster learning, it is essential that all possibilities are covered. If the model parameter is not covered by it's initial probabilities, the model is not correct and will probably not provide the desired results.

These model parameters will for simplicity's sake be universal in this master thesis, but should probably later on be possible to tweak for each individual, with the aid of a learned starting point.

#### Learning the parameters

In order to make our hypothesis as credible as possible given previously recorded classifications made by human observation, the thresholds need to be properly set. This is done by letting both our samples of the observed data of several Moments be fixed, as well as the classification that later is to be determined for other activities. The only thing that is then allowed to vary in order to make the model true, is the thresholds, our hypothesis, forcing these variables to take on relevant values.

By doing this for a decent amount of pre-determined classifications, and letting MCMC in PyMC fit the model by drawing thousands of samples of this distribution, by randomly walking over the set, something very close to the true distribution is learned, that can be used as the hypothesis in future classifications.

In this instance, a rather small sample is used, yielding a hypothesis in danger of being biased. In a real-world application, this sample of classification would be much bigger, but this sample size of 50 classifications should suffice to prove the concept.

### 2.1.4 The Bayesian Network

The dependencies between various stochastic variables can be made more over-viewable when represented graphically as a network, see figure 2.2. In this figure, the top ellipsoids with a solid border marks the evidence $E$ observed for each activity. The squares are the thresholds, or model parameters that have been learnt via Bayesian inference and fitting the model with pre-classified data. This is our hypothesis. The circles with a dashed border is the classes of which we try to determine our posterior belief after observing the evidence.

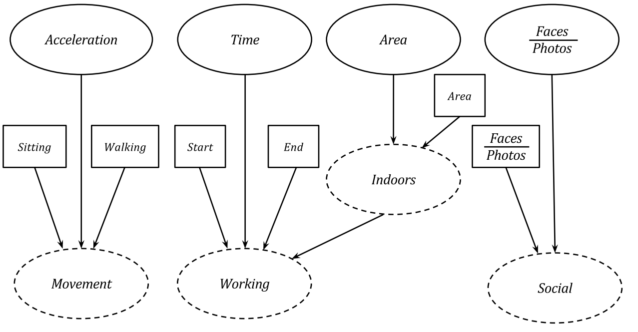



Figure 2.2: A graphical view of the bayesian network modelled for deriving the classes.

### 2.1.5 Curse of Dimensionality

The *curse of dimensionality* is a problem that arises in cluster analysis and data mining applications where a lot of dimensions or considered features in the regarded data causes data that are fairly similar to appear to be very dissimilar due a few to outlying, less important property values.

This problem arises when the observed data contains a lot of parameters that can take on very different values.

In this work, this is mainly a problem in the inference domain and not in the spatial clustering domain, as spatial data in it's nature is two-dimensional (at least in this case, as the earths surface can be regarded as two-dimensional, from a geographical point of view).

This is why clustering of spatial points precedes the Bayesian inference in this work, in order of decreasing the dimensionality and learning something useful from the spatial data before moving on to tackle other quantifiable data: as for each comparable spatial point in the data set, we would need to model some sort of random variable, mapping against one dimension. This could easily sum up to several hundreds of dimensions, in the spatial analysis alone! Clustering algorithms exist in Bayesian notations as well, and one might even attempt to formulate the ones mentioned in this report in a more statistical-oriented fashion, but the main advantage here is to decrease the number of dimensions for further analysis in several steps. A pitfall to watch out for with this approach is removing more information than necessary, and thus making a biased analysis at a later stage due to unintentional biased information loss.

### 2.1.6 Evaluating the Classification

The proof-of-concept implementation will double as an evaluation program visualizing users Moments and providing the deducted classifications, and at the same time receive feedback from the users.

This is implemented as a browser extension, adding content to Narratives web application and allows users to get classifications provided by the Bayesian inference framework set up for their own Moments. This as no one knows better how to classify an activity than the user who performed it, and therefore no one should be better at evaluating the algorithm performing classifications on it.

Firstly, the users are presented with the option to run the classification algorithm on a Moment (as they might choose not to provide every Moment for the study for privacy purposes). When choosing to classify, a visually comprehensive overview of their images and whereabouts during this Moment is presented to them, as well as a classification of the activity or activities. After this, the users are provided with a form where they evaluate the classifications quality on a 5-step scale, as well as perform the same classification as the algorithm did. A comment field is also present for commenting on the classification performance.

In this scenario, in order to evaluate the algorithms performance, the users classifications is regarded as the truth. Some error can of course be introduced in the form of users misinterpreting class definitions, but this will be assumed to be an negligible amount of error.

Weighed into this is also the amount of false positives and false negatives encountered. A false positive is considered to be a wrongful classification where a *semantically charged* class is chosen over a more neutral class, whereas a false negative denotes the opposite. These semantically charged classes consists of the a set of classes that would actually be visible to the end user in a real implementation, since these denotes that something special happening in an activity, and considered more interesting than the alternative. An example of this being that the social label *With Friends* is probably more interesting and attractive to the user than the alternative *Alone*. A false positive would in this case be for an algorithm to select a label *With Friends* for a users activity when the user actually was alone.

## 2.2 Clustering

Three algorithms are chosen for evaluating various algorithms for clustering, each being a representative from the traditional breakdown of clustering algorithm types[4]:

- CLARANS

[4]For a more precise overview of these algorithms than provided in the previous chapter, please see appendix A.

- DBSCAN
- SLINK

Because clustering algorithms differ very much, both in execution but also in output, these will be assessed in slightly different ways. The algorithms are tested on the same data sets and output will be compared both by using silhouettes and run-time, but also evaluated by the extra features that each algorithm bring. In the end, the suitability for this particular task of detecting clusters in data sets on the move is evaluated, and anything an algorithm can provide as an advantage will be taken into account. The results of the silhouettes and run-time will be presented in the following chapter, while the latter discussion of further algorithm advantages will be discussed in the discussion chapter.

### 2.2.1 Clustering parameters

When using clustering algorithms, the cluster parameters are important tools for describing what type of clusters that are desired. Therefore, some guidelines are introduced as to how the cluster parameters are set when evaluating the cluster performance of the algorithms.

#### CLARANS

CLARANS runs several times over the data set, with different $k$. Inspection shows that these data sets seldom contains more than a few clusters, so therefore $k$ will go from 1 to 5 in order of finding a suitable $k_{nat}$[5].

As for *num_local* and *max_neighbour*, these need to be large enough that it is likely that a good solution is found. Setting these to 10% and 20% of the desired data set respectively, seems to lead to consistent results.

#### DBSCAN

A main upside of DBSCAN is its ability to discard points as noise, which proves useful in this particular case where combinations of clusters and paths exists, and paths can be discarded by tweaking the clustering parameters $\epsilon$ and $minPts$. This is the case when we want to discard paths for instance walking speed, $v_{walking}$ if we choose $\epsilon$ and $minPts$ as

$$minPts \times v_{walking} \times 30 < \epsilon - C_{margin} \tag{2.2}$$

with some safety margin constant $C_{margin}$. This condition is illustrated in figure 2.3.

[5]In the original report, CLARANS is meant to throw away clusters producing clusters with no significant structure found. This is its way of disregarding noise. It is not done in this thesis, as for potential detection of activities, these clusters would be used as travels from one activity to another.

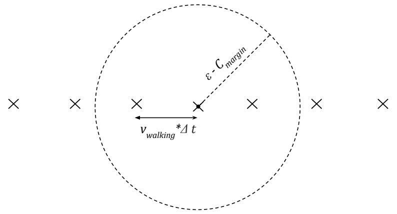



Figure 2.3: An illustration of the condition for choosing $\epsilon$ and $minPts$ to exclude paths.

In order of keeping clusters significant enough, we let $minPts$ be 10% of the size of the data set, and set $C_{margin}$ to $minPts \times v_{walking} \times 15$, and let $\epsilon$ take on the smallest value possible while still fulfilling equation 2.2.

**SLINK**

SLINK's cutoff function will consist of a distance cutoff condition same as DBSCAN's $\epsilon$.

### 2.2.2 Detected Clusters

A frequent scenario for using the Clip is when the user puts it on, then carries around for a long period of time at several locations, experiencing different activities. Deduction of qualitative information from life-logging experiences revolve partially around distinguishing these activities from each other, and this is where spatial clustering comes in handy. In this particular instance, a form of clustering has already been done, partitioning long series of images into Moments using timestamps and RGB-cubes from photos to detect the start of a new Moment.

Therefore it is preferable to run the proposed spatial clustering algorithms earlier in the pipeline than the proof-of-concept implementation in this paper suggests, and this is why these algorithms will be tested on data sets not only consisting of said Moments. But, as stated above, the proof-of-concept implementation will only contain spatial clustering on a Moment-level. This will be provided by DBSCAN, as it is better suited for small data-sets where only one cluster is found, or none at all for that matter. The algorithm comparison however, will run on bigger data sets.

A distinction between when a cluster has been detected and not has to be made as well, as the absence of a cluster can be interpreted as a user travelling between two sites.

### 2.2.3 Assessed Spatial Data Sets

The data sets on which the algorithms performance is assessed are real-world spatial GPS data from users, chosen in a representative manner. The sets displayed in this report do not contain any map background, in order to preserve anonymity.

These data sets consist both of data already divided into Moments, and longer data series merged together, providing more quantitative clustering possibilities, and more possible clusters.

## 2.3 Big Data Ethics

Given the current development of the technology revolving around Big Data and deducting user behaviour given statistical information where the privacy of the end users needs to be discussed. Current literature and articles are evaluated to get an overview of the current status of the debate, with the focus of life-logging devices as company services.

# Chapter 3

# Result

## 3.1 Clustering

*Most of the figures presented in this section are also available in appendix B as larger versions.*

### 3.1.1 Small Data Set Activity Detection

This section addresses data sets consisting of 822 Moments, ranging from a few data points to thousands in each set. All three algorithms have been given an attempt to cluster each Moment. The *haversine*[1] method is used for distance measurements. A computation is aborted if it takes longer than 100 seconds, as the clustering is intended to be done automatically and in real-time[2], where a run-time of close to a minute is not feasible. Results are excluded from a algorithms computation result set if it did not finish in time. In total, CLARANS timed out on 43 of the Moments, and DBSCAN and SLINK did the same with 1 each.

#### Performance

To evaluate the efficiency of the algorithms, the run-time for each algorithm over various Moments is plotted. Figure 3.1 provides an overview over the run-time on Moments ordered randomly[3].

[1]The haversine function, also called the great circle distance, takes the curvature of the earth in consideration when measuring long distances between latitudes and longitudes [20].

[2]This is implied by the server-side placement of the clustering algorithm, and the intention to automate the process. For an automated service in the cloud with many users, the cost of CPU computations are not feasible if a service such as this takes more than a few seconds.

[3]The Moments in this plot is actually ordered by an internal Moment ID provided by the database, although this is not of importance in this section. For all intents and purposes, these are randomly ordered.

