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## Abbreviations

**PCA** Principal Component Analysis. 1

# 1 Introduction

## 1.1 The problem of clustering

## 1.2 Motivation

The scope of the thesis is Big Data and Cluster Ensembles.

Success of EAC clustering on hard data sets.

Interesting problems from big data.

Combining the two.

## 1.3 Challenges and Motivation

## 1.4 Goals and Contribution

This dissertation aims to research and extend the state of the art of ensemble clustering, in what concerns the method of Evidence Accumulation Clustering and its application in large datasets, while also accessing alternative algorithmic solutions and parallelization techniques. The goal is to understand EAC's suitability for large datasets and find ways to respond to the challenges that that entails (speed and memory). In particular, efficient parallel version for the GPU of different parts of the method.

Throughout this dissertation, various clustering techniques are reviewed, implemented and tested.

## 1.5 Objectives

The main objectives for this work are:

- Review quantum inspired clustering methods
- Study possibility of integration of quantum inspired methods in EAC
- Review of scalability of EAC
- Review methods and techniques designed for processing large datasets
- Review of acceleration techniques for large datasets
- Review of the General Purpose computing in Graphics Processing Units paradigm
- Study possibility of integration of GPGPU in EAC
- Devise strategies to reduce complexity of EAC
- **Application of Evidence Accumulation Clustering in Big Data**
- Validation of Big Data EAC on real data (ECG for emotional state discovery and/or discovery of natural groups)

## 1.6 Outline

Explain briefly the work done

The scope of the thesis is Big Data and Cluster Ensembles. A main requirement in this context is to have fast clustering techniques. This may be accomplished in two ways: algorithmically or with parallelization techniques. The former deals with finding faster solutions while the later takes existing solutions and optimizes them with execution speed in mind.

The initial research was under the algorithmic path. More specifically, exploring quantum inspired clustering algorithms. The findings of this exploration revealed this algorithms to be a poor match for integration in EAC and turned the focus of the research to parallelization techniques. Two main paradigms of parallelization were found appropriate: GPGPU and distributed (among a cluster of workstations). While the first is a readily available resource in common machines, the second is able to address problems dealing with larger datasets.

## 2 State of the art

### 2.1 Quantum clustering

The field of quantum clustering has shown promising results regarding potential speedups in several tasks over their classical counterparts. There are two major paths for the problem of quantum clustering. The first is the quantization of clustering methods to work in quantum computers. This translates in converting algorithms to work partially or totally on a different computing paradigm, with support of quantum circuits or quantum computers. Literature suggests that quadratic (and even exponential in some cases) speedup may be achieved. Most of the approaches for such conversions make use of Groover's search algorithm, or a variant of it, e.g. [23]. Most literature on this path is also mostly theoretical since quantum circuits are not easily available and a working quantum computer has yet to be invented. This path can be seen as part of the bigger problem of quantum computing and quantum information processing.

An alternative to using real quantum systems would be to simulate them. However, simulating quantum systems in classical computers is a very hard task by itself and literature suggest is not feasible. Given that the scope of the thesis is to accelerate clustering, having the extra overhead of simulating the systems would not allow speedups.

The second approach is the computational intelligence approach, i.e. to use algorithms that muster inspiration from quantum analogies. A study of the literature will reveal that this path typically further divides itself into two approaches. One comprehends the algorithms based on the concept of the quantum bit (qubit), the quantum analogue of a classical bit with interesting properties found in quantum objects. The other approach models data as a quantum system and uses the Schrödinger equation to evolve it.

In the following two sections these approaches for quantum inspired computational intelligence are explored.

#### 2.1.1 Quantum bit

To understand the workings of the algorithms based on the concept of the qubit, it is useful to cast some insight about its properties and functioning. The quantum bit is a quantum object that has the properties of quantum superposition, entanglement and ...

