Pós-Graduação em Ciência da Computação

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SUPPORTING REAL-TIME MOBILITY SERVICES WITH SCALABLE FLOCK PATTERN MINING

M.Sc. Dissertation

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Advisor: Stênio Flávio de Lacerda Fernandes

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Dissertação de Mestrado apresentada ao programa de Pós-Graduação em Ciência da Computação da Universidade Federal de Pernambuco, como requisito parcial para obtenção do título de Mestre em Ciência da Computação.

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To my wife, my son and my parents!

Acknowledgements

To be honest, I thought that would not finish this. I was already seeing myself giving up this masters due to a lot of things: new country, new city, new job, huge load of work in my new job, baby coming... etc.. It was not easy to work on double journey for lots of months, sleeping only 3 to 4 hours a day. But yes! It is over! Some people helped me to no give up and keep up with that "stressful journey" and here they deserve my "Thank you!".

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...there are two paths you can go by, but in the long run there's still time to change the road you're on...

—LED ZEPPELIN, STAIRWAY TO HEAVEN

Resumo

Detecção de padrões em dados espaço-temporais tem se mostrado um tema de muita relevância nos dias atuais, tanto na academia quanto na indústria, devido a sua vasta aplicabilidade em auxiliar a solucionar problemas enfrentados na sociedade. Muitos desses problemas podem ser classificados no conexto de Cidades Inteligentes (*Smart Cities*), como Gerenciamento de Tráfego, Segurança e Planejamento de Cidades. Dentre os vários padrões espaço-temporais que podem ser extraídos de uma base de dados, o padrão de *flock* é um que vem atraindo muita atenção, devido a sua relação intrínseca com os problemas mencionados anteriormente. Muitas pesquisas vêm sendo feitas na academia, visando desenvolver algoritmos capazes de identificar esse padrão de movimentação. Porém, nenhum deles foi capaz de executar tal tarefa eficientemente, nem conseguiu escalar de maneira aceitável quando uma base de dados de grande tamanho foi analisada. Além disso, não foi encontrado nos trabalhos relacionados uma arquitetura de *software* que conseguisse ser simples e modular o suficiente para ser usada no problema de detecção de padrões de *flock* em dados espaço-temporais. Com isso em mente, essa dissertação propõe uma arquitetura de *software* modular, direcionada para solucionar problemas de detecção desse padrão e possivelmente ser utilizada para outros experimentos envolvendo mineração de padrões em dados espaço-temporais. Tal arquitetura foi então usada como base na implementação de um algoritmo de detecção de *flock*, focando em alcançar grandes ganhos em tempo de processamento, sem comprometer a precisão, visando então cenários de aplicações de tempo real em Cidades Inteligentes. No fim, nós propomos uma remodelagem no nosso algoritmo para poder utilizar ao máximo o poder de processamento oferecido pelas arquiteturas *multi-core* dos processadores modernos. Nossos resultados mostraram que nossa solução conseguiu superar propostas do estado da arte, alcançando 99% de redução no tempo de processamento total. Além disso, nossa remodelagem *multi-thread* conseguiu melhorar os resultados da nossa solução em até 96% em alguns casos. A eficiência e performance da nossa proposta foi comprovada com avaliações feitas com bases de dados geradas sinteticamente e coletadas em experimentos reais.

Palavras-chave: Cidades Inteligentes. Mineração de Padrões. Dados Espaço-temporais. Padrão de Flock

Abstract

Pattern mining in spatio-temporal datasets is a really relevant subject in the academia and the industry nowadays, due to its wide applicability in helping to solve real-world problems. Many of them can be found in the context of Smart Cities, like Traffic Management, Surveillance and Security and City Planning, to name a few. Among the various spatio-temporal patterns that one can extract from a spatio-temporal dataset, the flock pattern is one that has gained a lot of attention, because of its intrinsic relation with the aforementioned problems. A lot of work has been done in the academia, in order to provide algorithms able to identify the flock pattern. However, none of them could perform that task efficiently nor be able to scale well when a large dataset was the analysis target. Additionally, we found that there was no system architecture proposal that could be simple and modular enough to be used in that spatio-temporal pattern detection problem. Given that context, this dissertation proposes a modular system archicture designed to help solving flock pattern mining problems and possibly be reused to other spatio-temporal mining experiments. We then use such architecture as the infrastructure to implement an efficient flock detection algorithm, aiming at achieving considerable gains in execution time without compromising accuracy, thus targeting real-time deployment and on-line processing in Smart Cities. Last, but not least, we remodel our algorithm in order to take advantage of multi-core architectures present in modern computers. Our results indicate that our proposal outperforms the current state-of-the-art techniques, by achieving 99% CPU time improvement. Moreover, with our multi-thread model, we were able to reduce the processing time of our proposed algorithm by 96% in some cases. We prove the efficiency of our solution by performing evaluation with both real and synthetic large datasets.

Keywords: Smart Cities. Pattern Mining. Spatio-temporal data. Flock Pattern

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Introduction

The advances of positioning technologies are enabling lot of different objects present in our daily usage (e.g. vehicles, smartphones and wearable devices) to be shipped with location tracking systems. Those devices are able to collect and report mobility information of people, animals and natural phenomena (e.g. hurricanes), to name a few. That technological advance is enabling the generation of massive volumes of spatio-temporal data that can contain information ranging from the daily routine of residents of a city (FARRAHI; GATICA-PEREZ, 2008) to the behavior of wild animals in a specific region (LEE; HAN; WHANG, 2007; LI et al., 2010a). It is notorious the interest of both industry and academia in such subject, specially with the rising of Smart Cities, in which spatio-temporal datasets can provide important insights in the context of problems like traffic management and urban planning (JENSEN; GUTIERREZ; PEDERSEN, 2015; DING et al., 2016). Those datasets can be used to help solving a variety of issues and answer some questions, such as:

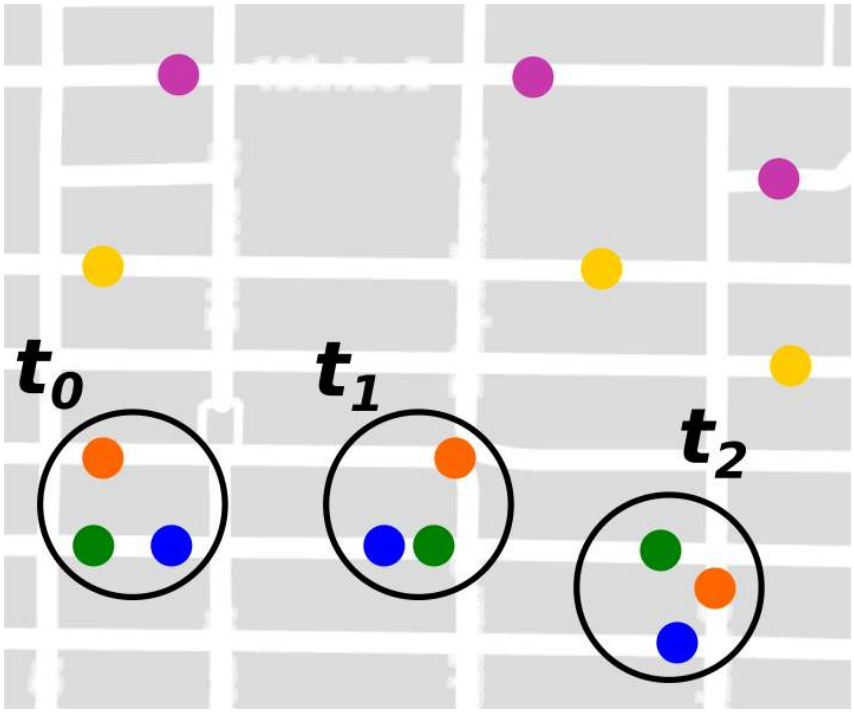
1. **What are the busiest times and locations (such as traffic jams locations) in a city?** (WANG et al., 2013)
2. **What are the movement patterns of the citizens of a city during work hours?**
3. **What is the migration pattern of inhabitants of a specific area?**
4. **What is the movement behavior of wild animals in their habitat?** (LI et al., 2011)
5. **Is there any suspicious movement of groups of objects during some specific time window?**

That list can grow indefinitely, as the scenarios and applications of spatio-temporal data analyses are vast. Some of the questions listed above are in the context of Smart Cities, which can take advantage of spatio-temporal data analysis as an aid to a broad set of applications, like urban planning, public security, and public health and commerce (PAN et al., 2013). Additionally, understanding the data in question and being able to take actions fast according to the conclusions extracted from such data is crucial to create and evolve a Smart City. However, due to the huge volume of data that is produced on a daily basis and the need analyze them to in order to help

those applications and answer those questions, the main problem is still the same: how to be able to analyze massive data volumes fast and efficiently so we can empower decision takers to act quickly?

In the aforementioned questions and applications, some of the queries are intrinsically related to collaborative or group patterns, such as flock (GUDMUNDSSON; KREVELD; SPECKMANN, 2004), convoy (JEUNG; SHEN; ZHOU, 2008), swarm (LI et al., 2010b), and the like. Those patterns contain moving objects that have a strong relationship by being close to each other, within a certain distance range and during some minimum time interval. Because we extract information about groups of people interacting, instead of just dealing with tracking of individuals alone, such patterns can be applied to a wide range of scenarios of Smart Cities (e.g. city roads planning, intelligent transportation, public security, etc.), causing the mining of those patterns to gain great importance within the research community. There are a number of research challenges in this topic, specially regarding the development of accurate algorithms to detect those patterns. In addition of being precise, it is of paramount importance to design fast algorithms so that they can keep up with real-time data. Hence, reiterating what as mentioned in the previous paragraph, efficiently extraction of data patterns empowering real-time analyses and on the fly decision-making is still an open challenge.

Figure 1.1: Orange, green and blue trajectories form a flock of size 3 with minimum length of 3 time steps, with a disk enclosing all trajectories at each time step t_i



Source: Made by the author.

Among those collaborative patterns, the flock pattern is one that has gained a lot of attention in the research community, since it can address all the scenarios and questions that were mentioned in this chapter and represents a very familiar behavior that is frequently seen in

our daily routines. A seminal formal definition of that pattern was proposed by Laube, Kreveld and Imfeld (2005) and Gudmundsson, Kreveld and Speckmann (2004) and since then, a lot of other studies has follow suit (we refer the reader to Chapter 2 for some of them), mainly due to the interests in developing mechanisms to solve real-world problems in the scope of Internet of Things (IoT) (TSAI et al., 2014) and Smart Cities (DJAHEL et al., 2015). According to Gudmundsson, Kreveld and Speckmann (2004), a flock pattern consists of a minimum number of entities that are within a disk of radius r at a given time. However, this definition only applies to one single time step and does not help on extracting some useful collective behavior information. Such initial definition was then extended by Benkert et al. (2008), introducing the minimum time interval δ that the entities should stay together in order to characterize a flock pattern, as depicted in Figure 1.1. That figure shows a flock pattern that lasts three time steps and is formed by the orange, green and blue trajectories. It is worth mentioning that the remaining trajectories (yellow and pink) are not part of a flock pattern because there are no disks enclosing them in all three time steps.

When it comes to flock pattern detection efficiency and speed, one major problem on doing that is to find the disks that enclose the trajectories in each time step. Since the disks centers do not need to match any point in the dataset, there can be infinite possible disks. Vieira, Bakalov and Tsotras (2009) proposed a way to limit the number of disks to generate and analyze, so a finite number of disks are in place to cluster the trajectories into them. They also proposed an algorithm to find the flock pattern, namely Basic Flock Evaluation (BFE). Even though BFE can find flock patterns in spatio-temporal datasets, it does suffer from some severe performance limitations, meaning that it is not able to scale properly when the dataset is really large. The main reason that we identified that makes it perform so inefficiently is that BFE is not smart enough to predict what portions of the data can really generate flock patterns, then it ends up wasting Central Processing Unit (CPU) cycles by processing data that is not relevant.

Despite the considerable number of research studies regarding flock pattern detection, there is still something that nobody ever got to it, based on the systematic literature revision field that we did, but it would be of great value if defined and formalized: A framework/system architecture that can be modular and simple, to serve as the building blocks for flock detection algorithms. By creating such architecture, researchers can take advantage of that as a starting point to develop their algorithms and can also have a common ground to compare and reuse work of others.

In our related work research, we noticed that the state of the art algorithms for flock pattern detection are not ready to aid the development and evolution of Smart Cities, since they are not able to efficiently process the huge volumes of data that are generated by them. With that in mind, this dissertation proposes an efficient flock detection algorithm aiming at achieving considerable gains in execution time, without compromising accuracy, thus targeting real-time deployment and on-line processing. With that algorithm, we could address Smart Cities scenarios, where decisions need to be made on the fly and rapidly enough in order to

keep up with their development pace (PAN et al., 2013; BATTY et al., 2012). Such gains were made possible by creating a filtering heuristic, based on bitmaps, in order to save processing time. Our proposal focuses on identifying Moving Objects (MOs) that can actually form a flock, resulting in a huge reduction in the number of disks generated and thus resulting in less data to be processed. Our results indicate that our proposal outperforms the current state-of-the-art techniques, by achieving 99% CPU time improvement and 96% disks generation reduction in some relevant scenarios. Going even further, we also remodeled our proposed algorithm to take advantage of multi-core architectures, having some components executing in parallel resulting in impressive speed gains. With our Multi-thread (MT) model, we were able to reduce the processing time of our proposed algorithm by 96% in some cases. It is worth mentioning that the gains achieved with the MT model are over the gains that we had already obtained over the state-of-the-art techniques.

Last, but not least, we also propose a modular system architecture, aiming at helping to find flock patterns in spatio-temporal datasets. We validate our architecture by implementing our algorithm and our MT model using it as the building blocks. To summarize, the contribution of this dissertation is threefold:

1. **An efficient flock pattern detection algorithm**
2. **A remodeled algorithm able to take advantage of multi-core architectures and rapidly find flock patterns**
3. **A simple and modular system architecture to aid solving spatio-temporal flock pattern detection problems**

The remainder of this dissertation is organized as follows. Chapter 2 highlights the related work in both flock detection and trajectory data mining and explain in more details the academic contribution of our work. Chapter 3 presents the technical background necessary to understand this dissertation, like the formal flock pattern definition and how an algorithm to find a flock pattern works. Our contribution is detailed in Chapter 4, whereas in Chapter 5 we show the results of our experimental evaluations, on the datasets that we picked, based on the chosen metrics. Lastly, in Chapter 6 we draw some concluding remarks and provide directions for future work.

2

Related Work

This is a research field that has had a lot of attention in both academia and industry in past and present years. Hence, the related work in this area and related fields is quite extensive and broad. With that in mind, we will split this section in (1) General trajectory data and pattern mining and (2) Flock pattern mining

It is worth noting that the only set of research studies that are pertinent to this work, are those in Section 2.2. Hence, those will be the only research studies that we will point out some flaws that are addressed by this dissertation.

2.1 General trajectory data and pattern mining

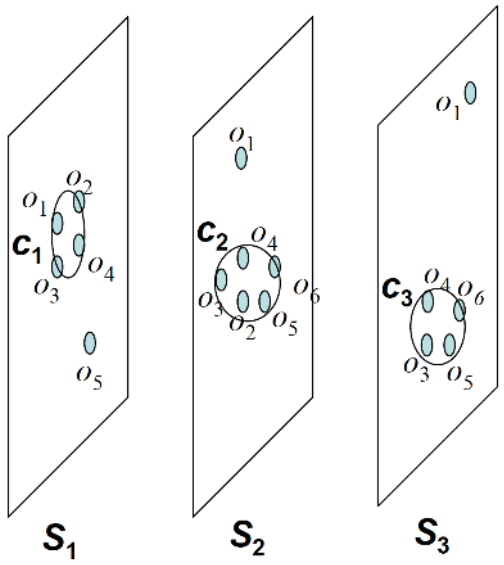
Here we present the broader scope of trajectory data and pattern mining that were useful to gather some understanding in the field and insightful ideas for this dissertation.

Laube, Kreveld and Imfeld (2005) proposed the RElative MOtion (REMO) concept, which analyzes motion attributes (speed, azimuth and location) of entities and relate to the motion of other entities that are close to them. They also introduced some moving patterns, such as flock, convergence, encounter, and leadership. In the end the authors went through some data structures and algorithms that could be used in order to detect those patterns. However, only high level abstract algorithms were presented, but neither concrete implementation nor evaluation were shown.