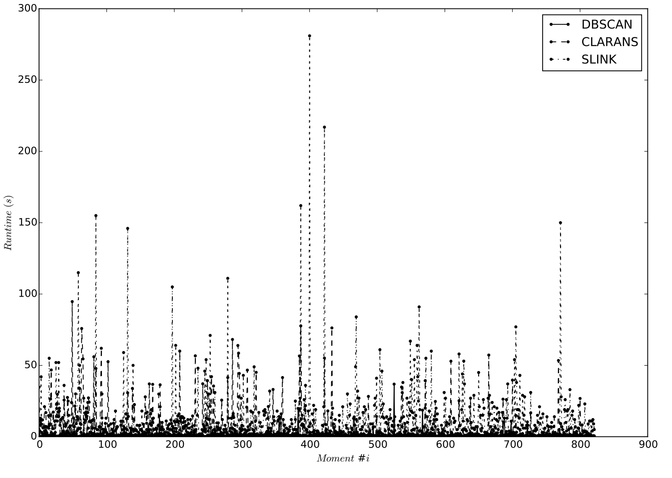



Figure 3.1: Run-time for clustering algorithms over Moments.

A more intuitive view is provided by figure 3.2, where the run time of each point is mapped with the number of points in each Moment. This obviously provides a hint towards the time-complexity of each algorithm, which becomes quite clear.

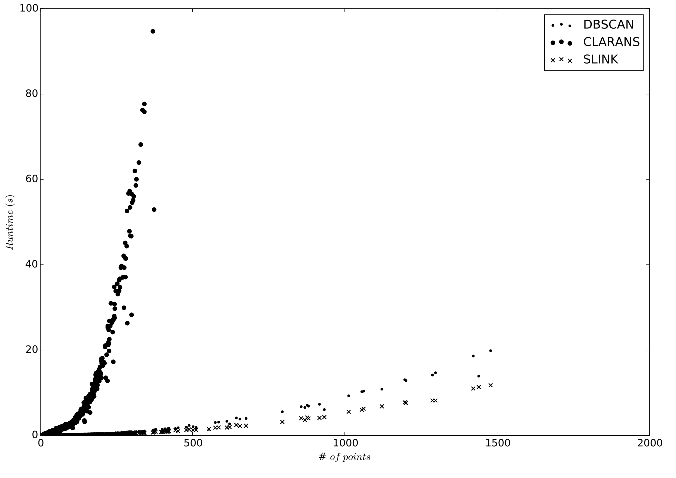



Figure 3.2: Run-time for clustering algorithms over Moments, by number of points in the Moment.

| Algorithm | Mean SC | Strong | Reasonable | Weak | No |
|---|---|---|---|---|---|
| CLARANS | 0.751818981799 | 457 | 167 | 155 | 0 |
| DBSCAN | 0.529126434287 | 54 | 2 | 765 | 0 |
| SLINK | 0.608986935167 | 250 | 69 | 486 | 16 |

Table 3.1: Mean silhouette coefficient per algorithm in the data set, and quantities within each defined Silhouette interpretation area.

### Silhouettes

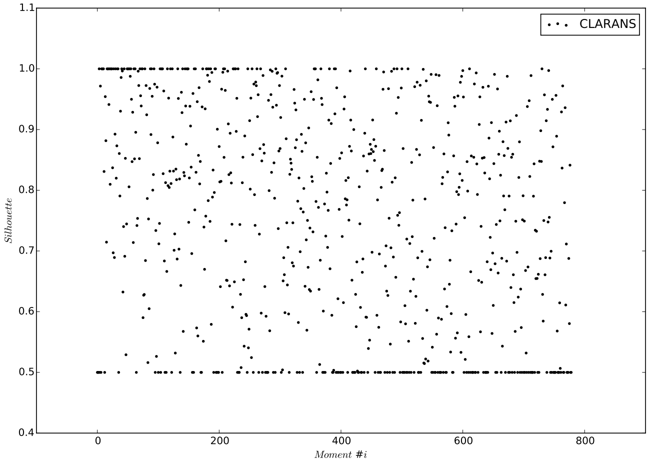



Figure 3.3: Moment-wise silhouette coefficients for CLARANS.

The Silhouette coefficients are plotted with the Moments sorted from the smallest number of data points to the largest, shown in figure 3.3, figure 3.4 and figure 3.5. The sorting is intended to visualize any potential correlation between the number of data points in a set, and the clustering results with regard to Silhouette coefficients.

The mean value of each plot is provided as a more comprehensible reference value in table 3.1, along with the quantities of coefficients with in each interpretation category, as suggested by Rousseeuw.

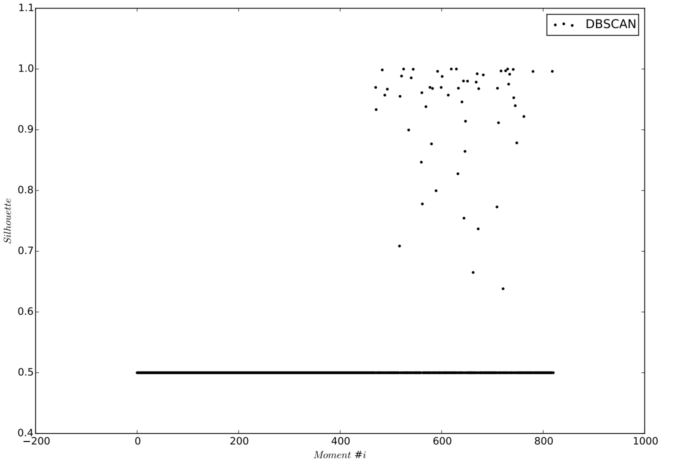



Figure 3.4: Moment-wise silhouette coefficients for DBSCAN.

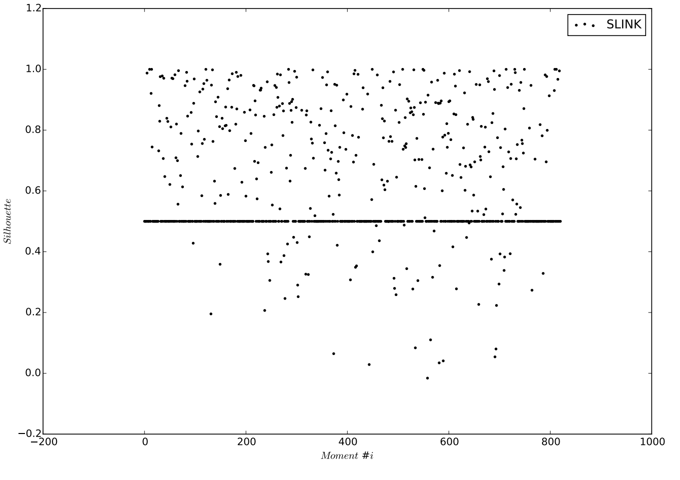



Figure 3.5: Moment-wise silhouette coefficients for SLINK.

### 3.1.2 Larger Data Set Activity Detection

This section addresses data set consisting of 59 photo sequences grouped by user id's, ranging from 200 data points to thousands in each set. All three algorithms have been given an attempt to cluster each photo sequence. The *haversine* method is used for distance measurements. A computation is aborted if it takes longer than 60 seconds. Results are excluded from a algorithms computation result set if it did not finish in time. In total, CLARANS timed out on 19 of the Moments, and DBSCAN and SLINK did the same with 1 each. In this data sets, multiple clusters are likely to be present, as it contains several Moments in each data set.

#### Performance

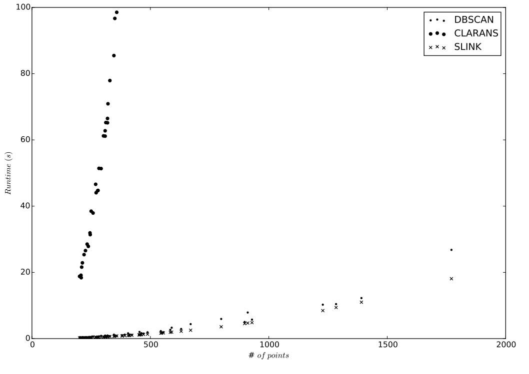



Figure 3.6: Run-time for clustering algorithms over users days, by number of points on the day.

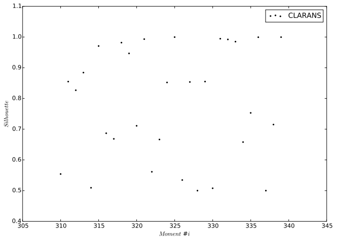
The plot depicting run-time in figure 3.6 now shows somewhat smaller spectrum of the x-axis.

| Algorithm | Mean SC | Strong | Reasonable | Weak | No |
|---|---|---|---|---|---|
| CLARANS | 0.783864065615 | 19 | 9 | 2 | 0 |
| DBSCAN | 0.581829108024 | 10 | 0 | 48 | 0 |
| SLINK | 0.63724366955 | 20 | 6 | 32 | 0 |

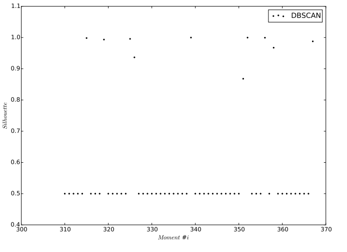
Table 3.2: Mean silhouette coefficient per algorithm in the larger data set, and quantities within each defined Silhouette interpretation area.

### Silhouettes

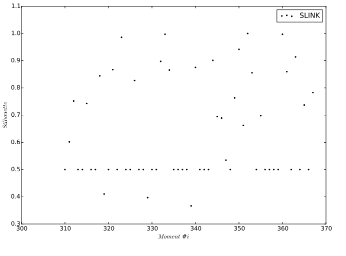
The Silhouettes have not changed from the smaller data set in any particular manner, and are therefore shown here for completeness.




(a) Moment-wise silhouette coefficients for CLARANS for a larger data set.




(b) Moment-wise silhouette coefficients for DBSCAN for a larger data set.




(c) Moment-wise silhouette coefficients for SLINK for a larger data set.

### 3.1.3 Cluster Detection Comparison

Different clustering methods result in different clusterings. As an attempt to illustrate this, comparisons displaying different clustering methods and the number of clusters detected in each data set is plotted in this section. The regarded data sets are sorted in increasing order based on the number of data points in each set.

Although figure 3.8, 3.9 and3.10 seem somewhat cluttered, the intention here is to show the difference in numbers of detected clusters as the data set increases.

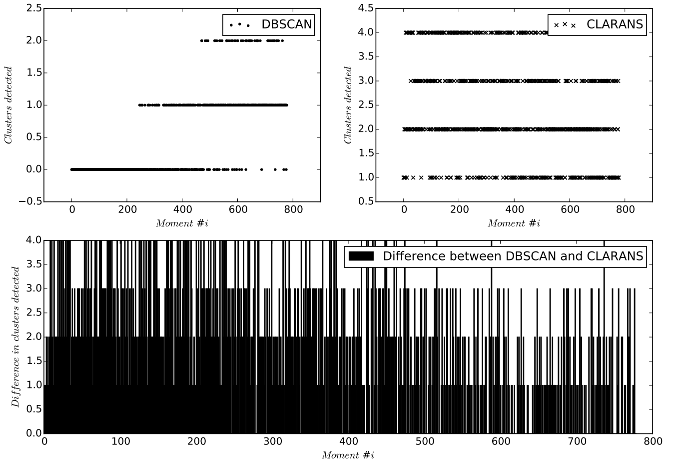



Figure 3.8: Cluster detection, comparison between DBSCAN and CLARANS.