A qubit can have any value between 0 and 1 (superposition property) until it is observed, which is when the system collapses to either state. However, the probability with which the system collapses to either state may be different. The superposition property or linear combination of states can be expressed as

$$[\psi] = \alpha[0] + \beta[1]$$

where  $\psi$  is an arbitrary state vector and  $\alpha, \beta$  are the probability amplitude coefficients of basis states  $[0]$  and  $[1]$ , respectively. The basis states correspond to the spin of the modelled particle (in this case, a fermion, e.g. electron). The coefficients are subjected to the following normalization:

$$|\alpha|^2 + |\beta|^2 = 1$$

where  $|\alpha|^2, |\beta|^2$  are the probabilities of observing states  $[0]$  and  $[1]$ , respectively.  $\alpha$  and  $\beta$  are complex quantities and represent a qubit:

$$\begin{bmatrix} \alpha \\ \beta \end{bmatrix}$$

Moreover, a qubit string may be represented by:

$$\begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ \beta_1 & \beta_2 & \beta_3 \end{bmatrix}$$

The probability of observing the state  $[000]$  will be  $|\alpha_1|^2 \times |\alpha_2|^2 \times |\alpha_3|^2$ . To use this model for computing purposes, black-box objects called *oracles* are used.

Def from wiki: In complexity theory and computability theory, an oracle machine is an abstract machine used to study decision problems. It can be visualized as a Turing machine with a black box, called an oracle, which is able to decide certain decision problems in a single operation. The problem can be of any complexity class. Even undecidable problems, like the halting problem, can be used.

### 2.1.2 Quantum K-Means

Several clustering algorithms [4, 5, 27], as well as optimization problems [21], are modelled after this concept. To test the potential of the algorithms under this paradigm, a quantum variant of the K-Means algorithm based on [5] was chosen as a case study.

### 2.1.3 Description of the algorithm

The Quantum K-Means (QK-Means) algorithm, as is described in [5], is based on the classical K-Means algorithm. It extends the basic K-Means with concepts from quantum mechanics (the qubit) and genetic algorithms.

Within the context of this algorithm, oracles contain strings of qubits and generate their own input by observing the state of the qubits. After collapsing, the qubit value becomes analogue to a classical bit.

Ideally, oracles would contain actual quantum systems or simulate them - this would correctly account for the desirable quantum properties. As it stands, oracles aren't quantum systems or even simulate them. The most appropriate description would be a probabilistic Turing machine. Each string of qubits represents a number, so the number of qubits in each string will define its precision. The number of strings chosen for the oracles depends on the number of clusters and dimensionality of the problem (e.g. for 3 clusters of 2 dimensions, 6 strings will be used since 6 numbers are required). Each oracle will represent a possible solution.

The algorithm has the following steps:

1. Initialize population of oracles
2. Collapse oracles
3. K-Means
4. Compute cluster fitness
5. Store
6. Quantum Rotation Gate
7. Collapse oracles
8. Quantum cross-over and mutation
9. Repeat 3-7 until generation (iteration) limit is reached

**Initialize population of oracles** The oracles are created in this step and all qubit coefficients are initialized with  $\frac{1}{\sqrt{2}}$ , so that the system will observe either state with equal probability. This value is chosen taken into account the necessary normalization of the coefficients.

**Collapse oracles** Collapsing the oracles implies making an observation of each qubit of each qubit string in each oracle. This is done by first choosing a coefficient to use (either can be used), e.g.  $\alpha$ . Then, a random value  $r$  between 0 and 1 is generated. If  $\alpha \geq r$  then the system collapses to  $[0]$ , otherwise to  $[1]$ .

**K-Means** In this step we convert the binary representation of the qubit strings to base 10 and use those values as initial centroids for K-Means. For each oracle, classical K-Means is then executed until it stabilizes or reaches the iteration limit. The solution centroids are returned to the oracles in binary representation.

**Compute cluster fitness** Cluster fitness is computed using the Davies-Bouldin index for each oracle. The score of each oracle is stored in the oracle itself.