An interesting approach for finding patterns that are frequently repeated by MOs was presented by Cao, Mamoulis and Cheung (2005). The authors presented an algorithm that focused on approximating the spatio-temporal series of a MO to a line, where the distance of each trajectory point of that MO to the line would be no greater than a pre-defined threshold. After that, bounding boxes were created based on those approximated lines and then lines that belong to the same box were declared as similar sequential patterns.

Algorithms aiming at finding moving clusters, with MOs coming in and out of the cluster, were presented by Kalnis, Mamoulis and Bakiras (2005). In that research paper, the authors consider a moving cluster as a moving region despite the identity of the objects that are part of it, but for each timestamp the intersection of points between subsequent clusters needs to be

Figure 2.1: A moving cluster composed by clusters S_0, S_1 and S_2 and $\theta = 0.5$

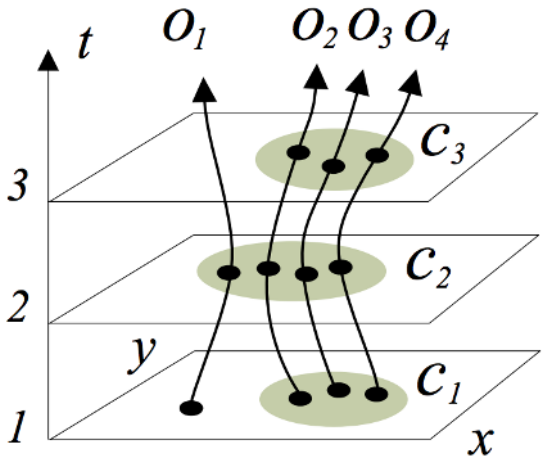


Source: (KALNIS; MAMOULIS; BAKIRAS, 2005).

above a certain threshold θ. In Figure 2.1 one can see a moving cluster composed by clusters S_0, S_1 and S_2, having $\theta = 0.5$, meaning that $\frac{|c_i \cap c_{i+1}|}{|c_i \cup c_{i+1}|} \geq 0.5$. They presented three different approaches to find moving clusters (with one of them being an approximation method), being supported by a density function. They claim that their proposal is applicable for large-temporal datasets, but that large dataset that they analyzed had only 50K entries. Yet on clusters, Jensen, Lin and Ooi (2007) added velocity as a parameter in order to help finding moving clusters (using dissimilarity functions), achieving some improvements in processing time. An approach using a trajectory similarity measure based on the Hausdorff distance was proposed by Atev, Miller and Papanikolopoulos (2010), where the sequential order of trajectories was preserved over time. The authors also presented a method aiming at clustering trajectories, taking advantage of some spectral clustering methods. A more recent research by Patel (2015) proposed a novel type of cluster classification: Influence-based Moving Cluster (IBMC). The author stated that an IBMC consists in a set of moving clusters where each MO, in each cluster, influences at least another MO in the next immediate cluster. It was shown that the space for discovering IBMC was very extensive and an algorithm for finding the maximal answer was proposed.

Jeung et al. (2008), Jeung, Shen and Zhou (2008) proposed the convoy pattern. They first pointed out the key difference between flock and convoy patterns: flock pattern relies on all trajectories being present in a disk of pre-defined radius, while convoy does not rely on any kind of shape to cluster its trajectories. That difference is depicted in Figure 2.2, where the second disk is of different size of the other disks and not all trajectories are present in the consecutive clusters (another difference from the flock pattern). The authors proposed three density based algorithms to find convoy patterns using line simplification techniques. Their work was inspired by the algorithms already proposed by Kalnis, Mamoulis and Bakiras (2005) and *Density-based Spatial Clustering of Applications with Noise (DBSCAN)* (ESTER et al., 1996). More work on

Figure 2.2: A Convoy pattern



Source: (JEUNG et al., 2008).

convoy patterns can be found with Aung and Tan (2010), where they divided convoy patterns in two different groups, namely *Dynamic Convoys (DCs)* and *Evolving Convoys (ECs)*. To this end, they presented three algorithms to identify EC patterns.

Gathering is another moving pattern that was analyzed by the academia. Zheng et al. (2013) stated that a gathering pattern consists in various grouped incidents such as celebrations, parades, protests, traffic jams, etc. They first formalized and modeled the gathering pattern and then proposed algorithms to find the such pattern. Effectiveness and efficiency evaluations were presented, showing an overall good result, however only one dataset was analyzed. Instead of looking for patterns that happen exactly at the same time (e.g. clusters and flocks), Li et al. (2010b) proposed the swarm pattern. Such pattern tries to group MOs that may actually diverge temporarily and congregate at certain timestamps, it is not required also that a trajectory stays all the time with the same swarm cluster. The authors in that work formalized the swarm concept and presented algorithms to find the pattern. The effectiveness of the algorithms was compared against convoy pattern algorithms and it was shown that, for some datasets, the swarm pattern was better suited.

An algorithm to find patterns in Origin-Destination databases, meaning that only the origin and destination points of a trajectory are recorded in the analyzed dataset, was presented by Guo et al. (2012). They proposed a way to model points of interest, since MOs going to the same place (e.g. airport) will report different Global Positioning System (GPS) coordinates. The proposed algorithm has a preprocessing phase that makes a Delaunay Triangulation of the points and then clusters those points based on two parameters: (k) the number of points to build a cluster and (θ) the minimum number of points (or weight) of a cluster. After building the clusters, they derive some mobility measures, in order to extract spatial and temporal mobility patterns, presenting an useful way of understanding traffic loads in a city.

Baratchi, Meratnia and Havinga (2013) proposed a way to find frequently visited paths between two points of interests. The authors presented an algorithm that deals with trajectory

uncertainty and uses cluster based techniques to map uncertain trajectories to actual paths in a map that were most likely to be followed by the MO. First they gathered points of interests (those where the MO stayed for at least 30 minutes with its speed close to 0) and grouped all subtrajectories that had the same start and end points of interest. They then applied their algorithm, which consists in dividing the space in grids and assigning each point to a grid, and partitioned those subtrajectories in even small subtrajectories based on breakpoints. After that partition step they used a score mechanism to decide which set of subtrajctories are more likely to be a frequent path. Their algorithm was mainly targeted to offline analyses and used a map matching algorithm in order to match GPS points to actual map segments. They did not present the dataset used for evaluation nor the numbers of such dataset. Their evaluation was somewhat shallow and did not present any take away results.

A comprehensive state-of-the-art review in trajectory data mining was presented by Zheng (2015). He covered relevant research topics, such as trajectory data preprocessing, trajectory data management, uncertainty of trajectories, trajectory pattern mining, and trajectory classification. He pointed out some public trajectory datasets that can be used to evaluate pattern detection algorithms, like the dataset TDrive (ZHENG, 2011) used in this dissertation.

2.2 Flock pattern mining

Gudmundsson, Kreveld and Speckmann (2004), Gudmundsson and Kreveld (2006) extended and formalized the flock concept proposed by the REMO Framework (LAUBE; KREVELD; IMFELD, 2005). They also introduced the concept that the flock pattern must contain a disk of radius R, enclosing all trajectories, in each time step. They proposed approximation and exact algorithms for flock pattern detection, but no performance evaluations were made and only theoretical analyses were presented, which does not show if the algorithms are efficient or not. Later on, the same authors (GUDMUNDSSON; KREVELD, 2006) extended the flock pattern definition by adding the temporal length variable: the entities must stay together during some time interval δ to be claimed as a flock. To this end, they presented some approximation algorithms that work on approximating the radius R of the disk used to cluster the flock, based on a defined ε. The evaluations performed (GUDMUNDSSON; KREVELD, 2006) varied only the δ parameter leaving all other parameters variation out of the experiments. Additionally, the performance results were not good, having scenarios where the algorithms took more than 1500 seconds to analyze a dataset containing 1 million of entries. It is important to say that all algorithms did waste time by analyzing disks that would not form a flock pattern, thus having a degradation in performance.

Vieira, Bakalov and Tsotras (2009) proposed a polynomial algorithm to find flock patterns of fixed duration, based in three parameters: minimum number of trajectories μ, the disk radius ε and a minimum time length δ. In order to discover the centers of the cluster disks for each time step, they paired the points that had distance less or equal to $2 * \varepsilon$, created two disks based

on that pair and tried to cluster other points into those disks. Their algorithm assumed that each point is sampled in a fixed time interval, assumption that does not reflect real-world datasets. Additionally, their algorithm suffered from wasting CPU cycles by processing disk candidates that were not real potential flock candidates. The authors also proposed some filtering heuristics to optimize the processing time, but the optimizations did not present good results, and our local tests showed that the optimizations affected the final number of flocks found by the algorithm.

An algorithm that mixed together BFE (VIEIRA; BAKALOV; TSOTRAS, 2009) with a "Frequent Pattern Mining" heuristic was proposed by Turdukulov et al. (2014). They made some performance comparison against BFE and were able to show some improvement in the processing time when varying the radius R of the disk. However, despite the improvements, their results did not propose a fair comparison: (1) BFE is an on-line algorithm and their implementation imposed an offline implementation; (2) they filtered out some trajectories based on random assumptions, e.g. trajectories with less than 10 minutes or 20 minutes, which might benefit their algorithm and cut out possible flocks of that length; (3) they only showed results varying the disk radius and not the other parameters used by BFE.

The problem of Maximal-duration Flock Pattern (MFP) was addressed by the work of Geng et al. (2014), which proposed algorithms to enumerate all MFP in a trajectory dataset. MFP, in other words, means that the flock cannot be extended without increasing the disk radius R. They proposed a set of algorithms for finding MFP and proved that they could indeed enumerate all MFP from a trajectory dataset. They also compared their algorithms with BFE from Vieira, Bakalov and Tsotras (2009) and showed that their implementations outperformed the later in some scenarios. However, they still wasted CPU cycles by analyzing disks that would be discarded later, by not being potential flock candidates.

Wachowicz et al. (2011) and Wirz et al. (2011) presented algorithms for finding flocks using pedestrian spatio-temporal data. The former performed a lot pre- and post-processing in the dataset (which makes not possible to be used in real-time analysis) and neither performance nor accuracy evaluations were presented. The latter, did not provide any performance evaluation either, only showing accuracy experiments with a tiny dataset of only 13 entities in a time span of 32 minutes.

Wang et al. (2013) proposed a framework for detecting traffic jams in trajectory data, which can be considered as a flock pattern, since MOs stay together in a road during an interval of time. They listed the requirements for both a data model and a visual interface for their system, in order to be able to expose useful information for users and extract conclusions from the analysis. Their algorithm was bound to a map network, which means that one part of data preprocessing would be to map the data points to the respective roads in a map. They claimed to be able to detect traffic jams with high accuracy, however they did not have any ground truth data to validate the assumptions. It is also worth noting that only one dataset was used to evaluate the proposed system, which did not show that the solution was ready for varied data scenarios.

There were also some studies focusing on indoor flock detection using mobile phone

sensors, in which Wi-Fi signal strengths were mapped into coordinates (KJÆRGAARD et al., 2012b), or a variety of mobile phone sensors (e.g. accelerometer, magnetometer and Wi-Fi) were used to detect flock patterns (KJÆRGAARD et al., 2012a). However, those studies only addressed flock detection in indoor environments, not using GPS coordinates, which are not in the scope of the problem addressed by this dissertation.

2.3 Academic Contribution

It is notorious, from the related work presented in Section 2.1 and Section 2.2, that there is a lot to cover in order to provide efficient flock pattern detection as well as a lack of elegant and modular system architecture to address the flock pattern detection problem (which was not seen in any of the presented works). All of that is a subject to care about due to the extensive number of scenarios that data pattern mining, as well as flock patterns, can help and be applied to. We can have flock pattern detection helping the following, to name a few (GUDMUNDSSON; LAUBE; WOLLE, 2008):

1. **Traffic Management**: Unusual grouping of vehicles, or abnormal traffic volume in certain regions can be detected with the help of flock pattern detection algorithms. That information can help the accountable entities to better plan cities or traffic spaces.

2. **Surveillance and Security**: Suspicious movements of groups of people or vehicles can indicate a security threat and automatic pattern detection systems can aid the detection of abnormal behavior in a group of MOs.

3. **Human Movement**: Governmental organizations can study how people are moving from one part of the city/country/state to another with the help of flock pattern detection. They can also acquire information about the habits of the population and provide resources to enhance life quality of those involved.

In Section 4.1 we will propose an elegant, modular and simple system architecture that will be able to address flock pattern detection problems. Such architecture will be divided in logic modules and components, each one with a very specific and self-contained goal, making then reusable and good candidates to address other data analysis problems. We will also show that by modifying a single component in that architecture will enable the usage of a different software paradigm, thus proving its modularity, extensibility and ease of use.

We could notice that the presented algorithms suffer from CPU cycles waste by processing data that will not generate any pattern, like the flock disks that contain points that are not present in subsequent time steps. Avoiding such unnecessary processing can boost the running time of a flock pattern detection algorithm and then provide information in a real-time fashion for decision takers. With that in mind, we will present an efficient algorithm, based on bitmaps, that will only

be concerned with data that can really generate flock patterns, saving a considerable amount of time in processing. Moreover, our algorithm will be able to provide information, about the datasets being analyzed, way faster than other algorithms. We will prove such efficiency by showing benchmarks comparing the running time of our solution against the state-of-the-art algorithm and also show how that our implementation generates way less unimportant data than the compared target algorithm, which dramatically affects the running time of the latter. Last, but not least, we will provide a multi-core aware implementation of our algorithm, taking advantage of the proposed system architecture mentioned in the previous paragraph, which will achieve even more savings in running time, without affecting the number of flocks that are found. Aiming at showing that our solution is ready for multiple types of data, we will perform experiments with 4 different datasets, being them real and synthetic generated and with a large amount of data entries, with some of them having more than 50 million records.

3

Technical Background

We now present some technical background that will be required to understand the remaining of this dissertation.

3.1 Trajectory and data information

Spatio-temporal datasets usually come in the form of a set of tuples $\{O_{id}, \phi, \lambda, t\}$. Where: O_{id} uniquely identifies a MO; t corresponds to the timestamp that the GPS position was extracted; ϕ and λ correspond to the latitude and longitude of the MO respectively, at the given timestamp t. Each MO represented by an O_{id} has a trajectory T_{id} associated with it, being a trajectory defined as follows.

Definition 3.1. Given an O_{id}, a trajectory T_{id} consists of a sequence of 3-D points, belonging to O_{id} in the form of $< (\phi_0, \lambda_0, t_0), (\phi_1, \lambda_1, t_1), ..., (\phi_n, \lambda_n, t_n) >$, with $n \in \mathbb{N}$ and $t_0 < t_1 < ... < t_n$.

Table 3.1: Conversion from WGS84 to $\mathbb{R}^2$

WGS84		$\mathbb{R}^2$	
ϕ	λ	x	y
0°	0°	0	0
38.018470°	23.845089°	2654452.0	4203597.2
39.9048°	116.368°	12954167.2	4412163.5
40.0623°	116.582°	12977989.8	4429577.9
40.0114°	116.551°	12974538.9	4423950.0
52.5863°	13.2363°	1473474.2	5814321.9

GPS coordinates are often represented using the WGS84 (NIMA, 1997), which can make some mathematical operations needed by the algorithm proposed in this dissertation (e.g. vectorial operations) harder to be performed. Given that limitation, once the coordinates are read from a dataset, transformations from WGS84 to the $\mathbb{R}^2$ system are made. We use 0° as both latitude and longitude coordinates for our equivalent origin point in the $\mathbb{R}^2$ system and execute the algorithm used by the Woods Hole Oceanographic Institution (WHOI) to perform

the conversion from WGS84 to $\mathbb{R}^2$ on the fly (WHOI, 2015). Please refer to Table 3.1 for some examples of WGS84 coordinates being translated to $\mathbb{R}^2$, using the algorithm provided by WHOI.