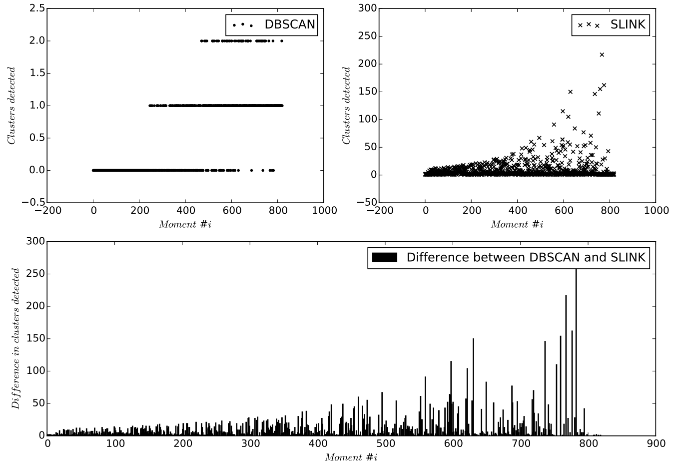



Figure 3.9: Cluster detection, comparison between DBSCAN and SLINK.

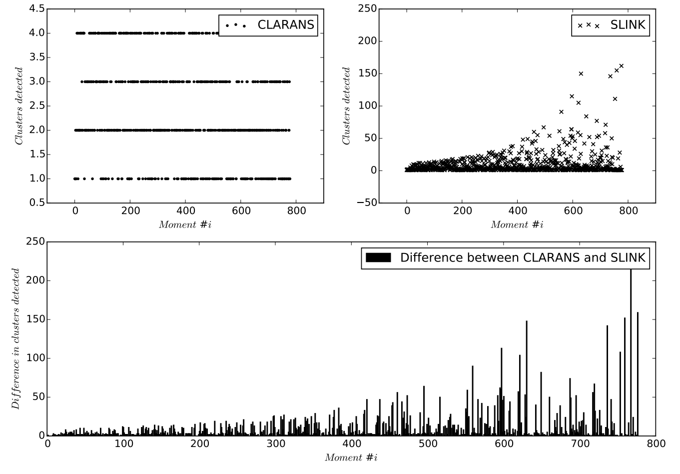



Figure 3.10: Cluster detection, comparison between CLARANS and SLINK.

| Movement | | Social | | Working | | Indoors | |
|---|---|---|---|---|---|---|---|
| User-assigned values | | | | | | | |
| Stationary | 40 | Social | 53 | Working | 57 | Indoors | 38 |
| Moving | 23 | Alone | 16 | Off Hours | 12 | Outdoors | 31 |
| Exercising | 6 | | | | | | |
| Algorithm-assigned values | | | | | | | |
| Stationary | 51 | Social | 22 | Working | 39 | Indoors | 69 |
| Moving | 18 | Alone | 48 | Off Hours | 31 | Outdoors | 1 |
| Exercising | 1 | | | | | | |
| Correctly assigned according to users. | | | | | | | |
| 75.81% | | 54.84% | | 56.45% | | 54.84% | |

Table 3.3: Classification results.

| Category | False Positive | False Negative |
|---|---|---|
| Movement | 1 | 12 |
| Social | 0 | 31 |
| Working | 27 | 1 |
| Indoors | 0 | 31 |

Table 3.4: False positives and negatives.

## 3.2 Classification

The classification is conducted after an initial activity detection, in this case the above shown spatial clustering. In this stage, the activity detection is considered correct and which type of clustering algorithm that is used is ignored, as all considered and approved algorithms should be able to produce desired clusters.

### 3.2.1 Data Set

The survey based on the user polling in the proof-of-concept implementation was conducted internally at Narrative.

A total of 11 people participated, and contributed to a total of 62 evaluated Moment classifications.

Taking all this into account, it is assumed that the data set still contains sufficient and a diverse enough user base to draw conclusions.

### 3.2.2 Evaluation Overview

The results after the users responded to the poll is presented in table 3.3. The quantities of assigned classifications by users are shown in the top part of the table, out of the 69 assessed Moments. So, for instance, in the Movement category there were 40 Moments assigned as Stationary, 23 as Moving and 6

| Movement | | Social | | Working | | Indoors | |
|---|---|---|---|---|---|---|---|
| User-assigned values | | | | | | | |
| Stationary | 40 | Social | 53 | Working | 57 | Indoors | 38 |
| Moving | 23 | Alone | 16 | Off Hours | 12 | Outdoors | 31 |
| Exercising | 6 | | | | | | |
| Algorithm-assigned values | | | | | | | |
| Stationary | 45 | Social | 27 | Working | 26 | Indoors | 44 |
| Moving | 18 | Alone | 43 | Off Hours | 44 | Outdoors | 26 |
| Exercising | 7 | | | | | | |
| Correctly assigned according to users. | | | | | | | |
| 78.57% | | 62.85% | | 73.21% | | 71.43% | |

Table 3.5: Classification results after model modification and learning.

| Category | False Positive | False Negative |
|---|---|---|
| Movement | 1 | 12 |
| Social | 0 | 26 |
| Working | 14 | 4 |
| Indoors | 7 | 13 |

Table 3.6: False positives and negatives after model modification and learning.

as Exercising. In the same manner below that, the algorithms assignments to different classes is presented. Note that this is not the same amount, as these are based on activities, and there can be (but rarely are) several activities in a Moment.

Table 3.4 presents the false negatives and positives within each category. The correct assignments are not included in this table, as only wrong assignments can provide false negatives and false positives.

### 3.2.3 Second Run

The table 3.5 presents its results in the same manner as table 3.3, but after modification of the model via Bayesian learning and lessons learnt after the first user tests. The upper area containing the users assignments remain the same as in table 3.3, but is kept in this table as well for easier reference.

In the same way, table 3.6 depicts false negatives and positives during the run within each category, after the model had been altered.

| Grade | Assigned | Mean | False Positive | | False Negative | |
|---|---|---|---|---|---|---|
| 5 | 22 | 0.00 | 0 | 0.00 | 0 | 0.00 |
| 4 | 16 | 1.19 | 4 | 0.25 | 15 | 0.94 |
| 3 | 13 | 2.15 | 8 | 0.62 | 20 | 1.54 |
| 2 | 16 | 2.88 | 14 | 0.88 | 32 | 2.00 |
| 1 | 2 | 3.00 | 2 | 1.00 | 4 | 2.00 |

Table 3.7: False positives and negatives correlated with user-assigned grades.

| User | Count | Mean Grade |
|---|---|---|
| User #1 | 17 | 4.47 |
| User #2 | 7 | 3.14 |
| User #3 | 12 | 3.33 |
| User #4 | 8 | 3.5 |
| User #5 | 7 | 4.0 |
| User #6 | 8 | 2.63 |

Table 3.8: Mean grades and number of classifications distributed among the users with most responses.

### 3.2.4 User Grades

*The reason that the number of values in the Assigned column of table 3.7 does not sum to 62 as the number of examined Moments were, is simply that these are scores for each activity, not for each Moment assessed, as there can be several activities in a Moment.*

Table 3.7 shows the correlation between false positives and negatives, along with the grades that users have assigned to the classification. The column marked mean shows the mean number of errors in order a classification getting the corresponding user grade. The first value in the false-columns shows the total number of false positives and negatives respectively in classifications that have received a certain grade. The real-valued column shows the number of false positives respectively per classification in that category.

# Chapter 4

# Discussion

## 4.1 Clustering Comparison

The three representatives were, as initially mentioned, chosen from each classical branch of clustering algorithm. The results more or less confirm what is expected from the theoretical background, and enhances the conviction of the suitability of different algorithms.

### 4.1.1 Performance

When comparing the run-time of the three assessed algorithms by consulting figures 3.2 and 3.6, it is clear that CLARANS is significantly slower than DBSCAN, which in its turn generally performs a bit slower than SLINK. These plots confirm the theoretical time complexities, with CLARANS being slowest. As per recommendation of Ng and Han, authors of the article "Clarans: A method for clustering objects for spatial data mining", this inner algorithm is then run several times for different numbers of desired clusters $k$ in order to find the most natural number $k_{nat}$. The assessment in each step is done by calculating the Silhouette coefficient for the computation, and the $k$ producing the best coefficient is elected as $k_{nat}$, with the belonging computation. Each Silhouette run is done at $\mathcal{O}(n^2)$, yielding a total time complexity of $\mathcal{O}(n^3)$ - $\mathcal{O}(n^5)$, depending on whether the clustering parameters *num_local* and *max_neighbour* rely on the number of data points or not.

SLINK and DBSCAN performs similar time-wise, both depicting a time-complexity of $\mathcal{O}(n^2)$, with different coefficients in front of the expression.

Using the polynomial fit for assessing *trend lines* together with the observed data, coefficients for the polynomials are found yielding the trend

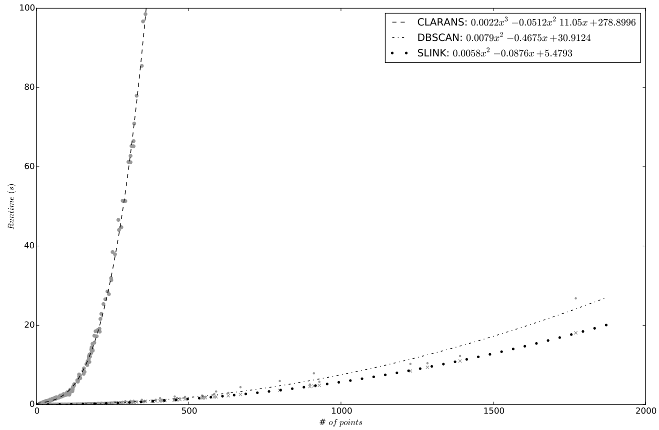



Figure 4.1: Scatterplot of timestamps including trend lines.

lines as follows:

$$
\begin{aligned}
y_{CLARANS} &= 0.0022x^3 + 0.0512x^2 + 11.05x + 278.9 \\
y_{DBSCAN} &= +0.0079x^2 + 0.4675x + 30.9 \\
y_{SLINK} &= +0.0058x^2 + 0.0876x + 5.5
\end{aligned}
\tag{4.1}
$$

Plotting these along with the observed data is done in figure 4.1, which makes the results seem feasible. It is likely to assume that these time complexities will hold for even larger numbers as well.

It is worth noting that the region query algorithm used for DBSCAN is currently based on exhaustive search done in $\mathcal{O}(n)$, which leaves DBSCAN with a time complexity of $\mathcal{O}(n^2)$. A more rigid look up algorithm based on some R*-tree approach performing in $\mathcal{O}(log(n))$ should produce a somewhat faster result[1]. An alternative to this if larger data sets are considered, is by either constructing some spatial index such as an R*-tree and inserting the data in it before performing spatial queries. Alborzi and Samet did show that a bulk insert construction takes less than $\mathcal{O}(n^2)$ time, and this spatial index implies a look up time of $\mathcal{O}(\log n)$. Many databases already contain such indexes, and thus such queries can be done with a well considered database choice with simplicity [1].

[1] Attempts were made at implementing this via RethinkDB:s spatial queries, but unsuccessful as a mean of improving running time efficiency loss. This is probable due to that RethinkDB is a database focused on being distributed, yielding a time loss when querying the database $n$ times. A faster approach was just to keep all data points in memory.

### 4.1.2 Quality - Silhouettes

Silhouettes are a measurement primarily for partitioning methods, and was originally developed with PAM and CLARA in mind by the authors Rousseeuw et al. An implicit assumption made, or a fact that is simply not considered, is that spatial points can be unassigned to clusters. The interpretation of Silhouettes here is simply not to treat these points and therefore, no evaluation of whether disregarding a point as noise is a good decision or not is taken into account.