**Store** The best scoring oracle is stored.

**Quantum Rotation Gate** So far, we’ve had classical K-Means with a complex random number generation for the centroids and complicated data structures. This is the step that fundamentally differs from the classical version. In this step a quantum gate (in this case a rotation gate) is applied to all oracles except the best one. The basic idea is to shift the qubit coefficients of the least scoring oracles so they’ll have a higher probability of collapsing into initial centroid values closer to the best solution so far. This way, in future generations, we’ll not initiate with the best centroids so far (which will not converge further into a better solution) but we’ll be closer while still ensuring diversity (which is also a desired property of the genetic computing paradigm). In conclusion, we want to look for better solutions than the one we got before in each oracle while moving in the direction of the best we found so far.

The genetic operations of cross-over and mutation are both part of the genetic algorithms toolbox. [23] suggests that that this operations may not be required to produce variability in the population of qubit strings. This is because, according to [13], use of the angle-distance rotation method in the quantum rotation operation produces enough variability, with a careful choice of the rotation angle. However, if they were used, their goal is to produce further variability into the population of qubit strings.

### 2.1.4 Horn and Gottlieb’s algorithm

The other approach to clustering that gathers inspiration from quantum mechanical concepts is to use the Schrödinger equation. The algorithm under study was created by Horn and Gottlieb and was later extended by Weinstein and Horn.

The first step in this methodology is to compute a probability density function of the input data. This is done with a Parzen-window estimator in [11, 22]. The Parzen-window density estimation of the input data is done by associating a Gaussian with each point, such that

$$\psi(\mathbf{x}) = \sum_{i=1}^N e^{-\frac{\|\mathbf{x}-\mathbf{x}_i\|^2}{2\sigma^2}}$$

where  $N$  is the total number of points in the dataset,  $\sigma$  is the variance and  $\psi$  is the probability density estimation.  $\psi$  is chosen to be the wave function in Schrödinger’s equation. The details of why this is are better described in [22, 11, 10].

Having this information we'll compute the potential function  $V(x)$  that corresponds to the state of minimum energy (ground state = eigenstate with minimum eigenvalue) [11], by solving the Schrödinger's equation in order of  $V(x)$ :

$$V(\mathbf{x}) = E + \frac{\frac{\sigma^2}{2} \nabla^2 \psi}{\psi} = E - \frac{d}{2} + \frac{1}{2\sigma^2 \psi} \sum_{i=1}^N \|\mathbf{x} - \mathbf{x}_i\|^2 e^{-\frac{\|\mathbf{x} - \mathbf{x}_i\|^2}{2\sigma^2}}$$

And since the energy should be chosen such that  $\psi$  is the groundstate (i.e. eigenstate corresponding to minimum eigenvalue) of the Hamiltonian operator associated with Schrödinger's equation (not represented above), the following is true

$$E = -\min \frac{\frac{\sigma^2}{2} \nabla^2 \psi}{\psi}$$

With all of this,  $V(x)$  can be computed. This potential function is akin to the inverse of a probability density function. Minima of the potential correspond to intervals in space where points are together. So minima will naturally correspond to cluster centres [11]. However, it's very computationally intensive to compute  $V(x)$  to the whole space, so we only compute the value of this function at the data points. This should not be problematic since clusters' centres are generally close to the data points themselves. Even so, the minima may not lie on the data points themselves. One method to address this problem is to compute the potential on the input data and converge this points toward some minima of the potential function. This is done with the gradient descent method in [11].

Another method [22] is to think of the input data as particles and use the Hamiltonian operator to evolve the quantum system in the time-dependant Schrödinger equation. Given enough time steps, the particles will converge to and oscillate around potential minima. This method makes the Dynamic Quantum Clustering algorithm. The nature of the computations involved in this algorithm make it a good candidate for parallelization techniques. [24] parallelized this algorithm to the GPU obtaining speedups of up to two magnitudes relative to an optimized multicore CPU implementation.