Table 3.2: Ideal dataset sample rate

O_{id}	ϕ	λ	t
0	38.018470	23.845089	0
1	38.018069	23.845179	0
2	38.018241	23.845530	0
3	38.017440	23.845499	0
4	38.015609	23.844780	0
0	38.015609	23.844780	1
1	38.014018	23.844780	1
2	38.012569	23.844869	1
3	38.011600	23.845360	1
4	38.010650	23.845550	1
0	38.010478	23.845100	2
1	38.010478	23.845100	2
2	38.010508	23.844640	2
3	38.010520	23.844530	2
4	38.010520	23.844530	2

Table 3.3: Real-world dataset sample rate

O_{id}	ϕ	λ	t
0	38.018470	23.845089	4
1	38.018069	23.845179	0
2	38.018241	23.845530	1
3	38.017440	23.845499	10
4	38.015609	23.844780	8
0	38.015609	23.844780	6
1	38.014018	23.844780	5
2	38.012569	23.844869	2
3	38.011600	23.845360	16
4	38.010650	23.845550	12
0	38.010478	23.845100	14
1	38.010478	23.845100	6
2	38.010508	23.844640	3
3	38.010520	23.844530	25
4	38.010520	23.844530	30

Table 3.4: Mapping points from Table 3.3 to its correspondent time slot, using $\sigma = 3$

O_{id}	ϕ	λ	t	**Time slot**
0	38.018470	23.845089	4	1
1	38.018069	23.845179	0	0
2	38.018241	23.845530	1	0
3	38.017440	23.845499	10	3
4	38.015609	23.844780	8	2
0	38.015609	23.844780	6	2
1	38.014018	23.844780	5	1
2	38.012569	23.844869	2	0
3	38.011600	23.845360	16	5
4	38.010650	23.845550	12	4
0	38.010478	23.845100	14	4
1	38.010478	23.845100	6	2
2	38.010508	23.844640	3	1
3	38.010520	23.844530	25	8
4	38.010520	23.844530	30	10

It is worth noting that real-world datasets do not guarantee that all points of all trajectories are sampled at the same rate. In a ideal world, a perfect spatio-temporal dataset would have its entries as described in Table 3.2, where one can see that each O_{id} has its position sampled in intervals of a consistent t unit (1 in that example). However, Table 3.3 presents how MOs

in real-world datasets have their position sampled over time: no fixed rate interval due to transmission noises, precision issues and other problems that can make the sample rate varying a lot from one O_{id} to another. Therefore, we need to have a way to be able to compare and group points belonging to the same logical time interval. With that in mind, we divided the time extent in buckets of size σ, where σ should be chosen accordingly to the dataset being analyzed, based on the sampling rate of points. Hence, from this point forward, every time when we refer to any timestamp t_i we are actually talking about the i_{th} time bucket (or time slot) of size σ.

After dividing the time extent of the dataset presented by Table 3.3 using $\sigma = 3$, Table 3.4 shows in which time slot each O_{id} entry will end up at. The assignment of the time slot is made by dividing the timestamp value by the bucket size σ and then performing a floor operation, as shown in equation (3.1).

$$s = \left\lfloor \frac{t}{\sigma} \right\rfloor \tag{3.1}$$

3.2 Flock pattern

We use the same definition of flock from Vieira, Bakalov and Tsotras (2009):

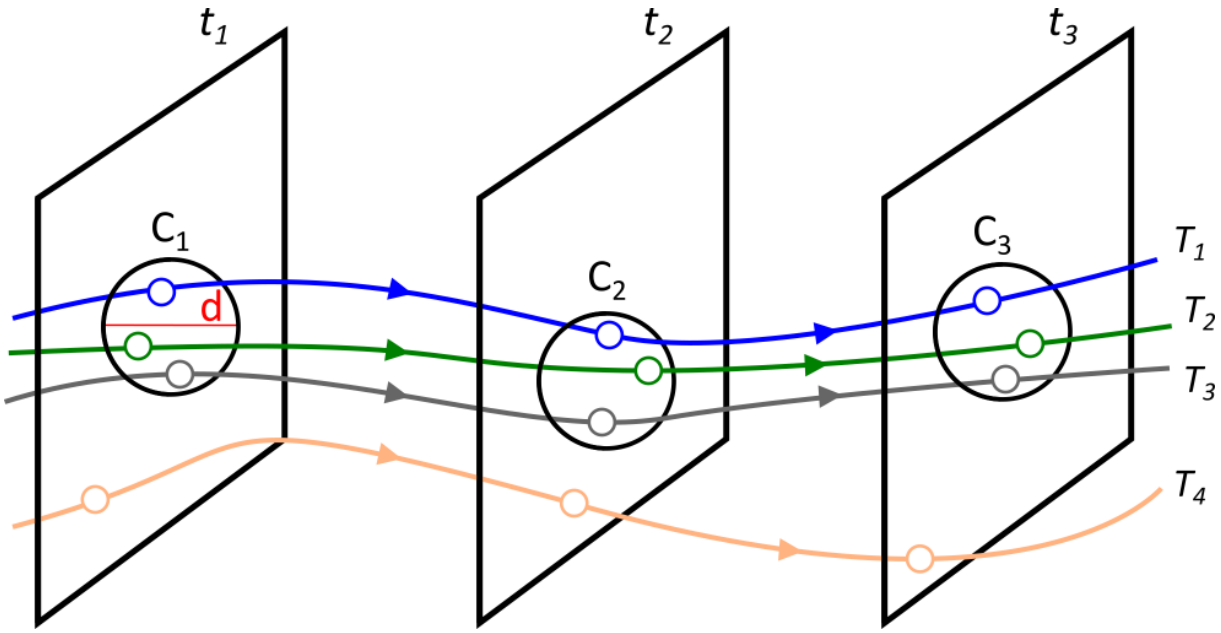
Definition 3.2. Given a set of trajectories $\mathscr{T}$, a minimum number of trajectories $\mu > 1$ ($\mu \in \mathbb{N}$), a maximum distance $\varepsilon > 0$ defined over the distance function d, and a minimum time duration $\delta > 1$ ($\delta \in \mathbb{N}$). A flock pattern $Flock(\mu, \varepsilon, \delta)$ reports all maximal size collections $\mathscr{F}$ of trajectories where: for each f_k in $\mathscr{F}$, the number of trajectories in f_k is greater or equal than μ ($|f_k| \geq \mu$) and there exist δ consecutive timestamps such that for every $t_i \in [f_k^{t_1} ... f_k^{t_1+\delta}]$, there is a disk with center $c_k^{t_i}$ and radius $\varepsilon/2$ covering all points in $f_k^{t_i}$. That is: $\forall f_k \in \mathscr{F}, \forall t_i \in [f_k^{t_1} ... f_k^{t_1+\delta}], \forall T_j \in f_k$: $|f_k| \geq \mu, d(p_j^{t_i}, c_k^{t_i}) \leq \varepsilon/2$.

In other words, what Definition 3.2 states is that a flock pattern basically consists in a set of at least μ trajectories (where each trajectory T_{id} belongs to the MO represented by O_{id}) that stay together for a minimum time extent δ. Additionally, in order to be considered a flock, there must exist a disk, with radius $\varepsilon/2$, that encloses all points of all trajectories for each time slot. Hence, we have a flock pattern relying on three key parameters:

1. μ: the minimum number of trajectories, in order to be considered a flock
2. ε: diameter of the disk that needs to enclose the trajectories for each time slot
3. δ: the minimum number of time slot units that the trajectories need to stay together

That definition is well depicted in Figure 3.1, where you can see that for each time slot t_i there is a disk of diameter $\varepsilon = d$ enclosing the points of trajectories T_1, T_2 and T_3. Thus, if we have set our flock parameters to $\mu = 3$, $\varepsilon = d$ and $\delta = 3$, we would have found the flock pattern $f = \{T_1, T_2, T_3\}$ shown in Figure 3.1. It is worth noting that trajectory T_4 could not be part of the

Figure 3.1: T1, T2 and T3 form a flock of size $\mu = 3$ with minimum length of $\delta = 3$ time slots and with a disk diameter of size $\varepsilon = d$



Source: Made by the author.

flock pattern because it was not possible to find a disk of diameter d that would enclose 2 more trajectories along with T_4 in each time slot t_i.

3.2.1 Disk discovery

One of the most important part, that enables the flock pattern identification, is how to efficiently discover the disks that can enclose potential flock patterns. Since the disk does not need to have its center matching any of the points in the dataset, there can be infinite places to look for them in the dataset space. Vieira, Bakalov and Tsotras (2009) proposed a way to reduce that search space to a finite number of locations, which we will explain in the remaining of this section and will be used in the algorithm proposed by this dissertation.

Algorithm 1 shows how we can find two circles that intersect two points, using some vectorial operations. Given two GPS points p_1 and p_2, we get the values of $x1$ and $y1$, which will correspond to the longitude and latitude in meters (such conversion is mentioned in Section 3.1) of p_1, and $x2$ and $y2$ being the equivalent of p_2 (lines 1 to 4). We know that the centers of the two disks c_1 and c_2 (that can be generated by those two points), lie in the line that is orthogonal to points p_1 and p_2 and passes through the midpoint p_m of those same points. After calculating p_m (lines 6 and 7) we convert those same points into a vector v (lines 9 and 10) and calculate its length (line 12), which will be used later to normalize v. Line 13 calculates the distance c_d from the centers tom p_m whereas lines 15 and 16 calculate the orthogonal vector o of v, which will guide the direction for the disks centers. The algorithm ends by finding the center c_1 by adding p_m to the product of o and c_d, and c_2 by subtracting p_m from the product of o and c_d. The disks that we could find are depicted in Figure 3.2.

Algorithm 1 Disks Discovery

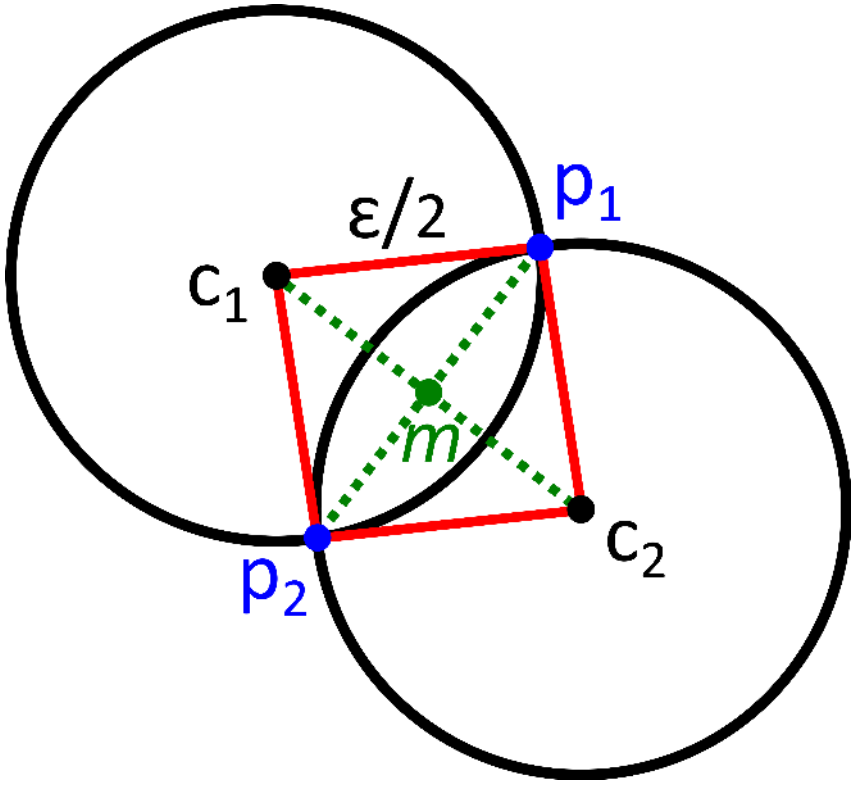
1: $x1 \leftarrow p1.longitudeMeters$
2: $y1 \leftarrow p1.latitudeMeters$
3: $x2 \leftarrow p2.longitudeMeters$
4: $y2 \leftarrow p2.latitudeMeters$
5:
6: $midX \leftarrow \frac{x1+x2}{2}$
7: $midY \leftarrow \frac{y1+y2}{2}$
8:
9: $vectorX \leftarrow x2 - x1$
10: $vectorY \leftarrow y2 - y1$
11:
12: $pointsDistance \leftarrow \sqrt{vectorX^2 + vectorY^2}$
13: $centerDistFromMidPoint \leftarrow \sqrt{(\frac{\varepsilon}{2})^2 - (\frac{pointsDistance}{2})^2}$
14:
15: $orthogonalVectorX \leftarrow vectorY$
16: $orthogonalVectorY \leftarrow -vectorX$
17:
18: $normalizedOrtVectorX \leftarrow \frac{orthogonalVectorX}{pointsDistance}$
19: $normalizedOrtVectorY \leftarrow \frac{orthogonalVectorY}{pointsDistance}$
20:
21: $c1X \leftarrow midX + (centerDistFromMidPoint * normalizedOrtVectorX)$
22: $c1Y \leftarrow midY + (centerDistFromMidPoint * normalizedOrtVectorY)$
23:
24: $c2X \leftarrow midX - (centerDistFromMidPoint * normalizedOrtVectorX)$
25: $c2Y \leftarrow midY - (centerDistFromMidPoint * normalizedOrtVectorY)$

In order to avoid running Algorithm 1 through all the points found in a time slot t_i, Vieira, Bakalov and Tsotras (2009) proposed a grid structure to reduce the search space for the set of points. In that approach, all points that belong to time slot t_i will be arranged into a grid with cells of size ε. After that, we will go through each cell $c_{i,j}$ in the grid and perform a search for points that are at most ε distant from each other. That search can be restricted to the cells $c_{i-1,j-1}...c_{i+1,j+1}$, as depicted in Figure 3.3, because all cells have ε as their sizes. It is important to note that the size of ε directly impacts in the number of cells and the number of points in each cell. For example, for a very small ε more cells will be created and less points will be present in each cell. On the other hand, large ε will create less but more populated cells.

Algorithm 2 shows how we will construct the grid structure for a set of points from a specific time slot t_i. In order to represent a grid structure, we will use a map of indexes to a list of points, which will then be populated as follows. For each point p in the point set, we will *bucketize* the longitude and the latitude of the point (both converted to meters, using equation (3.1)) by dividing them by the cell size ε (lines 5 and 6). Once we have the division results, we will convert them to string and concatenate them, forming a cell index (line 8). With the cell index in hand, we only need to add the point to the corresponding cell (line 9). It is worth

noting that this proposed approach will not create empty cells, saving memory and unnecessary cell traversing time.

Figure 3.2: Two disks with radius $\varepsilon/2$ that are found based on points p_1 and p_2. c_1 and c_2 stand for the disks centers and m represents the midpoint between p_1 and p_2.



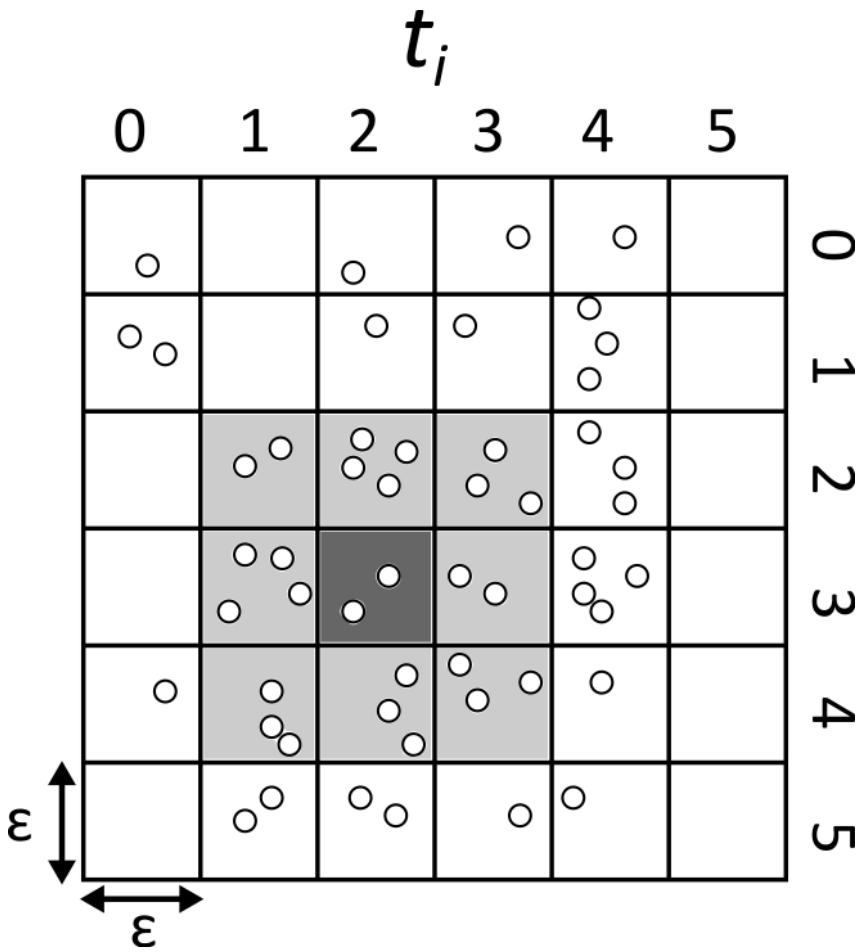
Source: Made by the author.