Looking at figures 3.3, 3.4 and 3.5, and taking the mean values depicted under each figure into account, it is clear that CLARANS produces the most qualitative clustering according to the criterion of maximizing the Silhouettes. This is expected, as the entire algorithms aim is to use the obtained Silhouette coefficients as feedback for how the algorithm is performing and which $k_{nat}$ to choose.

DBSCAN aims to eliminate bad clustering by regarding the entire observed Moment or data set as an activity. For the sake of being unbiased, a single detected cluster is awarded a Silhouette coefficient value of 0.5, which is why the algorithm produces that many clustering with the value of 0.5. It has also the ability, unlike both CLARANS and SLINK, to disregard points as noise. Glancing at figure 3.8 and 3.9 shows that DBSCAN generally produces few clusters given the set cluster parameters. This is desired, as we would not like a day to be divided into too many activities, and that a certain time should be spent at a certain location to deem it as an activity. Often for few data points, this setup yields a single cluster, disregardful of the Silhouette coefficient, which seems feasible as well as desirable.

SLINK produces poor clustering as well with regard to Silhouettes, partly because of the simple criterion on which the splitting is done. Unlike DBSCAN, it does not grant the ability to not use all the data points in the clustered result. During long, extended data sets right on the border of the limit value of breakpoints, a lot of clusters that are not very coherent will be detected, leading to many clusters and to a poor clustering result.

Taking one step back and evaluating the evaluation itself, it would seem like Silhouettes are not very suitable as a metric for comparing different clustering methods. However, it is one of few that is applicable at all regardless of which method is used, and therefore it is useful. One has to consider of course that the produced result is not easily interpretable, and requires prior knowledge about the algorithm being evaluated as well as insight in Silhouettes; how they are defined and some experience in how they behave when encountering different clustering. Given this, I argue that Silhouettes can be useful in a general manner and for a broader number of clustering applications, granted that one is familiar with the behaviour of Silhouettes. It serves as an aid to further evaluate why an algorithm performs as it does, and calls for another step of analysis. It is worth noting that a bad Silhouette score does not necessarily mean a bad clustering algorithm, it just means it is not optimized for this particular method.

### 4.1.3 Produced Clusters

Figure 3.8, 3.9 and 3.10 makes it very clear that different clustering methods produce a different amount and different types of clusters.

Generally, DBSCAN and CLARANS produce somewhat similar amount of clusters. This is due to that DBSCAN is not prone to produce many clusters given the current clustering parameters, with $minPts$ set to 10% of the data points, the absolute maximum number of clusters that is possible to obtain is 10. In a similar manner, CLARANS is only able to produce at most 5 clusters due to its limit set on the tests for $k_{nat}$. The produced clusterings therefore does not differ very much in amount.

SLINK on the other hand tends to produce a lot more clusters in larger data sets (as can be seen in both figure 3.8 and 3.10 where the number of clusters SLINK detects diverges from the other algorithms more as the size of the data set increases). This is due to it's inability to disregard points as noise, while bound to the same cutoff condition as DBSCANs $\epsilon$, yielding a lot of small clusters containing a small number of points. Removing these would be trivial in order to find remove noisy outliers with SLINK as well, but it would not serve any more comparison purposes than that.

### 4.1.4 Large vs Small Data Sets

Although CLARANS was specifically designed for working on larger data sets, both SLINK and DBSCAN outperforms CLARANS in the different sizes tested.

As DBSCAN and CLARANS has an upper bound on the number of clusters that they are able to detect in this instance as well, the results does not differ very much from the small data set. SLINK follows its previous trend with detecting even more clusters, since it is more flexible in its approach on where to cut off its dendrogram into clusters.

### 4.1.5 Method-specific qualities

Different clustering methods have different qualities to take into account, both from a life-logging perspective, and with regard to finding different types of clusters.

CLARANS was built to maximize the Silhouette coefficient, and is useful for finding clusters in very large data sets, especially large enough to not fit into the memory of the machine performing the clustering. Not keeping all data points in memory would be a drawback for the other algorithms (granted that DBSCAN keeps its exhaustive search for nearby regions), but as it is randomized, clusters must be well-defined as well in order for it to locate them. This can be due to poor start-seed selections, meaning that the node chosen as a starting node is not very well spread out. There exist methods for introducing starting seeds in partitioning algorithms, usually with k-means being the target, but could applicable in this scenario as well.

DBSCAN is easy to configure when working with activities and when following equation 2.2, as one only needs to define how many data points are required for a series of samples to be considered an activity. Disregarding outliers[2] is useful too, and making a qualitative estimate of where the activity has taken place falls naturally. However, a decent knowledge about the size and characteristics of the assessed data set is necessary in order to get the desired result, and clusters of varying densities are hard to distinct. Although the condition for selecting a good $\varepsilon$ and $minPts$ works well with determining activities in a single cluster, it is not as accurate with higher number of data points and an expected higher number of clusters. This since $minPts$ is set to contain a 10% fraction of the total points in the series to regard it as significant. A lower bound is also specified for this, and increasing DBCSANs performance of detecting more clusters in bigger data sets could be accomplished by introducing an upper bound as well.

SLINK is very customizable, as the splitting criterion defines which clusters are obtained. This would allow for more strict clustering distinction, for instance by allowing time to a significant member in the distance function, and thus allowing finding of breakpoints in the time-line, and performing more strict clustering than DBSCAN. SLINK also produces a hierarchical result. This hierarchical result is especially useful when multiple criteria need to be weighed in, and when allowing the result to be merged again or split further without re-running the entire algorithm.

### 4.1.6 Desired Clusters

From a life-logging point of view, there seem to be two different approaches to what is a desired cluster to detect.

One way, activity detection is of main interest and the output does not necessarily need to be in any specific form. What is desired is an estimate of a location, time of stay and other similar data which will be used for classification or activity detection. It is more important that this produces data that is neatly wrapped up and easy to present or use at a later step. This is the method used in the classification step of this thesis, when attempting to detect different activities.

The alternative is that clustering in some hierarchy is required, where attributes are subordinated one another to perform division of data into smaller, ordered sets of data. This is what Narrative uses for dividing long series of images, into Moments (although, position or accelerometer is currently not involved in this, only color data from images and timestamps are used for this clustering). Everything in this clustering is subordinated time, as Moments by Narratives definition is required to be coherent series of images. This calls for differently defined clusters, and thus differently behaving clustering algorithms.

[2] An outlier is a data point that is distant from the other data points with regard to the distance function being used.

## 4.2 Proof-of-Concept

The proof-of-concept implementation conducted in this thesis adds components such as clustering and classification to an already defined pipeline. The result of this implementation is presented earlier in this report, but the order of elements in this already defined pipeline can be discussed.

Long photo sequences are currently being divided into Moments solely based on timestamps and image analysis. It is at this point one would like to perform geo-spatial clustering if applicable, in order to get more natural Moments[3]. One might regard the existing implementation as a naive clustering algorithm, where introducing spatial data in the algorithm just increases the dimensionality, but also the possibility of less artificial clusters.

## 4.3 Classification of Moments

### 4.3.1 Assessed Data Set

As mentioned earlier, only employees were involved in the testing of the classification algorithm. It is feasible that employees of a company making a certain life-logging device might utilize it another manner than the common user, which might have caused somewhat skewed results, but such that should be sufficient for this thesis purposes.

### 4.3.2 Possible Pitfalls

As table 3.3 witnesses of, the initial classification performs rather poorly, with each classification assignment except for the movement category only barely produced better 54% correct approximations. There are many causes of this behaviour, and some being corrected led to big improvement:

- The small sample for the algorithm to learn of was not sufficient, and priors were not skewed enough to fit the model parameters to there correct location. This could have been prevented with a much bigger sample size.
- The sample for the learning algorithm were not diverse enough, and taken from a single user. Referencing table 3.8 it the mean value of users assessments are widely varying. This can of course be a result of the users preferences while grading, but it also hints that the model parameters are somewhat user-specific. For instance, a certain user

[3]The reason that no positional data is considered yet at this stage from Narratives point of view is that no GPS points is available yet when the *Momentification* is done. This is produced later in the pipeline by signal processing and by consulting servers for satellites positions. To perform geo-spatial clustering in Narratives Momentification, this has to be addressed first.

might move around more than another user while walking, therefore requiring somewhat different thresholds. Given this assumption, data from a small group of users will not reflect the entire population of users, yielding skewed model parameters.

- The assigned probability distribution might not be suitable for the actual distribution, and thus the expert failed at the first attempt.

The model was simple and loosely defined upon assumptions, that might prove more or less accurate. A model behaving incorrectly after many learning attempts is probably an inaccurate model, but this should be accommodated by updating ones model after observing its performance in a true Bayesian manner.

The original intent of introducing such a model was for it to be simple and general enough to evaluate the method itself rather than how this model would apply to Narratives employees and their Moments. Glancing ahead at the second attempt, it seems as the method holds.

### 4.3.3 False Positives and Negatives

Table 3.7 shows the correlation between users grades for an entire activity classification, where the false negatives outweigh the number of false positives. Naturally, it seems more appealing for a user to receive a false negative rather than a false positive, implying that nothing special happened instead of saying something special happened while it did not.

While the survey does not contain enough samples to statistically verify this conclusively, it seems as a higher amount of false negatives is tolerated before lowering the grade of a classification, while false positives are not tolerated at all. This backs our statements of false positives being less appreciated.

Given this information, one should focus on making an application that is less likely to produce a classification with greater semantic significance, as users seem more forgiving as towards missing out on classifications. As previously intended, assigned classes that are not semantically charged, which are assumed to be:

- *Alone* in the Social category.
- *Off Hours* in the Working category.
- *Stationary* in the Movement category.
- *Indoors* in the Indoors category.

should then not at all be shown to the end user, as they do not produce enough value.

The scenario above applicable when the intention is to show the classifications to the end users. When the target instead is statistical classification, for example in order for a company to determine the amount of activities its users engage in outdoors, these semantically charged notation is of less importance, as an overview of a whole group is of greater interest than being correct in every individual case.

### 4.3.4 Second Attempt

Analysis of the movement parameter is satisfactory, as it has three possible outcomes and still manages to produce the best accuracy.

Relearning based on the new values allow a better fit for the observed values, which are bound to be more diverse than samples from a single user, as well as being a better quantity.

Looking at the results of the first attempt along with the number of false positives and false negatives in table 3.3 and table 3.4, respectively, it is clear that the categories *Working* and *Indoors* are not balanced. Given that *Working* depends on *Indoors* (consulting figure 2.2), it seems logical in a first step to change *Indoors*. By manually lowering the threshold of the model parameter (which was somewhat misplaced due to huge variance in the area-distribution), the results in table 3.3 and table 3.4 were obtained.

Along with this, a relearning process is made where the percentages of the other assignments are somewhat improved, however not very significantly. Of course, this introduces a bias when the assessed data is the same as the learned data, but given the sample size other tests are not possible. This only illustrates the need of a larger data set for learning parameters, and the models influence in getting a faster convergence towards correct classification.

This signals that a model error is present in the *Indoors*-parameter, and a model change should be done. In a Bayesian manner, preserving uncertainty is desired, and therefore introducing a second model parameter denoting if the activity has any positional points could be introduced. If this is the case, the area threshold is used, while otherwise, the original distribution of the *Indoors* Bernoulli variable is kept, thus preserving uncertainty.