## 2.2 Evidence Accumulation Clustering

### 2.2.1 Clustering

Advances in technology allow for the collection and storage unprecedented amount and variety of data. Since data is mostly stored electronically, it presents a potential for automatic analysis and thus creation of information and knowledge. A growing body of statistical methods aiming to model, structure and/or classify data already exist, e.g. linear regression, principal component analysis, cluster analysis, support vector machines, neural networks. Many of these methods fall into the realm of machine learning, which is usually divided into 2 major groups: *supervised* and *unsupervised* learning. Supervised learning deals with labelled data, i.e. data for which ground truth is known, and tries to solve the problem of classification. Unsupervised learning deals with unlabelled data and tries to solve the problem of clustering.

Cluster analysis is the backbone of the present work. The goal of data clustering, as defined by [12], is the discovery of the *natural grouping(s)* of a set of patterns, points or objects. In other words, the goal of data clustering is to discover structure on data, structured or not. And the methodology used is to group patterns that are similar by some metric (e.g. euclidean distance, Pearson correlation) and separate those that are dissimilar.

Clustering is used in a wide variety of fields to solve numerous problems, e.g.:

- image segmentation in the field of image processing;
- generation of hierarchical structure for easy access and retrieval of information systems;

- recommender systems by grouping a users by their behaviour and/or preferences;
- clustering customers for targeted marketing in
- clustering gene expression data in biology;
- grouping of

### 2.2.2 Ensemble Clustering

**Ensemble clustering** Data from real world problems appear in different configurations regarding shape, size, sparsity, etc. Different clustering algorithms are appropriate for different data configurations, e.g. K-Means using euclidean distance as metric tends to group patterns in hyperspheres so it is more appropriate for data whose structure is formed by hypersphere like clusters. If the true structure of the data at hand is heterogeneous in configuration, a single clustering algorithm might perform well for some part of the data while other performs better for some other part. The underlying idea behind ensemble clustering is to use multiple clusterings from one or more clustering algorithms and combine them in such a way that the final clustering is better than any of the individual ones.

**Formulation** Some notation and nomenclature, adopted from [7], should be defined since it will be used throughout the remainder of the present work. The term *data* refers to a set  $X$  of  $n$  objects or patterns  $X = \{x_1, \dots, x_n\}$ , and may be represented by  $\chi = \{x_1, \dots, x_n\}$ , such that  $x_i \in \mathbb{R}^d$ . A clustering algorithm takes  $\chi$  as input and returns  $k$  groups or *clusters*  $C$  of some part of the data, which form a *partition*  $P$ . A clustering *ensemble*  $\mathbb{P}$  is group of such partitions. This means that:

$$\mathbb{P} = \{P^1, P^2, \dots, P^N\} \quad P^j = \{x_1^j, x_2^j, \dots, x_{k_j}^j\} \quad C_k^j = \{x_a, x_b, \dots, x_z\}$$

### 2.2.3 overview of EAC

The Evidence Accumulation Clustering (EAC) makes no assumption on the number of clusters in each data partition. Its approach is divided in 3 steps:

1. Produce a clustering ensemble  $\mathbb{P}$  (the evidence)
2. Combine the evidence
3. Recover natural clusters

A clustering ensemble, according to [7], can be produced from (1) different data representations, e.g. choice of preprocessing, feature extraction, sampling; or (2) different partitions of the data, e.g. output of different algorithms, varying the initialization parameters.

The ensemble of partitions is combined in the second step, where a non-linear transformation turns the ensemble into a co-association matrix, i.e. a matrix  $C$  where each of its elements  $n_{ij}$  is the association value between the object pair  $(i, j)$ . The association between any pair of patterns is given by the number of times those two patterns appear clustered together in any cluster of any partition of the ensemble. The rationale is that pairs that are frequently clustered together are more likely to be representative of a true link between the patterns [7], revealing the underlying structure of the data. The construction of this matrix is at the very core of this method.