Algorithm 2 Construct Grid

```
1:  grid ← map{index, [...]}          ▷ map of cell index to list of points that belong to that cell
2:  points ← GETPOINTSOFTIMESLOT(t_i)
3:
4:  for each point p in points do
5:      xIndex ← ⌊ p.longitudeMeters / ε ⌋
6:      yIndex ← ⌊ p.latitudeMeters / ε ⌋
7:
8:      index ← TOSTRING(xIndex) + "_" + TOSTRING(yIndex)
9:      grid[index].add(p)
10: end for
```

Another important concept to keep in mind is that we are only interested in the maximum disks. Once we have found the disks with the points that belong to them, we will check if any disk d_i is a subset of another disk d_j. By saying that d_i is a subset of d_j we mean that d_j has all the points that d_i has. This was identified as being a tremendous processing bottleneck for an algorithm that aims at finding flock patterns.

Figure 3.3: Cell grid for time slot t_i. The dark grey is the cell that is currently being processed and the light gray cells around are the grids that will be in the search space of the dark cell. Each small circle inside the grid, represents a GPS point that was collected in time slot t_i



Source: Made by the author.

4

Modular and Efficient Flock Pattern Identification

4.1 Modular System Architecture

After the related work research that was performed, we noticed a lack of system architecture in order to solve the flock pattern detection problem in spatio-temporal datasets. So far, no previous work has provided such system architecture that could be modular and simple in order to help address the issues related to flock pattern detection.

We first tried to approach this problem in a more generic fashion, since the flock pattern mining (and also a lot of other moving pattern mining problems) has the same workflow:

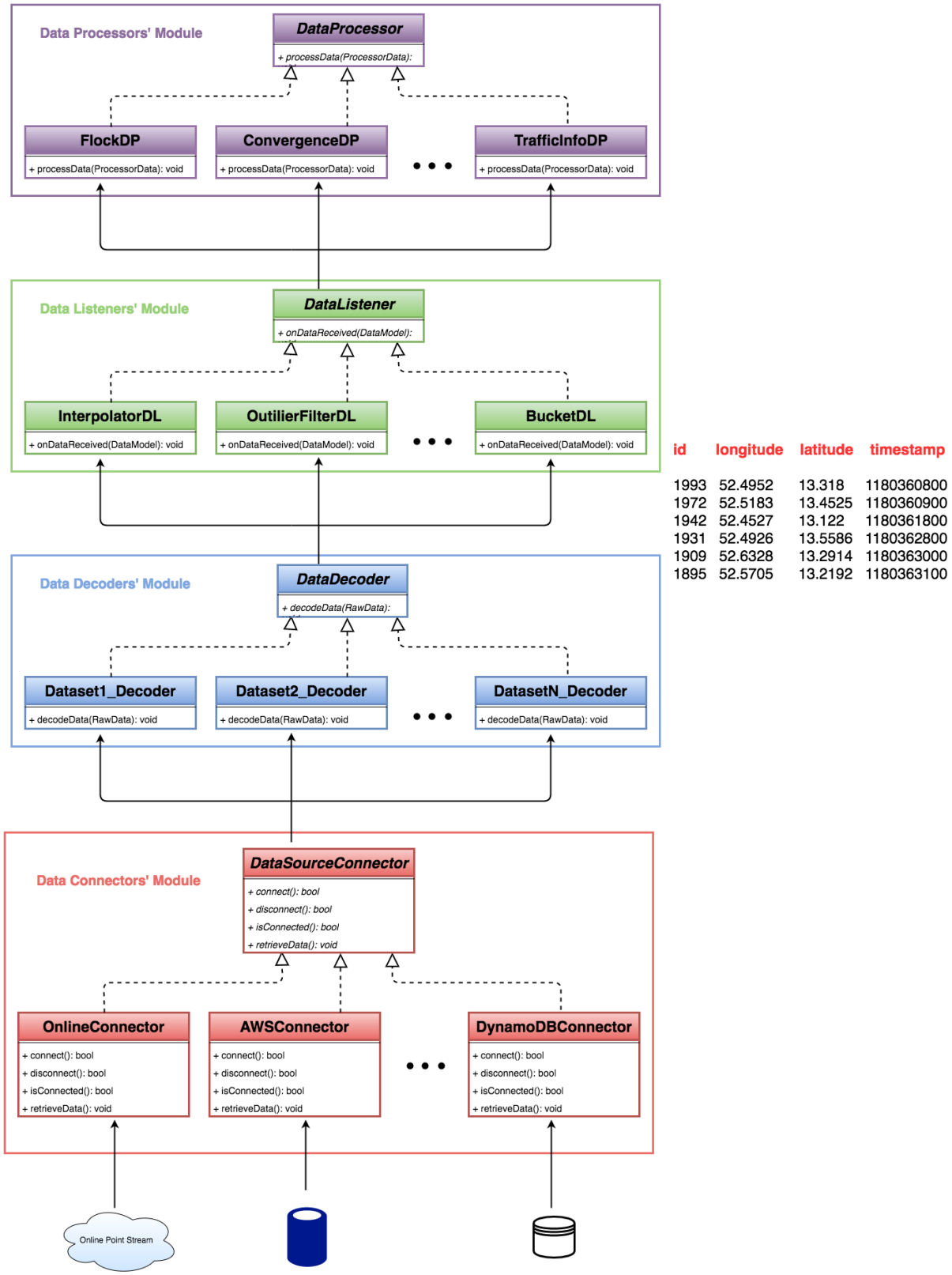
1. Connect to a spatio-temporal data source
2. Retrieve and aggregate spatio-temporal data
3. Process and mine that data in order to find the desired pattern (flock, in this case)

With that in mind, we designed a modular and simple system architecture that was built towards the flock pattern detection problem in spatio-temporal datasets, which is depicted by Figure 4.1. One can notice that we focus on 4 key building blocks, that can be easily registered/unregistered according to the targeting problem: (1) Data Source Connectors (DSCs); (2) Data Decoders (DDs); (3) Data Listeners (DLs) (Data aggregators); (4) Data Processors (DPs).

In layer (1) we are concerned on how to retrieve the data, meaning how to communicate properly to the data source in order to be able to extract each spatio-temporal record from it. Thus, each DSC depicted in the *Data Connectors' Module* in Figure 4.1 represents a logical piece that knows how to connect to and extract data from a specific data source. We can have a DSC that knows how to connect to a MySQL database, or another one that can connect to a cloud based storage system like Amazon Web Services (AWS) DynamoDB, or even a DSC that simply connects to an online data stream and listen for incoming data.

After connecting and retrieving data from a data source, we need to clean, decode and translate the incoming raw data to a format that is simple and understandable to our system. Aiming at achieving that, we will have a DD component, which knows how to interpret the

Figure 4.1: Modular system architecture overview



Source: Made by the author.

raw data format that comes from a DSC and translate it to a format that layer (3) onwards can understand. We can see in Figure 4.1 that a DD can register itself to a DSC in order to receive

each data record that such DSC gathers from a data source. It is important to note that a DD can register to only one DSC, but a DSC can have multiple DDs registered to it.

In any problem of data mining, aggregation is one of the most important phases, since it is there that the data gathering happens and necessary arrangements are made in order to get the data ready for processing. In our system, that phase happens in layer (4), which we call the Data Listeners' Module. We can have multiple types of DLs in that module, and each of them can perform different types of aggregation and pre-processing depending on the final goal. For example, we could have an aggregator (or listener) that *bucketize* the GPS points by their timestamp and filter out outliers, before sending to processing, or another one that performs point interpolation in order to reduce trajectory uncertainty. Similarly to the DD module, a DL can only register itself to one DD, but a DD can have multiple DLs registered to it. Later on we will see a DL implementation as one of the contributions of this dissertation, which will perform a *bufferized* aggregation of points.

The last, but not least, remaining piece is the Data Processors' Module, in layer (5). It is there that we will have the intelligence to perform a data mining task that will generate insights for decision making, detect moving patterns and the forth. We can have a DP that detects flock patterns, another one that detects convergence patterns and even another DP that provides traffic information in real-time, to name a few. Also, following the pattern of the aforementioned modules, each DP can only register itself to a single DL, but a DL can have multiple DPs registered to it. Fitting in the scope of this dissertation, we will implement and show a novel DP that can detect flock patterns, based on the BFE algorithm proposed by Vieira, Bakalov and Tsotras (2009).

Researchers and data analysts, working with flock pattern detection, can leverage from the proposed architecture in order to have some infrastructure to help on their spartio-temporal problems.

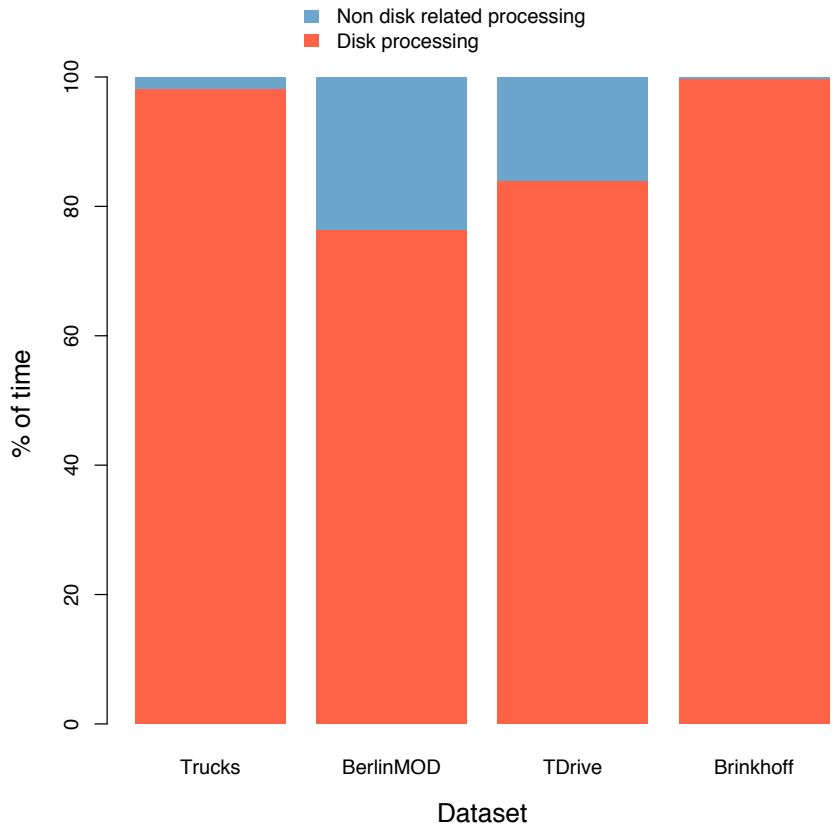
4.2 Aggregation and data processing efficiency

By analyzing some of the algorithms proposed in Section 2.2 and their respective running times, we noticed that most of the CPU cycles were spent in analyzing disks that will not generate flock patterns, due to the points not being present in δ consecutive time slots. In all algorithms, disks generated in time slot t_{i+1} are compared with the potential flocks found in t_i in order to check if an extension to a potential flock pattern is found. This operation has $O(nm)$ complexity, with n being the number of disks and m the number of potential flocks from previous time slots. Additionally, for each comparison between a disk and a potential flock, an intersection operation between them needs to be made.

Things get even worse in algorithms like BFE, where a new created disk d_j is checked if it is either subset or a duplicate of a previously found disk d_i (as already mentioned in Section 3.2.1). The running time of this step can result in a $O(n^2)$ time complexity in the worst case (with

n being the number of disks generated by that time slot) requiring an intersection operation between each pair of disks that are being compared. We can reduce significantly that number of disks by only creating disks with points that can potentially form a flock pattern, i.e. with points that appears in the dataset for δ consecutive time slots. In order to show how expensive those disk operations can be, we measured the time spent in such operations using the datasets that we will use in our experiments and present the results in Figure 4.2. The analysis shows that the disk and flock related operations can reach 99% of the overall processing time of the algorithm.

Figure 4.2: Percentage of time spent between disk and flock processing tasks against other tasks in the algorithm

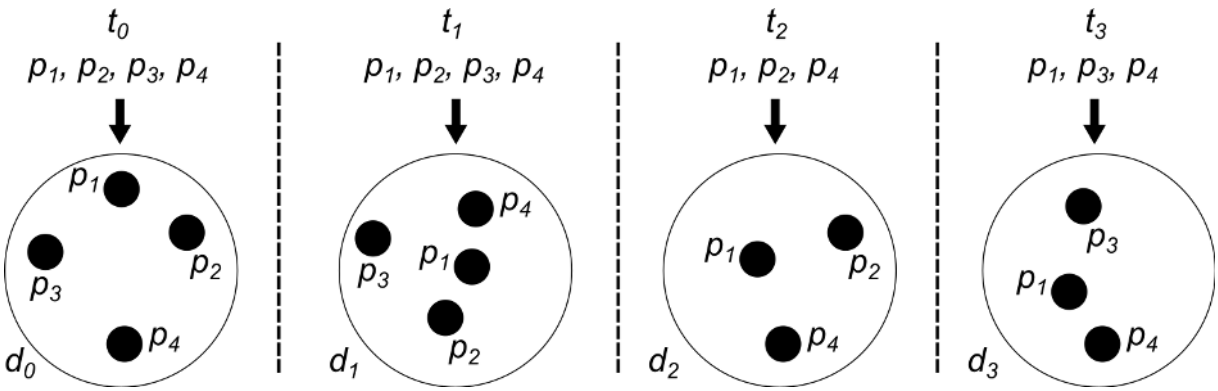


Source: Made by the author.

Consider the BFE algorithm running example depicted in Figure 4.3, where we are looking for flock patterns having $\mu = 4$ and $\delta = 4$ as its parameter values. As we can see, in time slot t_0 our dataset reported points p_1, p_2, p_3 and p_4 and, due to the proximity between them, disk d_0 was created enclosing all four points. In the subsequent time slot t_1 the same points were reported and again the BFE algorithm was able to create another disk d_1. However, in time slot t_2, p_3 was not present and the disk d_2 only contained three points, which is not enough to represent a flock pattern because of the number of trajectories being less than $\mu = 4$. With the disk d_2 being invalid in t_2, we will need to discard disks d_0 and d_1 created in the previous time slots, since they cannot generate a flock pattern starting from t_0. Hence, we could avoid the creation of disks d_0 and d_1 if we would know in advance that p_3 was missing in t_2, saving CPU cycles of disk

comparisons in t_0 and t_1. We argue that when scaled to a dataset with millions of records, doing real-time analyses, such processing for checking disks subsets and flock extension, performed by regular algorithms (like BFE), will lead to a severe degradation in performance. With that in mind, we can say with high confidence that reducing the volume of data that is processed by those flock and disk comparison tasks (by filtering out disks that will not generate flock patterns), can dramatically reduce the overall processing time of a flock detection algorithm.

Figure 4.3: Sequence of disks in 4 consecutive time slots and the points that were clustered to them



Source: Made by the author.

4.3 BitDF

Our solution consists on using **Bit**maps for **D**isk **F**iltering (BitDF), based on the BFE algorithm. BitDF is basically a DL and a DP components, as those in the architecture presented in Section 4.1. We call them GPS Stream Buffer (GSB) and Flock Processor (FP) the DL and DP respectively, and will have each of them keeping track of the history of every O_{id} in time.

Table 4.1: Bitmaps in GSB after buffering four time slots

O_{id}	Bitmap
1	1111
2	0111
3	1011
4	1111

Algorithm 3 shows a big picture of how GSB will work once it receives spatio-temporal data records from a DD. It will listen to the incoming GPS point stream in the procedure RECEIVEPOINTS, add each point to the *pointBuffer* structure (which is a hash map of points by time slot) and record the presence in time of that O_{id} in its bitmap structure (presence map) by calling ADDPOINTPRESENCE. When GSB has buffered δ time slots (line 23) it will

then send the points of $timeSlot - \delta$, along with the bitmaps, to FP. After FP is done with processing the points, GSB will discard the first bit of the bitmaps (which corresponds to the points of $timeSlot - \delta$ sent to FP), by calling SHIFTPRESENCEMAPS, and also discard the points collected in $timeSlot - \delta$, which were already processed by FP. The flow continues indefinitely by buffering the points from the next time slot t_i and send the points from $t_{i-\delta}$ and the bitmaps to FP for processing. It is worth noting that *timeSlotSize*, referred in line 21, represents the time slot σ introduced in Section 3.1.