### 4.3.5 Iterative Process

A way of looking at this attempt is simply as one stage of an iterative process. In order for a sound model to develop with rigid model parameters several attempts seem to be required, and the first steps of this process shows promise. It is also worth noting that the model was initially predicted to not be too correct, as it was a simple version in order to evaluate the process and not the model. For a real-world implementation more analysis is definitely required in order of creating more accurate predictions.

It has been shown that a learning step as well as a manual refinement of the model parameters result in a significant improvement. This is also an example of how it is possible to go from a simple model producing mediocre results, to a more complex and targeted model towards more specific problems.

## 4.4 Big Data Ethics

### 4.4.1 What is Big Data?

> "Common definitions of the popular phrase for the phenomenon "big data" are based on distinctions between the capabilities of legacy database technologies and new data storage and processing techniques and tools such as Hadoop clusters, Bloom filters, and R data analysis tools. Big data is data too big to be handled and analyzed by traditional database protocols such as SQL (which makes big data a term that may evolve over time; what is now big data may quite rapidly become small)." - Davis, author of *Ethics of Big Data: Balancing risk and innovation* [7].

What we particularly focus on in this thesis is just not the size, but the applicability to make assumptions and draw conclusions based on the observed user data. This is often the case for life-logging devices, and cause for both use and abuse.

### 4.4.2 Making Revenue

Big data is a relatively new subject, or at least the extent of how it is used. Many companies are being able to make revenue on "free" services, which are free in the sense that the end user is the product. Mapping demographics and studying user behavior is becoming more and more a source of power for big data companies. There are clearly different business models for the service providers, one being free-of-charge while collecting information about customers behaviours, the other being the classical approach of charging the end user for a service while not mining information about the user.

Simplified, it is two different payment methods for the users (while it might not be clear to the users themselves). The payment either comes in the form of money, or utilizing your data, with various steps between.

In any form - companies are not in the business of harming their customers, so the customers are not the sole potential victims. As the amount of data increases, so does the need to protect the data and store it in a safe manner by the service provider. The more variate data that needs to be stored in different ways, the more security holes need to be shut [7].

### 4.4.3 An Ethics Code

The need for an ethics code, or guidelines to follow when utilizing big data computing is increasing with the number of companies engaging in the business. King and Richards:

> "The problem is that our ability to reveal patterns and new knowledge from previously unexamined troves of data is moving faster than our current legal and ethical guidelines can manage."
> - *What's Up With Big Data Ethics?* [17].

As King and Richards states, the rapid development of Big Data services has made law making as well as setting ethical guidelines fall behind, partly by lack of interest and the number of people involved, but even more so the unfamiliarity of the field. Venturing into a new area of technical implementations makes it hard to estimate what the different consequences might be. One can only try to predict the implications of Big Data services and to make decisions based on the best judgment from there. If the guidelines are set too loose, the end users privacy will be endangered and will refer from using services where they feel violated and exposed. Being too strict can instead decrease quality of services.

Davis proposes 4 major questions that should be answered by such a code: [7]

- *Identity* - What is the relationship between our offline identity and our online identity?
- *Privacy* - Who should control access to data?
- *Ownership* - Who owns data, can rights to it be transferred, and what are the obligations of people who generate and use that data?
- *Reputation* - How can we determine what data is trustworthy? Whether about ourselves, others, or anything else, big data exponentially increases the amount of information and ways we can interact with it. This phenomenon increases the complexity of managing how we are perceived and judged.

It is important to realize that there can not be a single ethics code for all types of big data - as the services working with big data and lifelogging are too diverse, and restraining this in a too broad manner could drastically reduce very useful development of services. Utilizing a framework for companies to build their ethical guidelines regarding Big Data on seems like a productive way of streamlining the process, making company policies more transparent and users can easier expect certain elements to be covered.

### 4.4.4 Narratives Role

Narrative is of a particular interest, given that the provided service can seem intrusive to some users. This when capturing photographic information without the users active knowledge, but simply by wearing the Clip. This has been a factor in mind of the company since start-up, and measures have been taken in order to ensure the end users privacy.

The photos collected by the Clip is the users property, and by uploading it to Narratives paid cloud services no legal rights to the data is lost. The business model is the second one of the two mentioned above, meaning that the user demography data is not sold, and the intent of data collecting is to satisfy the end customer.

The Clip itself is also designed to look as a camera, in order to make the surrounding aware of the fact in the same manner as when taking a photograph with a handheld device.

From a legal perspective, the photographing by itself proves no complication, since the same laws dictate how a worn camera should be used as a hand-held camera; there is no distinction.

A necessity for a life-logging service like what Narrative provides is the need to communicate it's values regarding big data ethics, ownership of the data collected and similar. The ethics code need to be shared with the end users. In my own experience, when telling people about Narrative as a company or wearing the Clip, the most common questions are those regarding privacy issues or ethical discussions. Even if the end users are not concerned, it seems like an important marketing opportunity to let everyone that uses the Clip to be a part of the community aware of a companies ethical code, and thus becoming an ambassador for the service they are using and the device that they are wearing.

This seems like wearables in general can profit from, as they are usually target for ethical discussion as life-logging devices, as well as the users to some extent become walking billboards for the product. Doing so should also lead to a continuous discussion about this current topic, leading to the development of general ethics codes that are predictable and that does not seem alien to users.

### 4.4.5 Is Privacy Broken?

I would say no, it is not. But as more and more people utilize social services and log their life digitally - privacy needs to be defined in another manner. It is not possible to disappear off the grid as it was a couple of generations ago, and we leave digital breadcrumbs everywhere we go. But by making standardized, predictable ethical rules that users are aware of, ownership of data and awareness might control how we view our privacy in the future.

It is especially important when utilizing Big Data to treat it as such, as Big Data. Anonymous content is rarely purely anonymous, as presenting a large number of factors even when concealing the name and some other information about a person, it might still not be entirely anonymous.

Information can also be deducted from observations, making it possible to draw conclusion about a persons actions based on logged behaviour. Closely related to this is reputation, and particularly one about a person. Some decades ago, the reputation consisted (for a non-celebrity person) of the manners one had in conversations with others, and possibly to the next row of individuals based on what those other people said. Now it is possible for an individual to make an opinion about a person without ever meeting them, through social media. Yet alone, computers can make their "opinion" about persons and draw conclusions based on these observations, making the service feel intimidating and as a breach of privacy.

Deducting wrongful information can be just as bad, by implying that a user has done something or is interested in something that they in turn find offensive.

This calls for a question about the degree of ownership and to what extent we own our own traits, both in the offline world and the online, that enable services and people to make second hand deductions about private matters about us [7].

# Chapter 5

# Conclusion

Clustering and classification of data are two closely related subjects, that can utilize methodologies that diverge more or less. In this thesis various clustering methods consisting of representatives from different algorithm families have been evaluated based on their suitability for life-logging devices, and in particular, the Narrative Clip. Bayesian inference has then been used for classification of the activities detected by the clustering algorithms, allowing labels to be attached to each activity.

Comparing produced clusters and expecting exact similarity between different algorithms is not a good approach. As mentioned early in this report, there is no universal definition of a cluster and therefore no universal clustering algorithm. Taking this into account, it is a better approach to venture beyond strict similarity in produced clustering, and compare other metrics, such as number of detected cluster, performance, Silhouettes and so on. But the most important examination point is the cluster algorithms characteristics and abilities, basically what it was meant to do.

CLARANS was the representative from the category of partitioning clustering methods. While partitioning methods in general are easy to implement and to understand, they have drawbacks that are significant, embodied by the results of CLARANS. The performance is poor due to the knowledge about the number of clusters being a prerequisite, requiring several runs of the algorithm and evaluating the result. Choosing the clustering parameters for CLARANS is unintuitive, since it is based on random search of a solution graph, and may find different solutions to the same problem, with varying quality. Bearing all this in mind, partitioning methods and particularly CLARANS seem inappropriate for life-logging applications, as the knowledge of the number of clusters that exist on beforehand is a luxury that we usually do not have. The execution time necessary to find the appropriate number of clusters make usage of this not feasible, as it is implied by being automatic, that this should be used in real-time.

DBSCAN performs well in run time, both for small and for large sets of data points. The choice of clustering parameters affects the amount of clusters, and the type of clusters one is willing to find. In the tested configuration, the algorithm seems most suitable for finding a little bit more fuzzy clusters containing a rough position and outline, but not necessarily sorted by time. This is useful in activity detection, where a more neatly presented and approximated cluster is more appreciated and easier to use for a classification algorithm.

SLINK runs slightly faster than DBSCAN in the considered test cases, and is more flexible in the way it produces clusters. This allows for clusters to be cutoffs in a time-line, which is suitable for Moment detection, where a more strict definition of a cluster is required. The same could be said for several other applications, where time or other factors need to be sorted in first hand to produce clusters.

This yields two different areas where DBSCAN and SLINK are applicable, in activity detection and in Moment division, respectively. Life-logging is in its essence full of data mining problems that needs to be solved, and utilizing these or other algorithms on other problems is very likely, but examining the entire life-logging area is not within the scope of this article. The conclusion is just that these two applications is appropriate for these two problems.

Silhouettes are not a simple metric to use when evaluating different types of clustering algorithm, due to the different definitions of a cluster and the varying output from the algorithm. Although not being able to simply compare numbers in order of determining quality of a clustering algorithms produced output, Silhouettes could still be useful to examine how an algorithm behaves, and why the produced result look the way they do.

When it comes to classification, the results seem somewhat individualized, both when it comes to what users think is important regarding assigned classes, and especially the model parameters determining the classes.

From a simple model promising results were achieved, when allowing an iterative approach in a Bayesian manner. After all, there is nothing more Bayesian than updating beliefs after witnessing evidence! The used model was made simple to make it easy to perform an update step, thus showing that this improved the quality of the output significantly.

Model changes, even seemingly small, are more powerful than Bayesian learning via learning data and model fitting. In this thesis, a rather small set of learning data was used, due to both time and resource constraints. This caused parameters not to be set too robustly, especially parameters with great variance suffered by not being able to converge fast enough. From this, we learn that studying the parameter values is important as well after learning to be confident in a model.

## 5.1 Further Research

This report presents an overview for clustering and classification, and discusses suitability of some methods as well as identifying pitfalls. Life-logging in its essence is about in an automated fashion storing activities for the monitored object, in Narrative's case, the end user. This usually results in vast amounts of data that needs to be processed in order of retrieving summaries or more qualitative data. Everything that automates and improves the process of automation is interesting to this area, as it improves the quality of service.

Investigating model learning and Bayesian network learning would be an interesting next step for taking the automated process one step further.

#### Phone coupling

As of now, the GPS data obtained by the Clip is rather sporadic, and not very accurate. Phones today are however better at positioning, and utilizes other methods such as WiFi for a better positioning approximation [30].

It does also seem likely that a user carries his or her phone while wearing the Clip, and making use of this data should lead to a more quantitative and qualitative positional data, in its turn simplifying and making the result of clustering more useful to the end users. Examining what more quantitative and qualitative data produces from a starting point is appealing.

#### Momentification

Introducing other clustering factors than geo-spatial data and time labels seem feasible as well, and especially monitoring statistical breakpoints in sensor-data proves especially promising. To introduce this either as another dimension in the clustering data, or correlation the detected geo-spatial clusters with the proposed clusters based on statistical breakpoints.