The co-association matrix itself doesn't output a clustering partition. Instead, it is used as input to other methods to obtain the final partition. Since this matrix is a similarity matrix it's appropriate to use in algorithms take this type of matrices as input, e.g. K-Medoids or hierarchical algorithms such as



Single-Link. to name two. Typically, algorithms use a distance as the similarity, which means that they minimize the values of similarity to obtain the highest similarity between objects. However, a low value on the co-association matrix translates in a low similarity between a pair of objects, which means that the co-association matrix requires prior transformation for accurate clustering results, e.g. replace every similarity value  $n_{ij}$  between every pair of object  $(i, j)$  by  $\max\{C\} - n_{ij}$ .

**examples of applications** Evidence Accumulation Clustering (EAC) has been used with success in several applications:

- in the field of bioinformatics it was used for the automatic identification of chronic lymphocyt leukemia [18];
- also in bioinformatics it was used for the unsupervised analysis of ECG-based biometric database to highlight natural groups and gain further insight [?];
- in computer vision it was used as a solution to the problem of clustering of contour images (from hardware tools) [14].

**advantages**

**disadvantages** quadratic space and time complexities because of the  $n \times n$  co-association matrix

#### 2.2.4 Scalability of EAC

The quadratic space and time complexity of processing the  $n \times n$  co-association matrix is an obstacle to an efficient scaling of EAC. Two approaches have been proposed to address this obstacle: one dealing reducing the co-association matrix by considering only the distances of patterns to theirs  $p$  neighbours and the other by maximizing the sparsity of the co-association matrix.

**$p$  neighbours approach** The first approach, [7], proposes an alternative  $n \times p$  co-association matrix, where only the  $p$  nearest neighbours of each sample are considered in the voting mechanism. This comes at the cost of having to keep track of the neighbours of each pattern in a separate data structure and also of pre-computing the  $p$  neighbours. Still, considering that the quadratic space complexity is transformed to  $O(2np)$  and that usually  $p < \frac{n}{2}$ , the cost of storing the extra data structure is lower than that of storing an  $n \times n$  matrix, e.g. for a dataset with  $10^6$  patterns and  $p = \sqrt{10^6}$  (a value much higher than that used in [7]), the total memory required for the co-association matrix would decrease from  $3725.29GB$  to  $7.45GB$  (0.18% of the memory occupied by the complete matrix).

**Increased sparsity approach** The second approach, presented in [15], exploits the sparse nature of the co-association matrix. The co-association matrix is symmetric and with a varying degree of sparsity. The former property translates in the ability of storing only the upper triangular of the matrix without any loss on the quality of the results. The later property is further studied with regards to its relationship with the minimum  $K_{min}$  and maximum  $K_{max}$  number of clusters in the partitions of the input ensemble. The core of this approach is to only store the non-zero values of the upper triangular of the co-association matrix. The authors study 3 models for the choice of these parameters:

- choice of  $K_{min}$  based on the minimum number of gaussians in a gaussian mixture decomposition of the data;
- based on the square root of the number of patterns ( $\{K_{min}, K_{max}\} = \{\frac{\sqrt{n}}{2}, \sqrt{n}\}$ );

- or based on a linear transformation of the number of patterns ( $\{K_{min}, K_{max}\} = \{\frac{n}{A}, \frac{n}{B}\}, A > B$ ).

The paper compared how each model impacted the sparsity of the co-association matrix (and, thus, the space complexity) and the relative accuracy of the final clusterings. Both theoretical predictions and results revealed that the linear model produces the highest sparsity in the co-association matrix, under an ideal synthetic dataset consisting of a mixture of Gaussians. Furthermore, it is true for both linear and square root models that the sparsity increases as the number of samples increases. In fact, the number non-zero elements is approximately 1000 for each sample in the square root model, whereas it is only 100 in the linear model.