Algorithm 3 GPS Stream Buffer

```
1:  pointBuffer ← map{index, {id, point[...]}}
2:  presenceMap ← map{id, bitmap}
3:  lastTimeslot ← −1
4:
5:  procedure ADDPOINTPRESENCE(id)
6:      mask ← SHIFTLEFT(1, pointBuffer.size − 1)
7:      presence ← BITOR(presenceMap[id], mask)
8:      presenceMap[id] ← presence
9:  end procedure
10:
11: procedure SHIFTPRESENCEMAPS
12:     for all id ∈ KEYS(presenceMap) do
13:         shifted ← SHIFTRIGHT(presenceMap[id], 1)
14:         presenceMap[id] ← shifted
15:     end for
16: end procedure
17:
18: procedure RECEIVEPOINTS
19:     loop
20:         point ← gpsPointStream.dequeue
21:         timeSlot ← point.timestamp/timeSlotSize
22:         if timeSlot > lastTimeslot then
23:             if pointBuffer.size ≥ δ then
24:                 FP.PROCESS(pointBuffer.first)
25:                 delete pointBuffer.first
26:                 SHIFTPRESENCEMAPS
27:             end if
28:             lastTimeslot ← timeSlot
29:         end if
30:         pointBuffer[timeSlot][point.id].append(point)
31:         ADDPOINTPRESENCE(point.id)
32:     end loop
33: end procedure
```

Using Figure 4.3 as an example, we can see in Table 4.1 the state of the GSB bitmaps for each O_{id} after receiving the points in t_3. With those bitmaps, we can easily look up for a specific point occurrence in time and check whether that point in that specific time slot can potentially

form a flock pattern or not. We do that by checking if that O_{id} appears for δ consecutive time slots in the dataset, i.e. it has δ consecutive bits set to 1. The bitmaps in GSB will always refer to the *future* of a specific O_{id}.

Algorithm 4 Flock Processor Helper Procedures

```
1:  buffered ← 0                          ▷ max time span of the current flocks, max value is δ
2:  flockMap ← map{id, bitmap}
3:
4:  procedure IsPointEligible(id)
5:      presence ← Concat(presenceMap[id], flockMap[id])
6:      eligibleMask ← ShiftLeft(1, δ) − 1
7:      range ← pointBuffer.size + buffered
8:      checks ← Max(1, range − δ + 1)
9:      while checks > 0 do
10:         tmp ← BitAnd(presence, eligibleMask)
11:         if BitXor(tmp, eligibleMask) then
12:             return true
13:         end if
14:         checks ← checks − 1
15:         eligibleMask ← ShiftLeft(eligibleMask, 1)
16:     end while
17:     return false
18: end procedure
19:
20: procedure MapPointFlock(id)
21:     mask ← ShiftLeft(1, buffered)
22:     flockMap[id] ← BitOr(flockMap[id, mask)
23: end procedure
24:
25: procedure ShiftFlockMaps
26:     for all id ∈ Keys(flockMap) do
27:         flockMap[id] ← ShiftRight(flockMap[id], 1)
28:     end for
29: end procedure
30:
31: procedure StoreDiskIfEligible(diskSet, d)
32:     if Count(d) ≥ μ and not SubSet(d) then
33:         AddDisk(diskSet, d)
34:     else
35:         delete d
36:     end if
37: end procedure
```

Our DP is explained in more detail by Algorithm 4 and Algorithm 5 as follows. In Algorithm 4 we start by first listing the procedures that will help the core procedure of FP (the Process procedure, in Algorithm 5). It is also in Algorithm 4 that we list the most important piece of this DP that allows us to achieve such good optimizations, in both CPU cycles and

Algorithm 5 Flock Processor Process Procedure

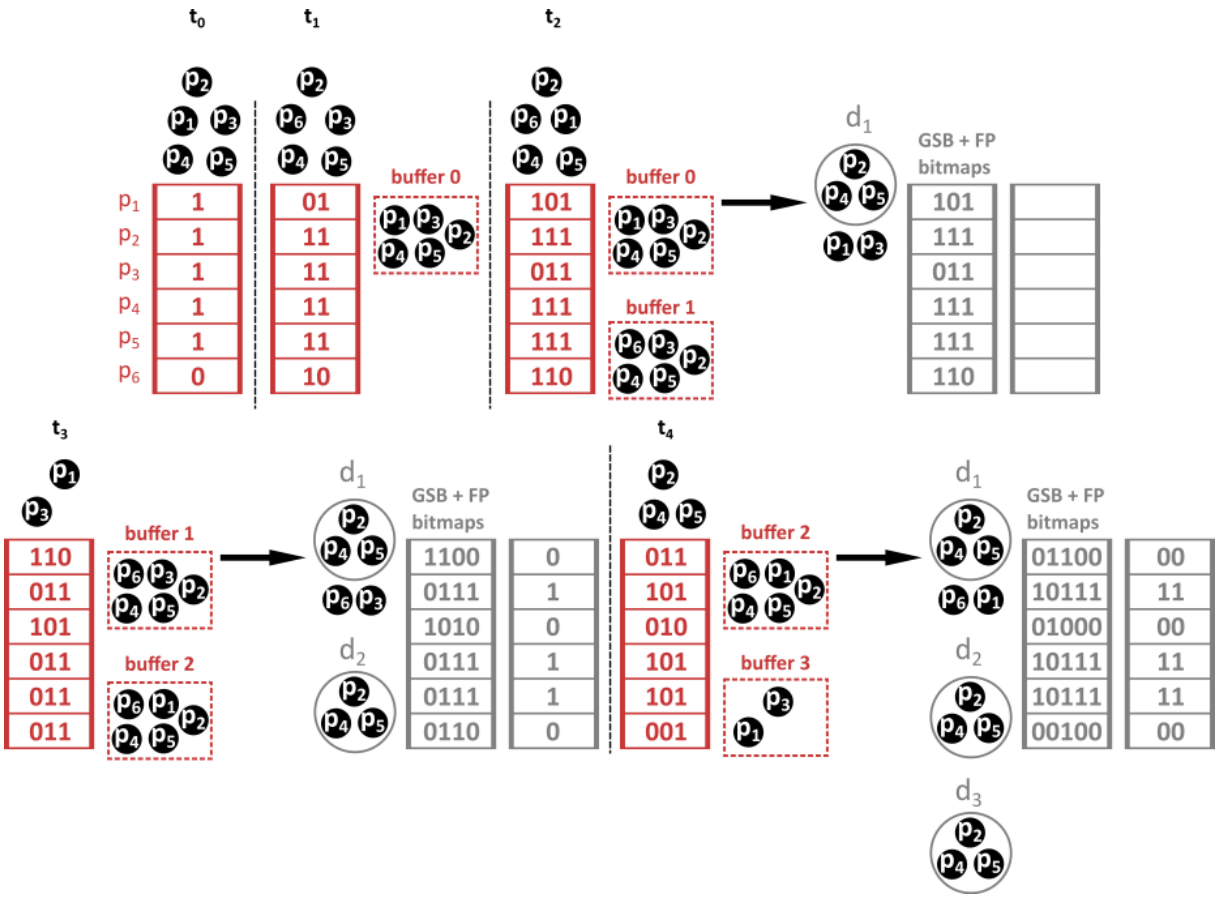
```
1:  procedure PROCESS(pointMap{id, point[...]}, timeslot)
2:      D ← ∅
3:      cells ← BUILDGRID(pointMap)
4:      if buffered ≥ δ then
5:          SHIFTFLOCKMAPS
6:          buffered ← buffered − 1
7:      end if
8:      for all c_{x,y} ∈ cells do
9:          cellRange ← [c_{x−1,y−1}...c_{x+1,y+1}]
10:         for all p1 ∈ c_{x,y} do
11:             for all p2 ∈ cellRange do
12:                 if d(p1, p2) ≤ ε then
13:                     d1, d2 ← CREATEDISKS(p1, p2)
14:                     for all p ∈ cellRange do
15:                         added ← false
16:                         if INDISK(d1, p) and ISPOINTELIGIBLE(p) then
17:                             ADD(D1, P)()
18:                             added ← true
19:                         end if
20:                         if INDISK(d2, p) and ISPOINTELIGIBLE(p) then
21:                             ADD(D2, P)()
22:                             added ← true
23:                         end if
24:                         if added = true then
25:                             MAPPOINTFLOCK(p.id)
26:                         end if
27:                     end for
28:                     STOREDISKIFELIGIBLE(D, d1)
29:                     STOREDISKIFELIGIBLE(D, d2)
30:                 end if
31:             end for
32:         end for
33:     end for
34:     buffered ← buffered + 1
35: end procedure
```

number of disks generated, which is the ISPOINTELIGIBLE procedure. Such procedure is responsible to put together what happened in the *past* and what is going to happen in the *future* for a given point p, in order to decide whether p can be part of a potential flock pattern or not. It does that by concatenating, for a given O_{id}, the bitmap from FP with the bitmap from GSB (line 5 of Algorithm 4) and searching for a sequence of δ bits set to 1 (lines 6 to 15 of Algorithm 4). That search is performed by combining AND and XOR bitwise operations against the presence bitmap assembled in line 5 of Algorithm 4. If a sequence of δ bits set to 1 is found, we can state with confidence that such point p can potentially be part of a flock pattern. Later on, if a

potential flock is found in a time slot t_i and p is part of it, we need to update the FP's bitmap of that point so when we process points of time slot t_{i+1} we have the correct bitmap representation of p and that is where MAPPOINTFLOCK (line 20) comes to play. MAPPOINTFLOCK does that by prepending 1 to p's bitmap in FP module by performing an OR bitwise operation.

Figure 4.4 shows how GSB (red) and FP (gray) will interact in a scenario where $\mu = 3$ and $\delta = 3$. In the first column we can see GSB receiving points p_1, p_2, p_3, p_4 and p_5 at time slot t_0 and then updating the bitmap for each of the points (red grid). Later on, at time slot t_1, GSB receives points p_2, p_3, p_4, p_5 and p_6 and again updates the presence bitmaps for each point. After the bitmap updates, one can notice that now p_1 has 01 as its presence bitmap value, meaning that p_1 was present at time slot t_0 but not at t_1, and GSB now has a buffer of points for time slot t_0 (red dashed box). When the points from time slot t_2 are received, and the presence bitmaps are updated, GSB sends the points buffered from time slot t_0 to FP for processing. At this time, FP has not received any set of points for processing, so its bitmaps are clean (rightmost gray grid) and the concatenation of the bitmaps from GSB and FP will end up being the same value as in GSB. After processing the buffered points from time slot t_0, FP will generate a disk d_1 with points p_2, p_4 and p_5, leaving p_1 and p_6 out because their bitmaps say that they will not appear in the next 2 consecutive time slots.

Figure 4.4: Interaction between GSB (red) and FP (gray) in 5 consecutive time slots, showing how the presence bitmaps are constructed. In the example we have $\mu = 3$ and $\delta = 3$



Source: Made by the author.

The same flow continues for time slot t_3, with GSB sending the buffered points from time slot t_1 to FP for processing. We can now notice that the points that formed disk d_1 in the time slot t_0 now have a bit set to 1 in their presence bitmaps in FP. Moreover, it is worth noting how we perform the bitmap concatenation in FP (when it receives points from t_1), in which the past time (FP bitmaps) goes at the right and the future (GSB bitmaps) goes at the left side of the concatenated bitmap. We then perform a search for $\mu = 3$ bits set to 1 in that concatenated bitmaps to figure out which points can potentially form a flock pattern and can be placed in a disk. Late in time slot t_4, when FP receives the points from time slot t_2, a flock pattern will be found, since we could find 3 consecutive disks containing at least $\mu = 3$ unique O_{id}.

4.4 Taking Advantage of Multi-core Architectures

It's well known that multi-core architectures are the current trend in technology. There is a myriad of multi-core processors in the market and many chipset companies taking advantages of those processor architectures too (even small devices, like smartphones, are being shipped with multi-core processors). Given that current scenario, there is no sense in not taking advantage of those multi-core processors and still executing our solution in a serial fashion. Thus, we will remodel our proposed architecture in a multi-threaded structure and parallelize some of the expensive tasks that our algorithm is doing, in order to make it more responsive and fast so it can empower decision makers to act in real-time.

One can see that the FP component, that we described in the previous section, is doing a lot of work in order to discover the flock patterns. Whenever the FP receives the set of points from GSB it performs the following actions:

1. Build the whole point grid
2. For each grid cell:
    (a) Get the Extended Grid Cell (EGC) (e.g. for cell $c_{x,y}$ it will get cells $c_{x-1,y-1} \cdots c_{x+1,y+1}$)
    (b) Process the EGC, trying to cluster the points into disks
3. Get the resulting disks and assure that there are neither duplicates nor subsets of other disks
4. Try to merge the disks with potential flocks from previous time slots
5. Report new found flocks

It can be easily perceived that the EGC processing (steps (a) and (b)) can be done in parallel for the multiple cells that will be processed, since there is no dependency and no concurrent writing operations between cells. Another step that is very CPU heavy is the

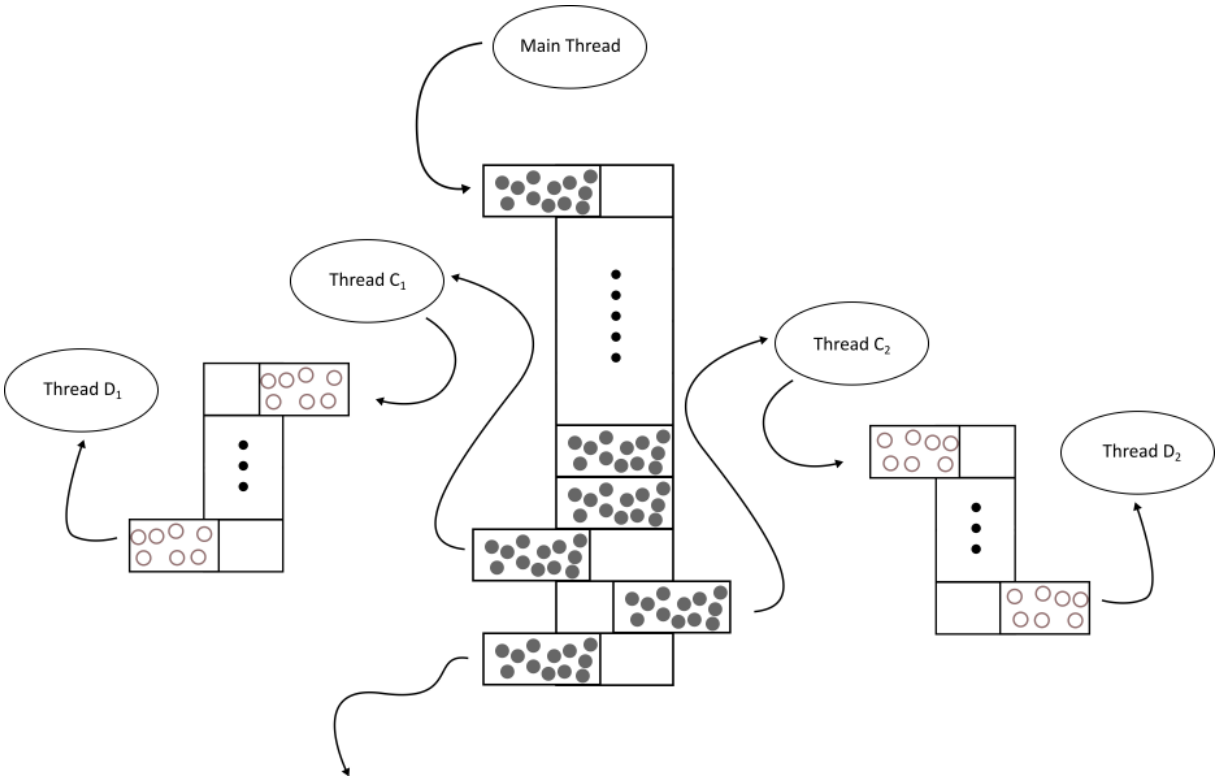
disk check described in step 3, but that step is very difficult to parallelize, as we could see in Algorithm 5. In that algorithm we showed that we start with an empty set of disks in the beginning of the PROCESS procedure and add disks to that set as we go finding them. However, before adding a disk d to the set, we check amongst the other disks that were previously there if d is neither a subset nor a superset of an existing disk. If d is a subset, then it is not added to the set, but if d is a superset of an existing disk d_2, that disk d_2 is then removed from the set and d is added instead (the superset check is done inside the procedure ADDDISK). Thus, if we try to parallelize that disk check procedure we would need to have synchronizing primitives to protect the concurrent writing operations to the shared disk set, which could end up being performance bottleneck in the system. Even without being able to fully parallelize the disk check steps, we can still take advantage of other techniques to gain some speed in processing, like using the divide and conquer approach. The idea would be to have multiple disk sets (one per independent worker thread processing EGCs) and have each independent thread add disks (and thus check for subsets/supersets) to its own set. When each worker thread has finished its processing we would have each thread's set being merged with the global disk set in FP, leaving less checks to be performed by the global disk set.