#### Dynamic Learning

An interesting approach for extending the classification would be to introduce dynamic learning for the classification algorithm. As is stated previously, the model parameters seem somewhat individualized, and making these depend on user feedback. Such feedback can both come in the form of explicit evaluations on a web-based service, or by observing user behaviour and assessing whether certain actions are a positive or a negative stimuli.

# Bibliography


[1] Houman Alborzi and Hanan Samet. “Execution time analysis of a top-down R-tree construction algorithm”. In: *Information processing letters* 101.1 (2007), pp. 6–12.

[2] Daniel Aloise et al. “NP-hardness of Euclidean sum-of-squares clustering”. In: *Machine Learning* 75.2 (2009), pp. 245–248.

[3] Mihael Ankerst et al. “OPTICS: ordering points to identify the clustering structure”. In: *ACM Sigmod Record*. Vol. 28. 2. ACM. 1999, pp. 49–60.

[4] Norbert Beckmann et al. *The R*-tree: an efficient and robust access method for points and rectangles*. Vol. 19. 2. ACM, 1990.

[5] José M Bernardo and Adrian FM Smith. *Bayesian theory*. Vol. 405. John Wiley & Sons, 2009.

[6] Cam Davidson-Pilon. *Probabilistic Programming & Bayesian Methods for Hackers*. URL: `http://camdavidsonpilon.github.io/Probabilistic-Programming-and-Bayesian-Methods-for-Hackers/` (visited on 04/02/2015).

[7] Kord Davis. *Ethics of Big Data: Balancing risk and innovation.* ” O’Reilly Media, Inc.”, 2012.

[8] Martin Ester et al. “A density-based algorithm for discovering clusters in large spatial databases with noise.” In: *Kdd*. Vol. 96. 34. 1996, pp. 226–231.

[9] Vladimir Estivill-Castro. “Why so many clustering algorithms: a position paper”. In: *ACM SIGKDD Explorations Newsletter* 4.1 (2002), pp. 65–75.

[10] Christopher J. Fonnesbeck. *PyMC User’s Guide*. 2014. URL: `http://pymc-devs.github.io/pymc/` (visited on 04/06/2015).

[11] JA Garcia et al. “A dynamic approach for clustering data”. In: *Signal Processing* 44.2 (1995), pp. 181–196.

[12] Antonin Guttman. “R-trees: A Dynamic Index Structure for Spatial Searching”. In: *SIGMOD Rec.* 14.2 (June 1984), pp. 47–57. ISSN: 0163-5808. URL: `http://doi.acm.org/10.1145/971697.602266`.

[13] John A Hartigan and Manchek A Wong. "Algorithm AS 136: A k-means clustering algorithm". In: *Applied statistics* (1979), pp. 100–108.

[14] Toby Dylan Hocking et al. "Clusterpath an algorithm for clustering using convex fusion penalties". In: *28th international conference on machine learning*. 2011, p. 1.

[15] Panos Kalnis, Nikos Mamoulis, and Spiridon Bakiras. "On discovering moving clusters in spatio-temporal data". In: *Advances in spatial and temporal databases*. Springer, 2005, pp. 364–381.

[16] Leonard Kaufman and Peter J Rousseeuw. *Finding groups in data: an introduction to cluster analysis*. Vol. 344. John Wiley & Sons, 2009.

[17] Jonathan H King and Neil M Richards. *What's Up With Big Data Ethics?* 2014. URL: `http://www.forbes.com/sites/oreillymedia/2014/03/28/whats-up-with-big-data-ethics/` (visited on 05/17/2015).

[18] Slava Kisilevich, Florian Mansmann, and Daniel Keim. "P-DBSCAN: a density based clustering algorithm for exploration and analysis of attractive areas using collections of geo-tagged photos". In: *Proceedings of the 1st international conference and exhibition on computing for geospatial research & application*. ACM. 2010, p. 38.

[19] Raymond T. Ng and Jiawei Han. "Clarans: A method for clustering objects for spatial data mining". In: *Knowledge and Data Engineering, IEEE Transactions on* 14.5 (2002), pp. 1003–1016.

[20] Doctor Rick. "Deriving the haversine formula". In: *The Math Forum, April*. 1999.

[21] Peter J Rousseeuw. "Silhouettes: a graphical aid to the interpretation and validation of cluster analysis". In: *Journal of computational and applied mathematics* 20 (1987), pp. 53–65.

[22] Robin Sibson. "SLINK: an optimally efficient algorithm for the single-link cluster method". In: *The Computer Journal* 16.1 (1973), pp. 30–34.

[23] Christian Strobl. "Dimensionally Extended Nine-Intersection Model (DE-9IM)". In: *Encyclopedia of GIS*. Springer, 2008, pp. 240–245.

[24] Richard Tsai. *Richard's Blog - GSoC2014: Recent progress*. 2014. URL: `http://richardtsai.me/posts/gsoc14-recent-progress` (visited on 05/03/2015).

[25] Aditya Vailaya et al. "Bayesian framework for semantic classification of outdoor vacation images". In: *Electronic Imaging'99*. International Society for Optics and Photonics. 1998, pp. 415–426.

[26] Aditya Vailaya et al. "Content-based hierarchical classification of vacation images". In: *Multimedia Computing and Systems, 1999. IEEE International Conference on*. Vol. 1. IEEE. 1999, pp. 518–523.

[27] Howard Wainer. “The Most Dangerous Equation Ignorance of how sample size affects statistical variation has created havoc for nearly a millennium”. In: *American Scientist* 95.3 (2007), pp. 249–256.

[28] Maximilian Walther and Michael Kaisser. “Geo-spatial event detection in the twitter stream”. In: *Advances in Information Retrieval.* Springer, 2013, pp. 356–367.

[29] Christopher KI Williams and David Barber. “Bayesian classification with Gaussian processes”. In: *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 20.12 (1998), pp. 1342–1351.

[30] Paul A Zandbergen. “Accuracy of iPhone locations: A comparison of assisted GPS, WiFi and cellular positioning”. In: *Transactions in GIS* 13.s1 (2009), pp. 5–25.

[31] Ying Zhao and George Karypis. “Evaluation of hierarchical clustering algorithms for document datasets”. In: *Proceedings of the eleventh international conference on Information and knowledge management.* ACM. 2002, pp. 515–524.

# Appendices

# Appendix A

# Clustering Theory

This presents the algorithms used in the paper more in-depth, and presents the implementation used during test (to some extent). Python is used as implementation language due to its expressibility, and in order to get somewhat more of a standard than just pseudo-code.

Each example starts with an overview of the suggested pros and cons presented in each article introducing the algorithms.

The code examples have been slightly altered for readability purposes, and functions used have been omitted for brevity. The intent is to show the core functionality of each algorithm.

## A.1 CLARANS

*CLARANS - Clustering Large Applications based on RANdomized Search)* is a partitioning clustering algorithm which divides the given data set into $k_{nat}$ clusters, each cluster represented by a medoid point.

CLARANS can essentially be viewed as a graph search, where each node in the graph represents a distinct selection of medoid representatives of each cluster. Each node in the graph is considered to have vertexes to all nodes which differ in the selection of mediod nodes by one. The graph search is randomized, and thus CLARANS is not deterministic, meaning that inputting the same problem twice can lead to different solutions.

As all clustering algorithms, CLARANS needs parameters to specify the way the clustering is performed. *maxneighbour* determines how many random neighbours of a solution node should be examined and *numlocal* decides how many local minima should be tried out before halting. $k$ could also be considered as a parameter for the algorithm, and dexides how many clusters to find. The solution for ignoring $k$ as a parameter, suggested by Ng and Han, is to run the algorithm several times with different $k$ and examine the result of each turn, in order of finding the $k$ that will be used as $k_{nat}$.

Given this, it is obvious that the size size of this graph $G$ is

$$\mid G_{v,k} \mid = \binom{n}{k} \tag{A.1}$$

and that each the degree

$$deg(v) = k(n-k) \tag{A.2}$$

Therefore, when presented with equation A.2, it is clear that letting *maxneighbour* exceed this value is inefficient, since this means re-examining nodes that has already been deemed unfit.

The algorithm is in it's original paper as follows

1. Initialize parameters *numlocal* and *maxneighbour*. Initialize $i$ to 1 and *mincost* to a large number.
2. Set *current* to an arbitrary node in $G_{n,k}$.
3. Set $j$ to 1.
4. Consider a random neighbour S of *current*, and based on [equation 5], calculate the cost defferential of the two nodes.
5. If $S$ has a lower cost, set *current* to $S$ and go to step (3).
6. Otherwise, increment $j$ by 1. If $j \leq maxneighbour$, goto step (4).
7. Otherwise, when $j > maxneighbour$ compare the cost of *current* with *mincost*. If the former is less than *mincost*, set *mincost* to the cost of *current* and set *bestnode* to *current*.

8. Increment $i$ by 1. If $i > numlocal$, output *bestnode* and halt. Otherwise go to step (2).

### A.1.1 Algorithm

```python
def CLARANS(S, k_nat, numlocal, maxneighbour):
    min_cost    = float('inf')
    best_nodes  = None

    for i in range(numlocal):
        # Random selection of a starting node.
        random.shuffle(S)
        current = S[ -k_nat:]
        points  = S[:-k_nat]

        current_cost = self.cost(current, points)

        j = 1
        s_p = points
        while j <= maxneighbour:
            # Select a random neighbour
            nbr = current
            s_p = [s.pop(random.randrange(len(nbr)))] + s_p
            nbr.append(s_p.pop())

            if self.cost(s, s_p) < current_cost:
                current, points = (s, s_p)
                current_cost = cost(current, points)
                j = 1
            else:
                j += 1

        if current_cost < min_cost:
            min_cost    = current_cost
            best_nodes  = current

    return best_nodes
```

## A.2 SLINK

SLINK is an hierarchical algorithm which in practice does not actually perform any clustering, but structures the data into a dendrogram using a specific pointer notation. This pointer notation is what makes SLINK's improved run-time $\mathcal{O}(n^2)$ possible, as an improvement over traditional hierarchical clustering algorithms which runs in $\mathcal{O}(n^3)$.

SLINK is an aggleromative method, constructing the clusters bottom up, with the starting point of each datum in the clustered data set to be its own cluster, and continuing to combine clusters until all data is in the same cluster. The combining of clusters is done using Single Linkage criterion [1], which is also where the algorithm gets its name.

This algorithm is proven to be optimally efficient in hierarchical clustering. [22]

### A.2.1 Pointer notation

As mentioned above, what makes SLINK significantly faster than classical, naive implementations of clustering algorithms is its utilization of a pointer notation. The pointer notation used in the SLINK is defined as follows:

Lets introduce two functions that are defined on the set of indexes for the $N$ data objects to be clustered:

**Definition A.2.1 (Pointer definitions for SLINK)** *Let*

$$\pi : 1, ..., N \rightarrow 1, ...N$$

*so that* $\pi(N) = N$*, and let*

$$\lambda : 1, ..., N \rightarrow [0, \infty]$$

*so that* $\lambda(N) = \inf$*, and*

$$\pi(i) > i \quad \lambda(\pi(i)) > \lambda(i) \quad , i < N$$

The interpretation of $\pi$ and $\lambda$ respectively should be that $\pi(i)$ is the last object in the cluster which $i$ joins, and $\lambda(i)$ is the distance to that cluster.

#### Example

This is an example of where SLINK has already been performed, and transformed a given data-set into a dendrogram. Table A.1 shows the pointers value, while figure A.1 displays the corresponding dendrogram interpretation.