For real datasets, the performance of the three models differed little as the number of samples of the datasets increased. It was found that the chosen granularity of the input partitions ( $K_{min}$ ) is the variable with most impact, affecting both accuracy and sparsity. The authors reported this technique to have linear space and time complexity on benchmark data.

The number of samples of the datasets analysed in [15] was under  $10^4$ . Although the results appear promising, the present work aims to deal with datasets much larger than this and, as a consequence, this technique should be further evaluated and tested to attest to its usefulness to very large datasets.

## 2.3 Clustering with Big Data

### 2.3.1 The concept of Big Data

examples of success application

characteristics and challenges

### 2.3.2 Computation in Big Data

When big data is in discussion, two perspectives should be taken into account. The first deals with the applications where data is too large to be stored efficiently. This is the problem that streaming algorithms such as X,Y try to solve by analysing data as it is produced, close to real-time processing. The other perspective (the more common) is big data that is actually stored and processed. The latter is the perspective the present work deals with.

Scalability of EAC within the big data paradigm is the concern of this work. Although this line of research hasn't been pursued before, cluster analysis of big data has. Since EAC uses traditional clustering algorithms (e.g. K-Means, Single-Link) in its approach, it is useful to understand how scalable the individual algorithms are as they'll have a big impact in the scalability of EAC. Furthermore, valuable insights may be taken from the techniques used in the scalability of other algorithms.

Clustering algorithms' flow typically involves some initialization step (e.g. choosing  $k$  centroids in K-Means) followed by an iterative process until some stopping criteria is met, where each iteration updates the clustering of the data [1]. In light of this, to speed up and/or scale up an algorithm, three approaches are available: reduce the number of iterations, reduce the number of patterns the process or parallelizing and distributing the computation. The solutions for each of this approaches are, respectively, one-pass algorithms, randomized techniques that reduce the input space complexity and parallel algorithms.

Parallelization can be attained by adapting programs to multi core Central Processing Unit (CPU), GPU, distributed over several machines (a *cluster*) or a combination of the former, e.g. parallel and distributed processing using GPU in a cluster of hybrid workstations. Each approach has its advantages and disadvantages. The CPU approach has access to a larger memory but the number of computation units is reduced when compared with the GPU or cluster approach. Furthermore CPUs have advanced techniques such as branch prediction, multiple level caching and out of order execution - techniques for optimized sequential computation. GPU have hundreds or thousands of computing units but typically the

in device available memory is reduced which entails an increased overhead of memory transfer between host (workstation) and device for computation of large datasets. Furthermore, the scalability cost of these approaches is higher than that of a cluster. Finally, a cluster offers the best solution for truly distributed computation while at the same time allowing for extremely large datasets. The main disadvantage is that there is a high communication and memory I/O cost to pay. Communication is usually done over the network with TCP/IP, which is several order of magnitude slower than the direct access of the CPU or GPU to memory (host or device).

## 2.4 General Purpose computing on Graphical Processing Units

Using GPU for other applications other than graphic processing, commonly known as General Purpose computing on Graphic Processing Units (GPGPU), has become a trend in recent years. GPU present a solution for "extreme-scale, cost-effective, and power-efficient high performance computing" [6]. Furthermore, GPU are typically found in consumer desktops and laptops, effectively bringing this computation power to the masses.

GPUs were typically useful for users that required high performance graphics computation. Other applications were soon explored as users from different fields realized the high parallel computation power of these devices. However, the architecture of the GPUs themselves has been strictly oriented toward the graphics computing until recently as specialized GPU models (e.g. NVIDIA Tesla) have been designed for data computation.

GPGPU application on several fields and algorithms has been reported with significant performance increase, e.g. application on the K-Means algorithm [3, 25, 28, 26], hierarchical clustering [19, 2], document clustering [8], image segmentation [20], integration in Hadoop clusters [16, 9], among other applications.