4.4.1 Multi-threaded Design

The multi-threaded idea described in Section 4.4 can be modeled as a Producer-Multiple Consumers problem, where we would have a single producer assembling the EGCs and multiple consumers taking a EGC from a shared queue and clustering the points in the disks that it might find for that specific EGC. On a step further, each consumer thread t_c will also spawn another thread t_d that will process disks that t_c has found and will check for subsets and supersets in its own private disk set.

Figure 4.5 illustrates how the FP will be rearchitected in order to take advantage of parallel execution. We can see that the main thread will collect the EGCs for each cell grid and enqueue them in a shared queue that will be accessed by N consumers. Whenever a consumer (t_c thread) dequeues an EGC, it will then try to find a pair of disks for each pair of points in the EGC, cluster the remaining points in those disks and then enqueue those disks in another shared queue. Such shared queue will only be shared with the disk thread t_d belonging to the t_c thread that created it. Then, each t_d will be responsible to check for subsets and supersets in its own set of disks, saving a lot of processing time when those disks are merged (and also checked for subsets and supersets) with the global disk set in the PROCESS procedure.

Figure 4.5: Modeling the FP in a Producer-Multiple Consumers architecture



Source: Made by the author.

5

Experimental Results

As explained in Chapter 3, the flock pattern detection relies mainly in 3 parameters, namely *number of trajectories* (μ), *flock extension (or length)* (δ) and *disk radius* ($\varepsilon/2$). Those parameters impact significantly in the number of patterns found as well as the time taken to find those patterns, depending on the dataset being analyzed. To validate the efficiency of BitDF, we chose 4 datasets referred by Zheng (2015), that are being widely used in trajectory data mining researches in the academia. Of those 4 datasets, 2 were collected from real-world experiments and 2 were synthetic generated.

Before evaluating the performance of BitDF using those datasets, we first gathered some metadata information about them, in order to choose wisely the value for the aforementioned parameters, so we could indeed find a good number of flocks patterns. Such metadata were collected by running BitDF multiple times with various values for those parameters. Thus, based on the dataset description, we picked some starting values for them and then increased or decreased the values according to the number of flock patterns that we were able to find. After finding at least 100 flock patterns, we then settled on a range of values for those parameters and used them to evaluate each dataset.

Figure 5.1 shows the components (using the architecture proposed in Section 4.1) that will be part of our experiments and how our experiments are going to be performed. For each dataset (which will be presented individually in the subsections to come) that we used, we simulated an online stream of GPS data arriving at the OnlineConnector DSC in our system. Then, that incoming GPS data would be forwarded to a DD that knows how to translate each entry in that specific dataset to a structure that can be understood by the GSB DL. When the GSB DL gets the data, the Algorithm 3 will take care of it, buffering it and building the necessary presence bitmap for that O_{id}. After we have buffered δ time slots of points in GSB, the next destination of the GPS data is the FP DP, which is composed by three different components, as depicted in Figure 5.2:

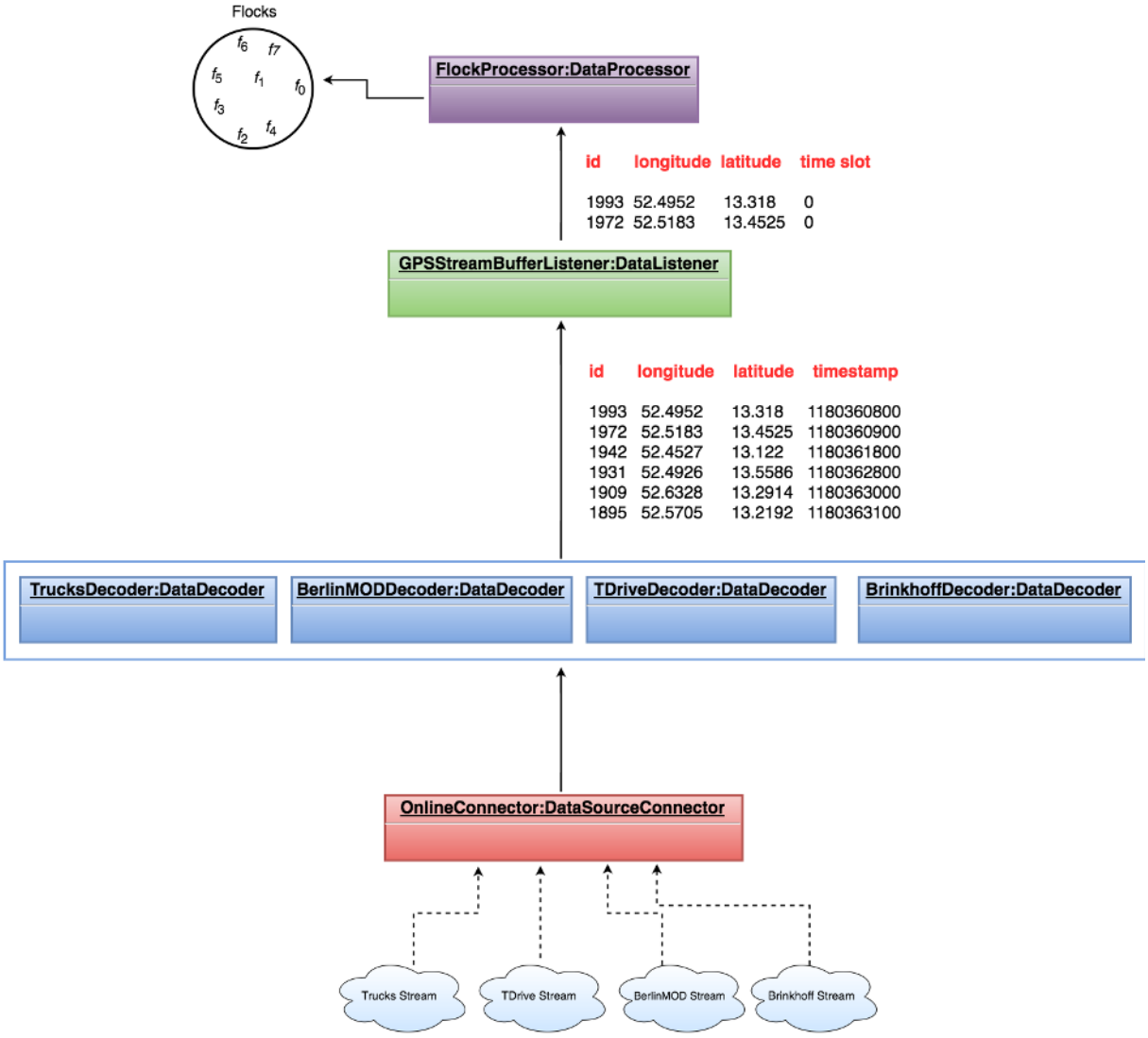
1. **Grid Manager**: Will get the GPS data and build the grid depicted in Figure 3.3 and provide the EGC for each grid cell.

2. **Disk Manager**: Gets each disk generated by FP and will check for duplicates/superset

disks and add it to the global disk set, if that disk is unique.

3. **Flock Manager**: Stores the potential flock patterns from previous time slots and merges the disks generated by the current time slot in order to find new flock patterns.

Figure 5.1: System design implemented for the experiments

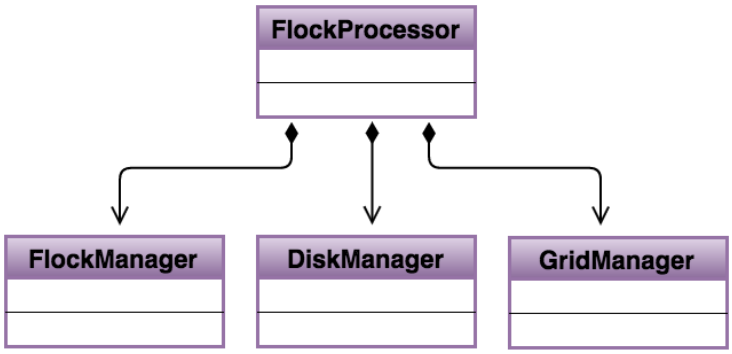


Source: Made by the author.

The metrics that we chose to measure the efficiency of BitDF were (1) Running Time and (2) Number of Disks Generated. For (1) we went through each individual parameter (μ, δ and ε), fixed it in a specific value and varied the remaining others based on the range that we settled from our metadata gathering. We picked (2) as an evaluation metric because it will show with numbers the reason why BitDF can run way faster than the comparison baseline algorihtm. Finally, in order to have a baseline to compare against BitDF, we implemented the BFE algorihtm proposed by Vieira, Bakalov and Tsotras (2009) and ran our benchmarks with it as well.

We implemented the system architecture proposed in Figure 5.1 in C++, using g++ 4.8.4 and the C++11 (ISO, 2012) features. Our test machine used to run our performance experiments

Figure 5.2: FlockProcessor class composition



Source: Made by the author.

was a Linux box with Intel Xeon Quad processor and 14GB of main memory running Ubuntu Server 14.04 Long Term Support (LTS). As already mentioned, we used four datasets (real and synthetic) in our experiments, with some of them having more than 50M entries and 2K unique O_{id}.

Before showing the results, there are some Analysis Outcome (AO) that will hold for any dataset being analyzed here:

1. δ **variation**: The longer the flock patterns we try to find (long δ), the more disks will stay cached being analyzed and trying to be merged with new disks from time slots to come. This can have a big impact in running time.

2. ε **variation**: As the disk radius ($\varepsilon/2$) gets bigger, more points will be clustered inside a disk and thus more intersections and duplicates of those disks as more likely to be found. This will impact the time spent in analyzing disks from one time slot to another.

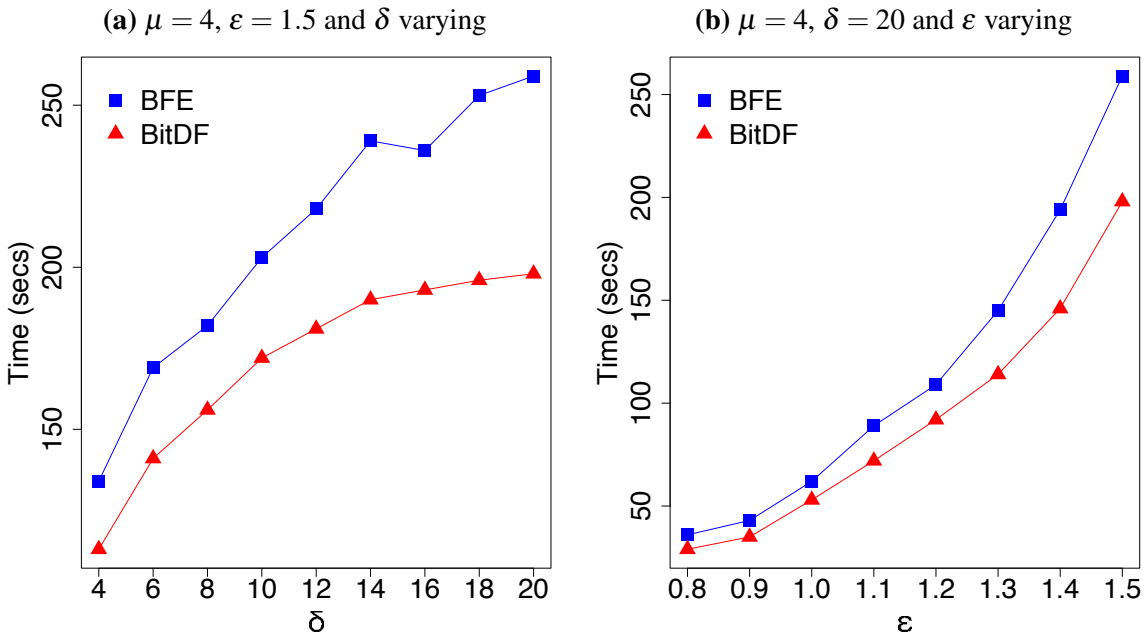
3. μ **variation**: By increasing μ, it gets more and more difficult to find disks that are flock candidates ($|d| \geq \mu$), so less disks are generated. This scenario is where BitDF will achieve less improvements.

5.1 Trucks Dataset

This was one of the datasets that Vieira, Bakalov and Tsotras (2009) used in the experiments of BFE, but the authors modified such dataset (CHOROCHRONOS, 2012), resulting in a dataset which is way far from those found in real-world analyses. In their modification, every time interval is of one second, the GPS coordinates were mapped to a $\mathbb{R}^2$ coordinate system (ranging from 0 to 1000) and most of the points are present in each time interval. The modified dataset resulted in 112,203 entries and 276 unique O_{id} (instead of 50 in the original dataset).

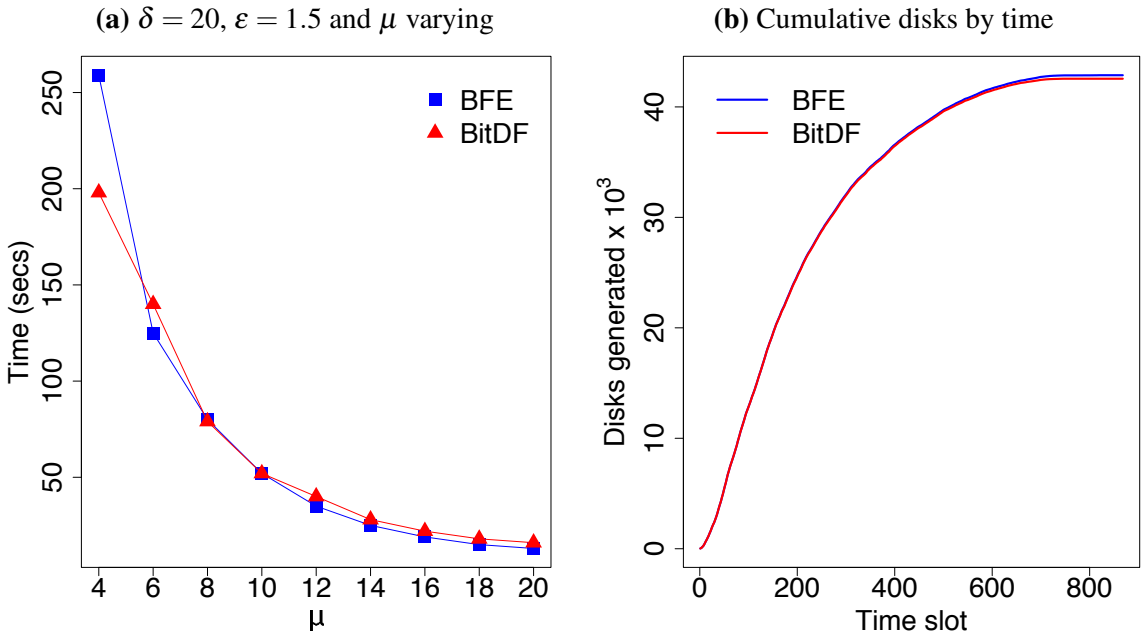
By looking at Figure 5.3 and Figure 5.4, we can see that BitDF had some gains in execution time. However, they were not too significant due to the fact that the number of

Figure 5.3: Results varying δ and ε for Trucks dataset



Source: Made by the author.

Figure 5.4: Results varying μ and number of disks generated over time for Trucks dataset



Source: Made by the author.