[1] Single Linkage (or nearest-neighbour) is a measurement of the similarity of two clusters defined by the two most similar members. Alternatives to this is Complete Linkage, which compares the two most dissimilar members, and Average Linkage.

| Index | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| $\pi$ | 6 | 3 | 3 | 5 | 9 | 9 | 8 | 9 | 9 | 9 |
| $\lambda$ | 1.94 | 0.42 | 0.83 | 1.56 | 3.12 | 10.9 | 1.63 | 1.20 | 4.99 | $\infty$ |

Table A.1: Pointer representation example [24].

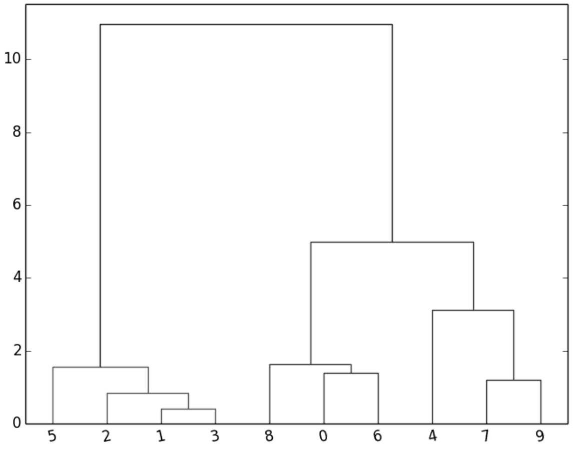



Figure A.1: An example of the pointer representation of SLINK [24].

### A.2.2 Algorithm

The algorithm takes some data set $S$ with $n$ data points in it, and utilizes three arrays of length $n$ to store the pointer representation. These are called $\Pi.\Lambda, M$.

1. Set $\Pi(n+1)$ to $n+1$, $\Lambda(n+1)$ to $\infty$.

2. Set $M(i)$ to $d(i, n+1)$ for $i = 1, ..., n$.

3. For $i$ increasing from 1 to $n$
   if $\Lambda(i) \geq M(i)$
   set $M(\Pi(i))$ to $min\{M(\Pi(i)), \Lambda(i)\}$
   set $\Lambda(i)$ to $M(i)$
   set $\Pi(i)$ to $n+1$
   else
   set $M(\Pi(i))$ to $min\{M(\Pi(i)), M(i)\}$

4. For $i$ increasing from 1 to $n$
   if $\Lambda(i) \geq \Lambda(\Pi(i))$
   set $\Pi(1)$ to $n+1$.

```python
def SLINK(S):
    points   = S.get_points()
    n        = len(points)

    pi, _lambda, M = [0]*n, [float("inf")]*n, [None]*n

    for i in range(1, n):
        pi[i] = i

        for j in range(i):
            M[j] = distance(points[i], points[j])

        for j in range(i):
            if _lambda[j] >= M[j]:
                M[pi[j]] = min(M[pi[j]], _lambda[pi[j]])
                _lambda[j] = M[j]
                pi[j] = i
            else:
                M[pi[j]] = min(M[pi[j]], M[j])

        for j in range(i):
            if _lambda[j] >= _lambda[pi[j]]:
                pi[j] = i

    return (_lambda, pi)
```

# A.3 DBSCAN

*DBSCAN - Density Based Spatial Clustering of Applications with Noise* is an algorithm proposed by Ester et al. in 1996. It relies heavily on 6 definitions, which provides an outline for the algorithm.

Two input parameters are required, $\varepsilon$ which defines the neighborhood size of a point (see A.3.1), and $MinPts$ that determines the minimum number of points in a cluster. These together define a notation of cluster density.

## A.3.1 Definitions

**Definition A.3.1 ($\varepsilon$-neighborhood of a point)** *The $\varepsilon$-neighborhood of a point $p$, denoted by $N_\varepsilon(p)$, is defined by*

$$N_\varepsilon(p) = \{q \in D | dist(p,q) \leq \varepsilon\}$$

**Definition A.3.2 (Directly Density-Reachable)** *A point $p$ is directly density-reachable from a point $q$ with regard to $\varepsilon$ and $MinPts$ if*

1. *$p \in N_\varepsilon(q)$ and*
2. *$|N_\varepsilon(q)| \geq MinPts$ (core point condition).*

**Definition A.3.3 (Density-Reachable)** *A point $p$ is density-reachable from a point $q$ with regard to $\varepsilon$ and $MinPts$ if there is a chain of points $p_1, p_2, \ldots, p_n$, $p_1 = q$, $p_n = p$ such that $p_{i+1}$ is directly density reachable from $p_i$.*

**Definition A.3.4 (Density-Connected)** *A point $p$ is density-connected to a point $q$ with regard to $\varepsilon$ and $MinPts$ if there is a point $o$ such that both $p$ and $q$ are density-reachable from $o$ with regard to $\varepsilon$ and $MinPts$.*

**Definition A.3.5 (Cluster)** *Let $D$ be a database of points. A clustrer $C$ with regard to $\varepsilon$ and $MinPts$ is a non-empty subset of $D$ satisfying the following conditions:*

1. *$\forall p, q$: if $p \in C$ and $q$ is density-reachable from $p$ with regard to $\varepsilon$ and $MinPts$, then $q \in C$: Maximality)*
2. *$\forall p, q \in C$: $p$ is density-connected to $q$ with regard to $\varepsilon$ and $MinPts$.*

**Definition A.3.6 (Noise)** *Let $C_1, ...C_k$ be the clusters of the database $D$ with regard to parameters $\varepsilon_i$ and $MinPts_i$, $i = 1, ...k$. Then we define the noise as the st of points in the database $D$ not belonging to any cluster $C_i$, i.e. $noise = \{p \in D | \forall i : p \notin C_i\}$*

### A.3.2 Algorithm

```
def DBSCAN(S, eps, minPts)
 # The initial set of points S is initialized
 # with clusterID set to UNCLASSIFIED.
 clusterID = nextId(NOISE)

 for point in S
  if point.clusterId == UNCLASSIFIED
   if expandCluster(S, point, clusterID, eps, minPts)
    clusterID = nextID(clusterID)

def expandCluster(S, point, clusterID, eps, minPts)
 seeds = S.regionQuery(point, eps)

 # Core point criterion not fulfilled for point,
 # so this is temporary regarded as noise.
 if len(seeds) < minPts
  point.clusterID = NOISE
  return False

 for p in seeds
     p.clusterID = clusterID

 seeds.remove(point)

 while not seeds.empty()
  current = seeds.pop()
  result = s.regionQuery(current, eps)

  if len(result) >= MinPts
   for p in result
    if p.clusterID in [UNCLASSIFIED, NOISE]
     if p.clusterID = UNCLASSIFIED
      seeds.append(p)
     p.clusterID = clusterID
 return True
```

# Appendix B

# Larger figures

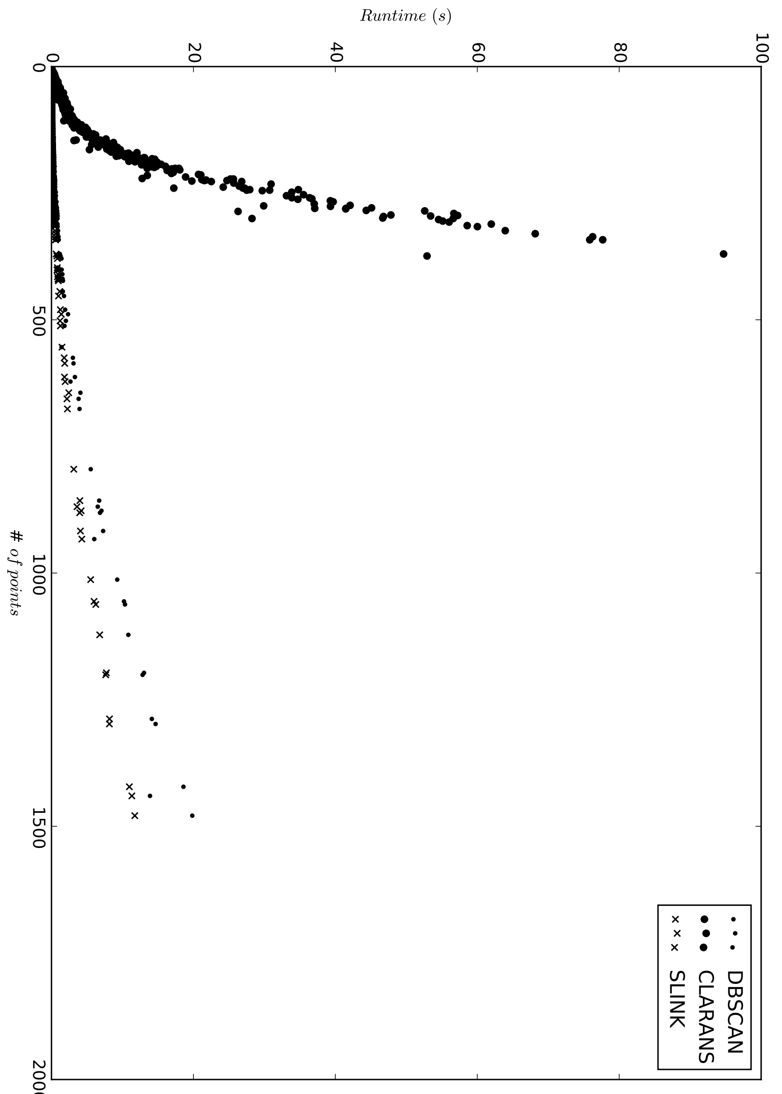



Figure 3.2: Run-time for clustering algorithms over Moments, by number of points in the moment. (repeated from page 28)

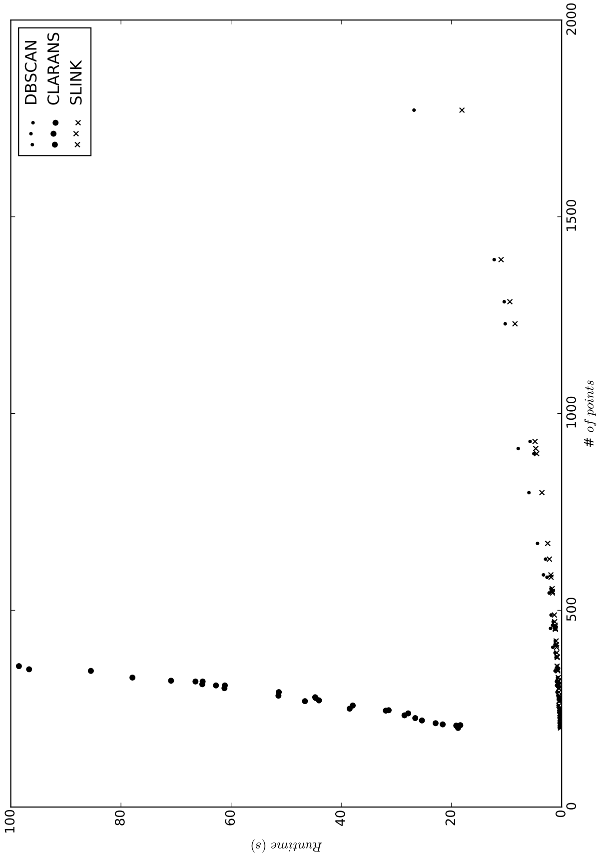



Figure 3.6: Run-time for clustering algorithms over users days, by number of points on the day. (repeated from page 32)