Current GPUs pack hundreds of cores and have a better energy/area ratio than traditional infrastructure. GPU work under the Single Instruction Multiple Data (SIMD) framework, i.e. all the cores in the device execute the same code at the same time and only the data changes over time.

### 2.4.1 Programming GPUs

In the very beginning of GPGPU, programming was done directly through graphics Application Programming Interface (API)s.

Programming for GPUs was traditionally done within the paradigm of graphics processing, such as DirectX and OpenGL. If researchers and programmers wanted to tap into the computing power of a GPU they had to learn and use these APIs and frameworks, which is a challenging task since their general problems had to be modelled to the graphics-oriented primitives [17]. With the appearance of DirectX 9, shader programming languages of higher level became available (e.g. C for graphics (Cg), DirectX High Level Shader Language (HLSL), OpenGL Shading Language (GLSL)), but they were still inherently graphics programming languages, where computation must be expressed in graphics terms.

More recent programming models, such as CUDA and OpenCL, removed a lot of that burden by exposing the power of GPUs in a way closer to traditional programming.

At the time of writing, the major programming models used for computation in GPU are Open Computing Language (OpenCL) and Compute Unified Device Architecture (CUDA). While the first is widely available in most devices the later is only available for NVIDIA devices. It should also be noted that the MapReduce framework has been implemented on GPU.

It basically boils down to OpenCL vs CUDA. OpenCL has the advantage of portability with the issues of performance portability and hard to program. Programming under CUDA, performs well since it was designed alongside with the hardware itself but only works on NVIDIA devices.

In the end, the choice of GPU computing framework was CUDA. All the infrastructure available for developing and testing supports CUDA. Another reason for the choice is that all the work is being developed in Python and Python has a CUDA API of very high level - part of the Numba module developed by Continuum Analytics.

#### 2.4.2 MapReduce on GPU

As Google's MapReduce computing model has increasingly become a standard for scalable and distributed computing over big data, attempts have been made to port the model to the GPU. This translates in using the same programming model over a wide array of computing platforms.

#### 2.4.3 Overview of CUDA

A GPU is constituted by one or several streaming processors (or multiprocessor). Each of this processors contains several simpler processors, each of which execute a the same instruction at the same time at any given time. In the CUDA programming model, the basic unit of computation is a *thread*. Threads are grouped into *blocks* which are part of the block *grid*. The number of threads in a block is typically higher than the number of processors in a multiprocessor. For that reason, the hardware automatically partitions threads in a block into smaller batches, called *warps*.

Block configuration can be multidimensional, up to and including 3 dimensions. Furthermore, there is a limit to the amount of threads in each dimension that varies with the version of CUDA being used, e.g. for GPUs with CUDA compute capability 2.x the number of threads is 1024 for the x- or y-dimensions, 64 for the z-dimension, an overall maximum number of threads is 1024 and a warp size of 32 threads. For the previous example, it's wise for the number of threads used in a block to be a multiple of 32 to maximize processor utilization, otherwise some blocks will have processors that will do no work.

Depending on the architecture, GPUs have several types of memories. Accessible to all processors are the global memory, constant memory and texture memory. Blocks share a smaller but significantly faster memory called shared memory. And each thread has it's own, even smaller and faster, local memory.

#### 2.4.4 Parallel K-Means

K-Means is one of the building block of the EAC chain. Other algorithms can be used, but due to its simplicity and speed it is often used to produce ensembles varying the number of centroids to be used. Furthermore, it is a very good candidate for parallelization. K-Means is composed by two main steps:

1. computation of the labels of each pattern in the dataset, e.g. the label of the  $n - th$  pattern is 0 if the closest centroid is 0.
2. recomputation of the centroids based on the labels assignment, e.g. the new centroids will be the mean of all the patterns assigned to it.