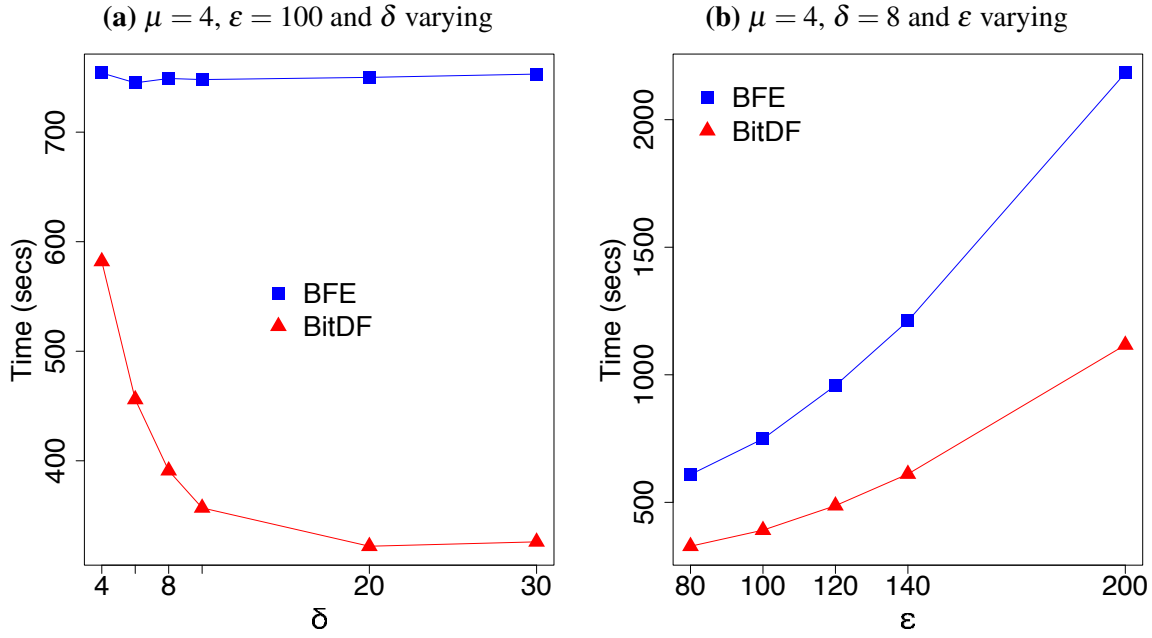
disks generated by each time slot does not differ too much between BFE and BitDF, as we can see in Figure 5.4b. This happens because almost all points appear in every single time slot, then buffering and mapping the O_{id} presence in time does not make a big impact, since we will not be able to filter out disks created with points not being present in δ consecutive time slots. Figure 5.3a and Figure 5.3b show some running time improvements against BFE, which

are backed up by the explanations given at AO 1 and AO 2. A different behavior is observed in Figure 5.4a, in which BitDF starts better but ends up almost tied with BFE, which can be explained by AO 3, but is also very influenced by the dataset modifications.

5.2 BerlinMOD Dataset

BerlinMOD consists in a traffic generation model (DüNTGEN; BEHR; GüTING, 2009b) used to create sythentic datasets of MOs. This particular dataset that we are analysing was the biggest one that we could find in the set of synthetic datasets that are available in their website (DüNTGEN; BEHR; GüTING, 2009a) and consists of 56,127,943 entries and 2,000 unique O_{id}.

Figure 5.5: Results varying δ and ε for BerlinMOD dataset



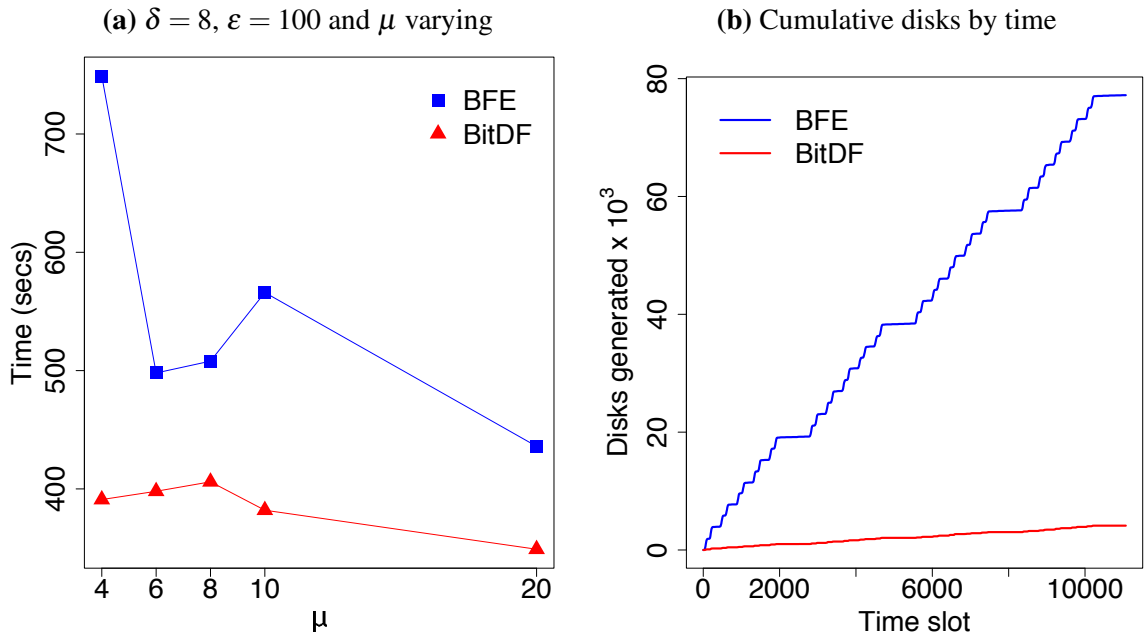
Source: Made by the author.

As we can see by the results presented in Figure 5.5 and Figure 5.6, BitDF was able to achieve great performance gains over BFE, in some cases being 57% faster (Figure 5.5a). In Figure 5.6b it is shown that BitDF reduces the cumulative number of disks created over time in 94%, by only creating disks that can indeed form flock patterns, which justifies the great improvements that BitDF was able to get in this dataset. Differently from the results presented in Section 5.1, BitDF was able to get great improvements over BFE, ranging from 20% to 48%, even when increasing the value of μ as depicted in Figure 5.6a. Lastly, as depicted in Figure 5.5b, BitDF was able to outperform BFE in almost 50% when varying the parameter ε.

5.3 TDrive Dataset

This is a real dataset, having spatio-temporal data describing one week of trajectories of taxis in Beijing, China, available in (ZHENG, 2011). It has 17,762,489 entries with 10,336

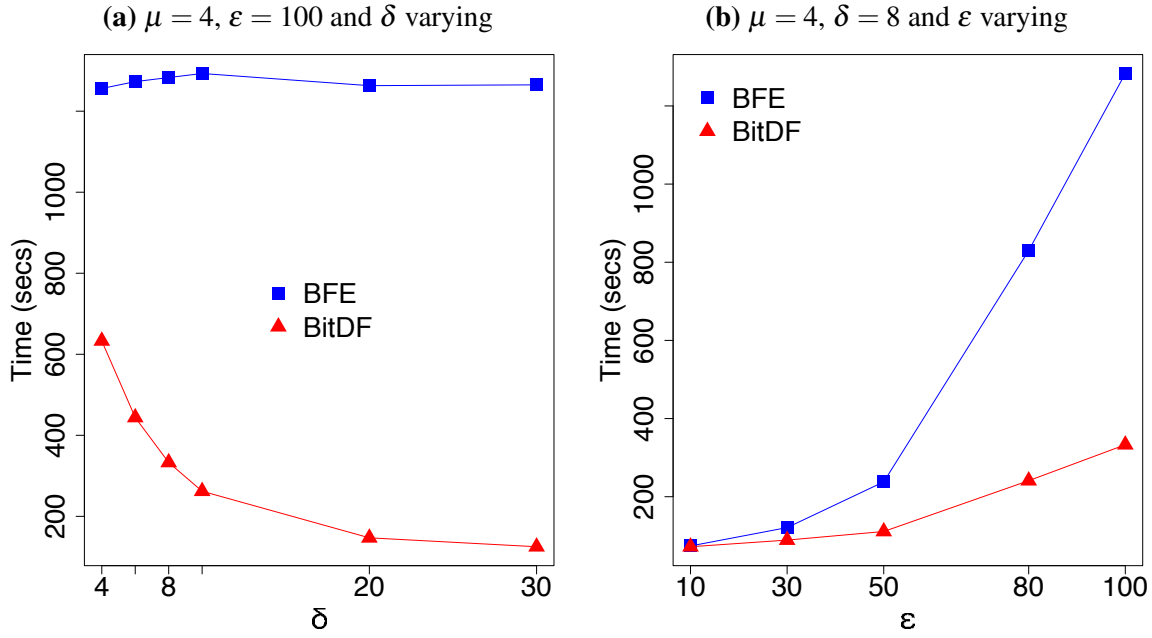
Figure 5.6: Results varying μ and number of disks generated over time for BerlinMOD dataset



Source: Made by the author.

unique O_{id}.

Figure 5.7: Results varying δ and ε for TDrive dataset



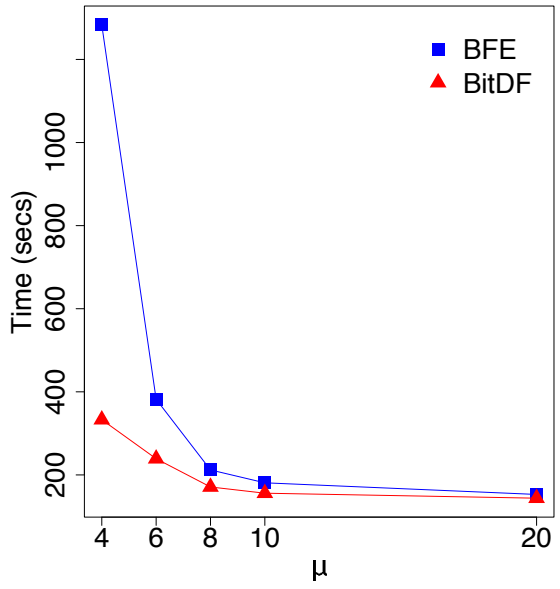
Source: Made by the author.

One can see by the results presented in Figure 5.7 and Figure 5.8, that BitDF was able to dramatically reduce the execution time, when compared to BFE. When varying the δ parameter, the running time improvement was of almost 90%, droping from 1,265 seconds to only 125 seconds of processing time, as shown in Figure 5.7a. Continuing the improvements,

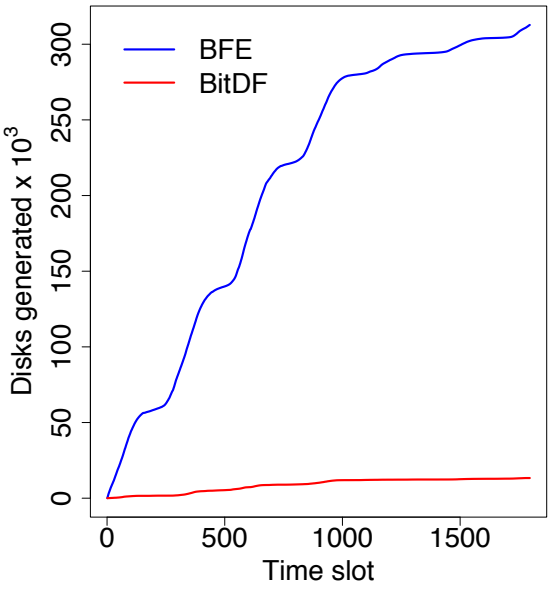
in Figure 5.7b we can see that BitDF reduced the execution time up to 74% when varying ε. Additionally, despite seeing some similar behavior with the other analyzed datasets (like presented in Section 5.1) when varying μ, Figure 5.8a shows that BitDF was able to improve the execution time by 74% in some cases. It is also worth noting that the results achieved are a reflex of the huge decrease of disks that were generated by time, as depicted in Figure 5.8b, reaching almost 96% of reduction.

Figure 5.8: Results varying μ and number of disks generated over time for TDrive dataset

(a) $\delta = 8$, $\varepsilon = 100$ and μ varying



(b) Cumulative disks by time



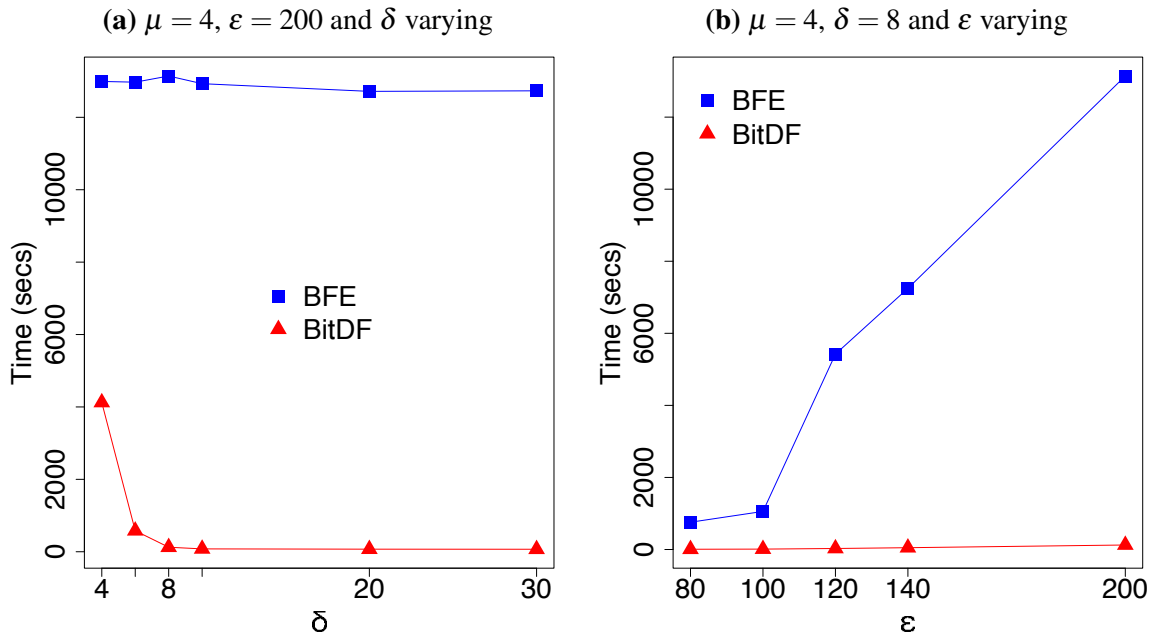
Source: Made by the author.

5.4 Brinkhoff Dataset

Likewise BerlinMOD, Brinkhoff is also a city traffic generation model (BRINKHOFF, 2002). We generated a synthetic dataset using the Minnesota Web-based Traffic Generator (MINNESOTA, 2013), having 2,000 as the "Starting Vehicles" and 100 as the "Simulation Time" parameters, which are the largest allowed numbers by the generator. The result dataset has 314,523 entries and 7,000 unique O_{id}.

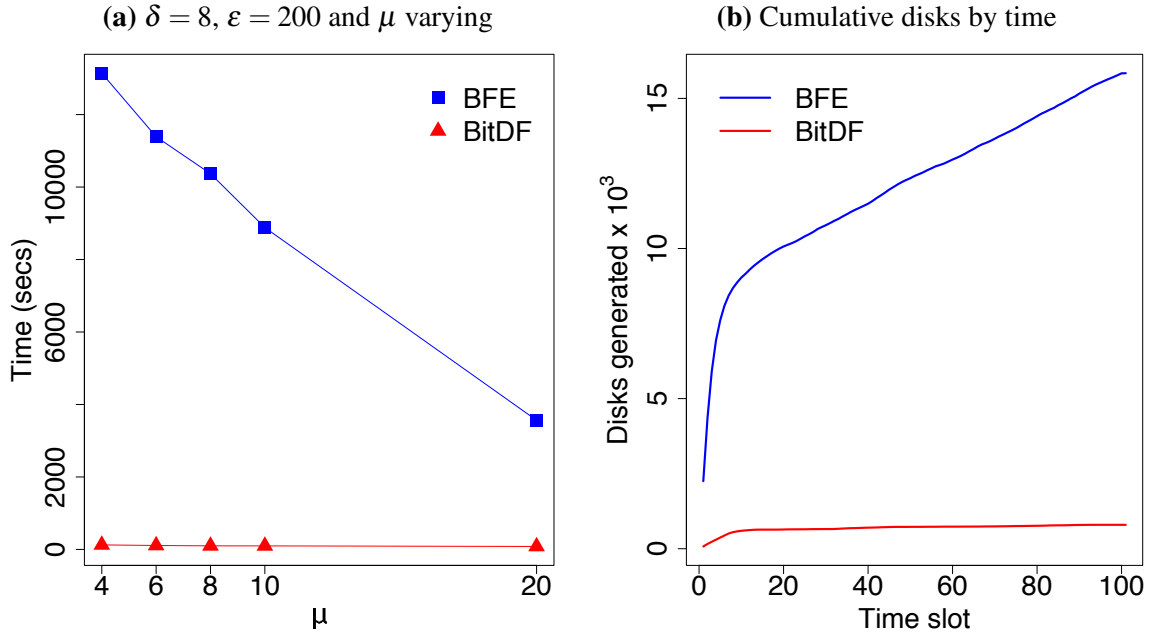
The results achieved with this dataset were the best that BitDF was able to get amongst the other datasets analyzed in this dissertation, as one can notice by looking to Figure 5.9 and Figure 5.10. There were huge drops in execution time, as depicted in Figure 5.9a, where BitDF analyzed the whole dataset in only 69 seconds, while BFE took 12,732 seconds, representing an improvement of 99.5%. Another great running time improvement of 99% can be seen when we varied the ε parameter, as shown in Figure 5.9b, droping from 13,141 seconds to only 125 seconds. We can see in Figure 5.10a that even with the variation of μ, BitDF was able to show huge improvement, with results ranging from 98% to 99% of CPU time reduction. Additionally,

Figure 5.9: Results varying δ and ε for Brinkhoff dataset



Source: Made by the author.