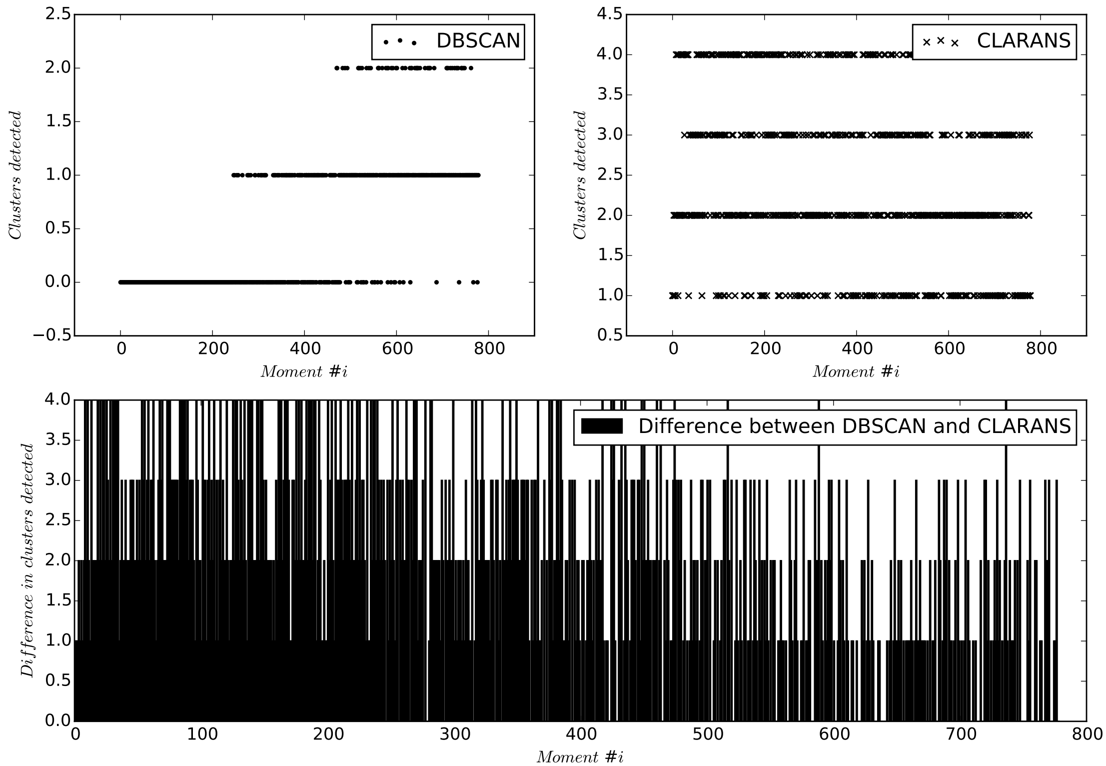



Figure 3.8: Cluster detection, comparison between DBSCAN and CLARANS. (repeated from page 34)

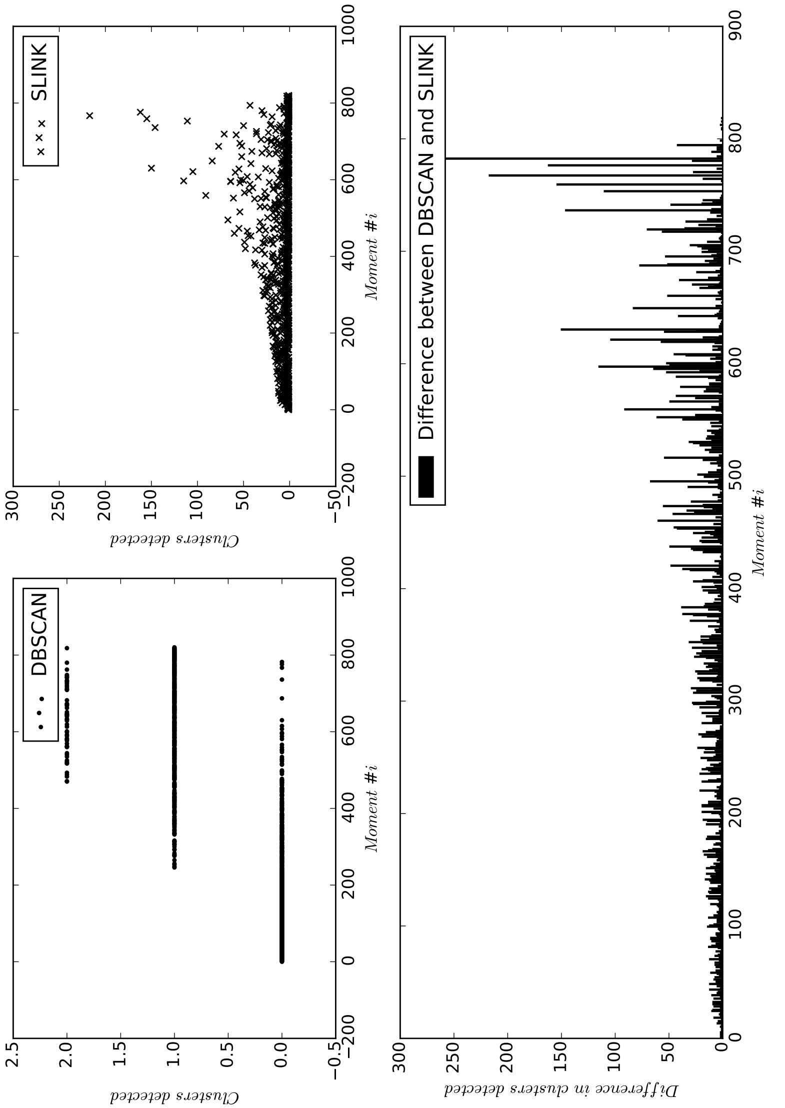



Figure 3.9: Cluster detection, comparison between DBSCAN and SLINK. (repeated from page 35)

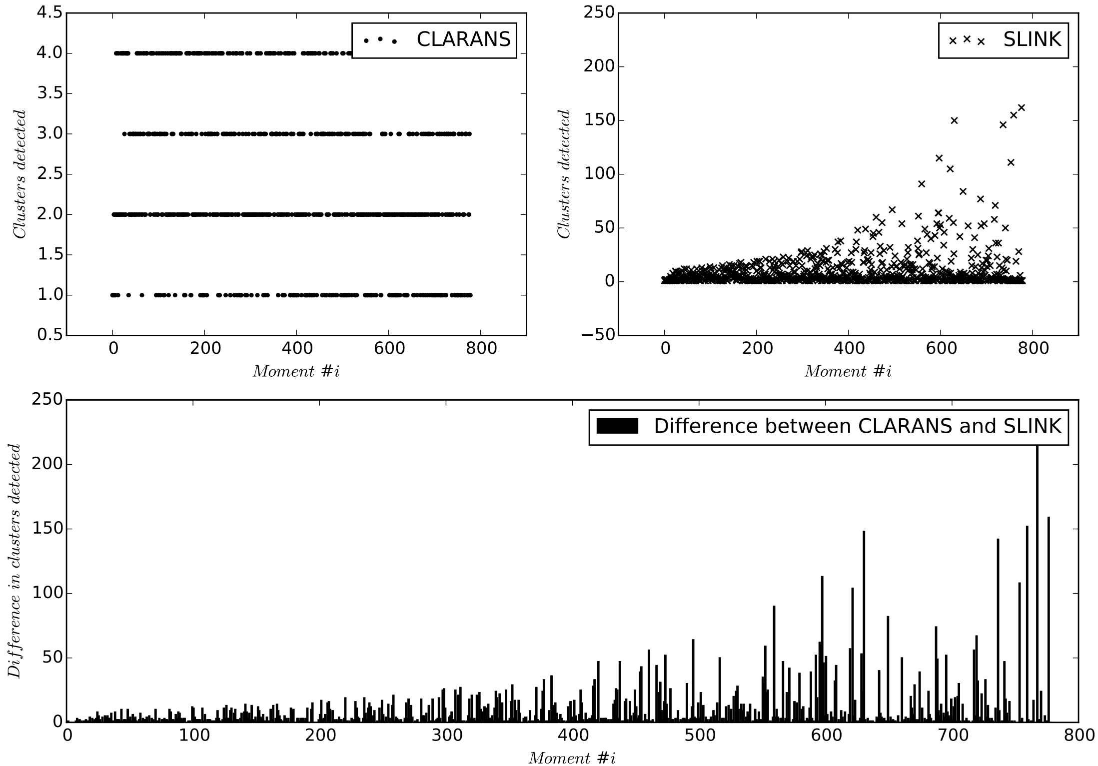



Figure 3.10: Cluster detection, comparison between CLARANS and SLINK. (repeated from page 35)

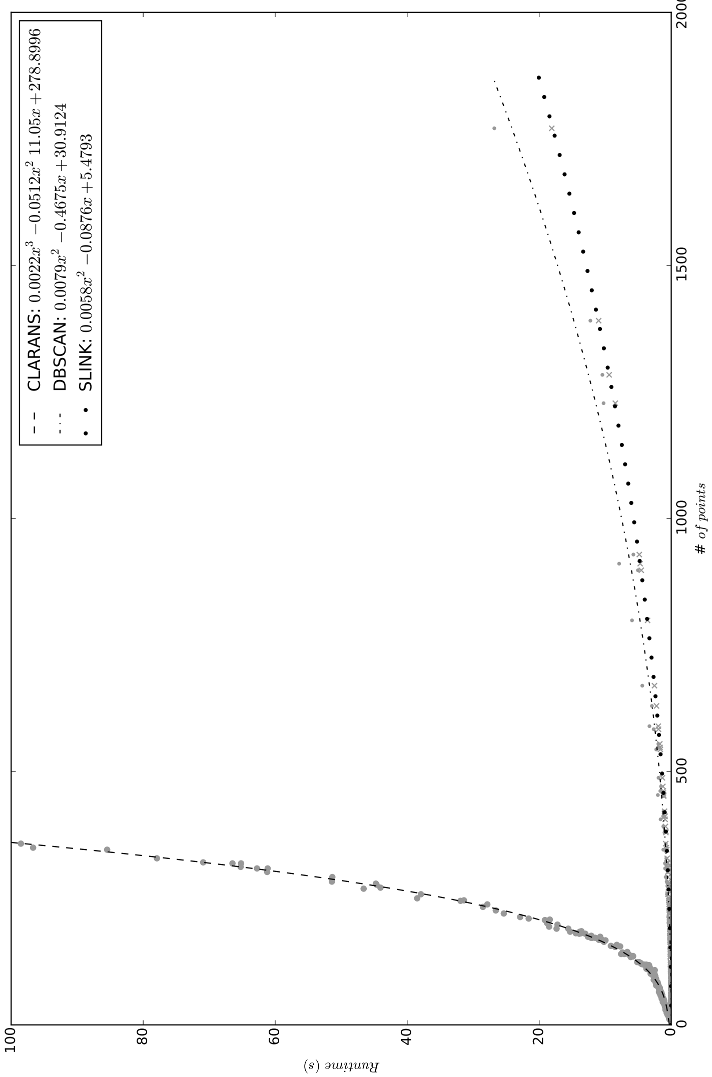



Figure 4.1: Scatterplot of timestamps including trend lines. (repeated from page 40)

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