The first step is inherently parallel as the computation of the label of the  $n - th$  pattern is not dependent on any other pattern, but only on the centroids. Two possible approaches to parallelize this step on the GPU are possible, a data-centric and a centroid-centric. In the former, a parallel computation unit will compute the distance from one pattern to all centroids and assign the pattern to the closest centroid. In the later, each computation unit will

#### 2.4.5 Parallel Hierarchical Agglomerative Clustering

Hierarchical Agglomerative Clustering is an algorithm that is not easily parallelized since it has several dependencies

### 3 Methodology

The aim of this thesis is the optimization and scalability of EAC, with a focus for big data. EAC is divided in three steps and each has to be considered for optimization.

The first step is the accumulation of evidence, i.e. generating an ensemble of partitions. The main objective for the optimization of this step is speed. Using fast clustering methods for generating partitions is an obvious solution, as is the optimization of particular algorithms aiming for the same objective. Since each partition is independent from every other partition, parallel computing over a cluster of computing units would result in a fast ensemble generation. Using either or any combination of these strategies will guarantee a speedup. Furthermore, it is not necessary for algorithms to produce accurate clusterings, e.g. K-Means doesn't have to converge - 3 iterations should suffice. The reason for this is the want for variability within the partition population.

The second step is mostly bound by memory. The complete co-association matrix has a space complexity of  $\mathcal{O}(n^2)$ . Such complexity becomes prohibitive for big data, e.g. a dataset of  $2 \times 10^6$  samples will result in a complete co-association matrix of 14901 GB if values are stored in single floating-point precision.

The last step has to take into account both memory and speed requirements. The final clustering must be able to produce good results, fast while not exploding the already big space complexity from the co-association matrix.

Initial research was under the field of quantum clustering. After this pursuit proved fruitless regarding one of the main requirements (computational speed), the focus of researched shifted to parallel computing, more specifically GPGPU.

#### 3.1 Quantum Clustering

Research under this paradigm aimed to find a solution for the first and last steps. Two venues were explored: Quantum K-Means and Horn and Gottlieb's quantum clustering algorithm. For both, the experiments that were setup had the goal of evaluating the speed and accuracy performances of the algorithms.

Under the qubit concept, no other algorithms were experimented with since the results for this particular algorithm showed that this kind of approach is infeasible due to the cost in computational speed. The results highlight that fact.

#### 3.2 GPGPU K-Means

K-Means is an obvious candidate for the generation of partitions since it is simple, fast and partitions don't require big accuracy - variability in the partitions is a desirable property which translates in few iterations. For that reason, optimizing this algorithm would ensure that the accumulation of evidence would be performed in an efficient manner.

#### 3.3 Dealing with space complexity of coassoccs

In the literature review, two approaches to deal with the space complexity of the co-association matrix were reported. It would be ideal to combine both approaches to further reduce space complexity, but they're not compatible as it might seem. When the neighbour approach is used, it is unlikely that a sample will never be clustered with its closest  $p$  neighbours. This means that the  $n \times p$  co-association matrix will likely not have many zeros which translates in little return for using the sparsity augmentation approach. To illustrate this point, let's consider a dataset of  $10^6$  patterns.

Which method is more effective in very large datasets, however, would depend on the dataset. The sparsity maximization approach got very low densities for some datasets, close to 0.01 in some cases. This is already a very improvement

## 4 Discussion?

When a problem of clustering of big data is at hand, the user should reflect upon what the problem at hand really requires: speed or accuracy. The user should take into consideration the nature of the data and the requirements of the problem (concerning speed and accuracy) before proceeding to the execution of the analysis. The present body of work reflects a method of clustering over big data using a high accuracy, but also high cost, method. Other methods offer the opposite, low cost, low to average accuracy.

## 5 Future work

Adaptation of the present implementation to OpenCL. This brings major benefits in respect to portability since OpenCL supports most devices. Moreover, OpenCL's performance is catching in on that of CUDA's and since its programming model was based on CUDA, it should be straightforward for developers to make the switch.

Application of EAC to the MapReduce framework will further expand the possibilities of application of EAC.

Study the integration of other clustering algorithms within the the EAC toolchain.

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