Figure 5.10: Results varying μ and number of disks generated over time for Brinkhoff dataset



Source: Made by the author.

we can see in Figure 5.10b that we were able to reduce the number of disks by 95%, which is a dramatic improvement and is reflecting directly in the running time improvements that we could see with this dataset.

5.5 Multi-threaded evaluation

After implementing the architecture proposed in Section 4.1, evaluating it in Chapter 5 and seeing great improvements in the running time when compared with other algorithms, we decided to test how our system would perform by taking advantage of the multi-core paradigm that is been widely used nowadays. We then took a step further and implement a new DP, that we called Parallel Flock Processor (PFP). PFP was implemented having in mind the MT model described in Section 4.4.1, which we call BitDF MT.

In order to see how BitDF MT would perform, we took from Chapter 5 the worst performances of BitDF for each dataset and compared such performance against BitDF MT running with a varied number of worker threads executing in parallel.

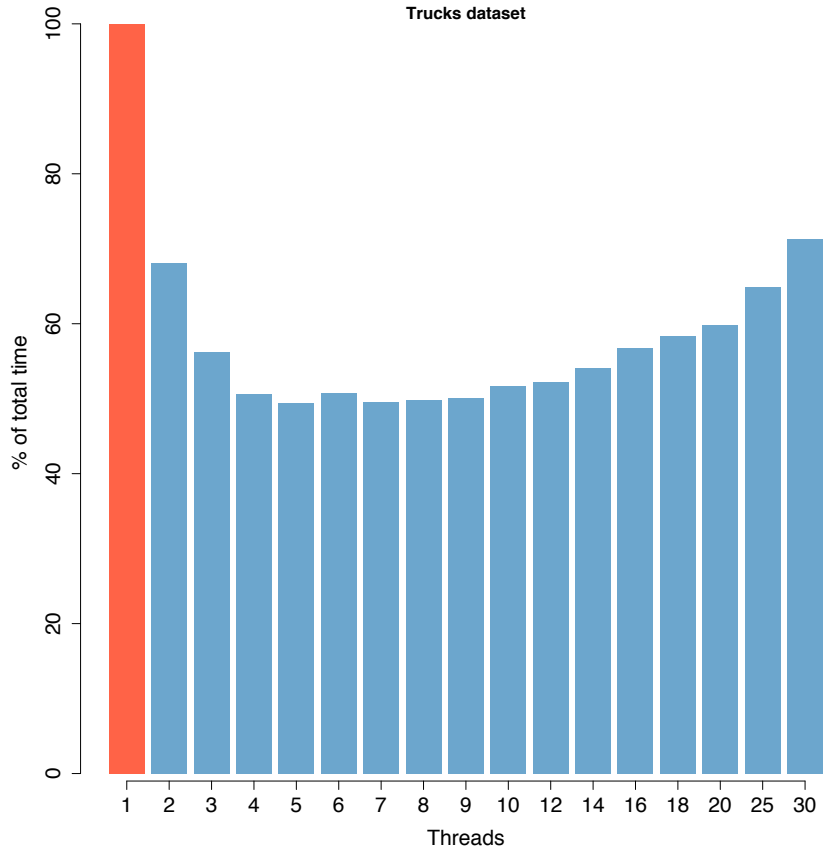
Our benchmarks were executed in a different machine from that one mentioned in the beginning of Chapter 5, in a way that we opted to get a better multi-core processor setup. Hence, we ran our experiments in a Linux box, running Ubuntu 16.04 LTS, having an Intel Xeon CPU, with 2.3 GHz and 4 physical cores, using Intel Hyper-Threading technology (MARR et al., 2012) meaning that we would theoretically have 8 different processing units.

Below we will present the benchmarks that were executed for each dataset already seen in Chapter 5, namely Trucks, TDrive, BerlinMOD and Brinkhoff. For each of the aforementioned datasets, we ran BitDF MT with the same parameters as the longest BitDF execution presented in Chapter 5, varying the worker threads from 1 (pure BitDF) to 30. With variations of 1 worker thread from 1 to 10, 2 worker threads from 10 to 20 and 5 worker threads from 20 to 30. It is important to notice that when we say that we are running with x worker threads, we are actually running with $2 * x$ threads: having x t_c threads processing different EGCs plus 1 t_d thread (attached to its t_c thread) processing the disks generated by its parent t_c. We set the result of pure BitDF as being 100% of the total execution time and highlighted it with red color and all BitDF MT runs are in blue, always being a percentage of the red highlighted result. It is worth mentioning here that the only metric that we are evaluating in these experiments is the running time of BitDF MT, because the number of generated disks will be the same that we have seen in the previous results shown for BitDF in Chapter 5, since we are still using the same bitmap filtering heuristic proposed by BitDF. Moreover, in order to have a better idea on how BitDF MT outperforms BitDF and BFE, we show some graphs depicting the running time of them together, for each dataset. For such comparion, we picked 5 and 7 as the number of worker threads for BitDF MT, since those are the values that show the best peformance overall.

First we present the results for the Trucks dataset, which we ran with the following parameters (based on previous results from Section 5.1): $\mu = 4$, $\delta = 20$ and $\varepsilon = 1.5$. That dataset would be the most difficult one to show running time improvements due to its small size and running times being already fast (with the longest one being around 200 seconds for BitDF). Despite that, we can see in Figure 5.11 that we were able to reduce as much as 51% when running with 5 t_c threads, which totalizes 10 threads. After that we can see that we could

stay almost stable, not gaining any performance but also not deteriorating it too much. Such performance stabilization is an expected result, as the processor would start to schedule and pause the execution of threads, because of having all its resources busy, as the number of executing threads exceeds too much the number of available processing units.

Figure 5.11: Execution time reduction by number of threads for the Trucks dataset

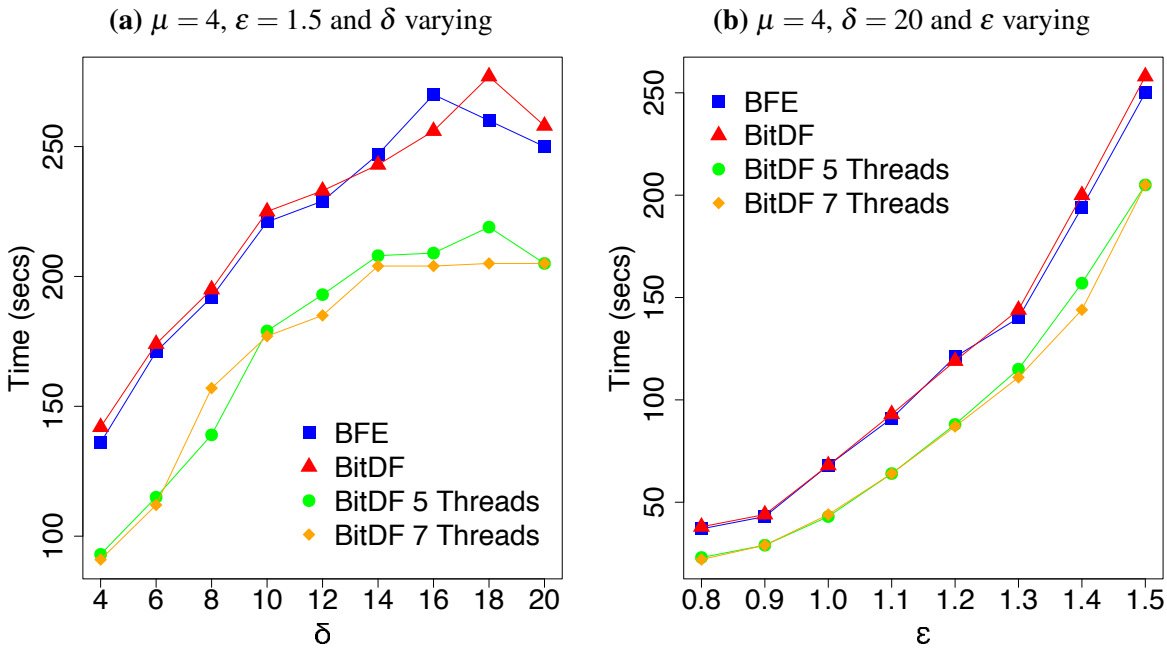


Source: Made by the author.

Figure 5.12 and Figure 5.13 show that we were able to achieve more meaningful results with BitDF MT, than those presented in Section 5.1 and that the improvements obtained with BitDF MT runing with both 5 and 7 worker threads were almost the same. We could reduce the running time of BitDF by 18% when varying μ (Figure 5.13) and ε (Figure 5.12b) and by 30% when varying δ (Figure 5.12a).

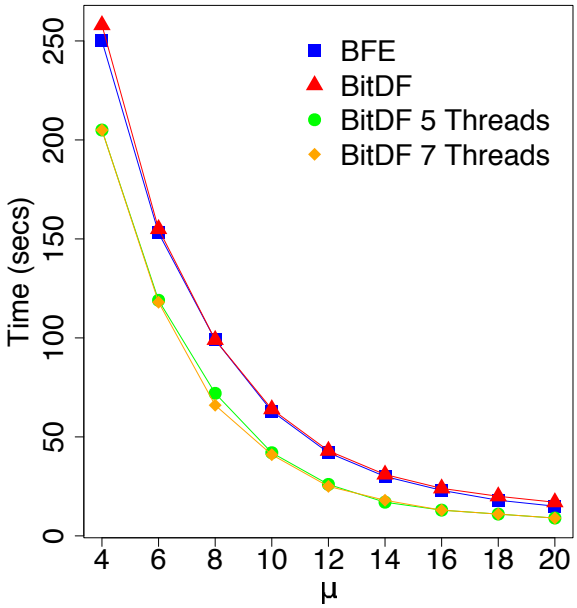
In Figure 5.14, we show the graph with the results for the BerlinMOD dataset. Due to its large size and somewhat long execution times (as previously presented in Section 5.2) we expected to obtain good results in running BitDF with independent worker threads. We have set our parameters to have the following values: $\mu = 4$, $\delta = 8$ and $\varepsilon = 200$, as we had those resulting in the longest running time (around 1,000 seconds) in our first experiments with this dataset. It is noticed by Figure 5.14 that the results also tend to stabilize when we reach 5 worker threads (10 in total), but we reach our best running time with 8 worker threads, with an improvement of 62%. It is also seen that the running time starts to get worse as we exceed the number of processing units available (shown when BitDF MT is executing with 30 worker threads, being 60 in total).

Figure 5.12: Results varying δ and ε for Trucks dataset



Source: Made by the author.

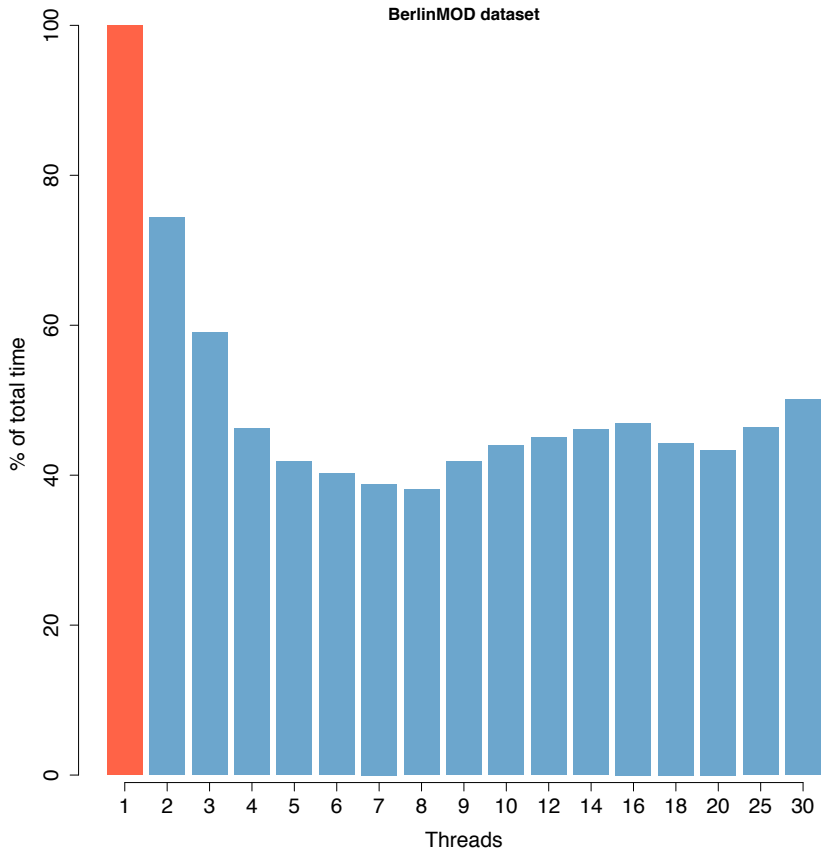
Figure 5.13: Results having $\delta = 20$, $\varepsilon = 1.5$ and μ varying for the Trucks dataset



Source: Made by the author.

By looking at Figure 5.15 and Figure 5.16, one can see that even where BitDF had the worst results, BitDF MT was able to achieve important reductions in running time, showing how a good multi-threaded remodeling is important in order to get the most out of a multi-core architecture. BitDF MT improved the running time of BitDF by 50% when running with both 5 and 7 worker threads, as shown in Figure 5.15a. BitDF MT also achieved good results when we varied the μ parameter, having 45% of running time decrease as it is depicted in Figure 5.16.

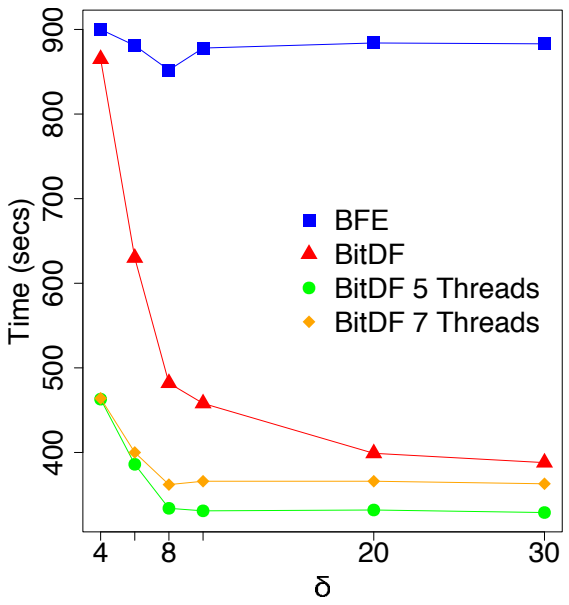
Figure 5.14: Execution time reduction by number of threads for the BerlinMOD dataset



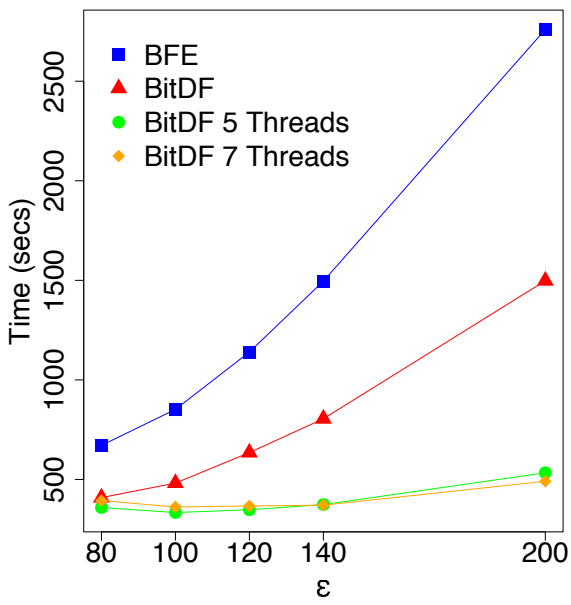
Source: Made by the author.

Figure 5.15: Results varying δ and ε for BerlinMOD dataset

(a) $\mu = 4$, $\varepsilon = 100$ and δ varying

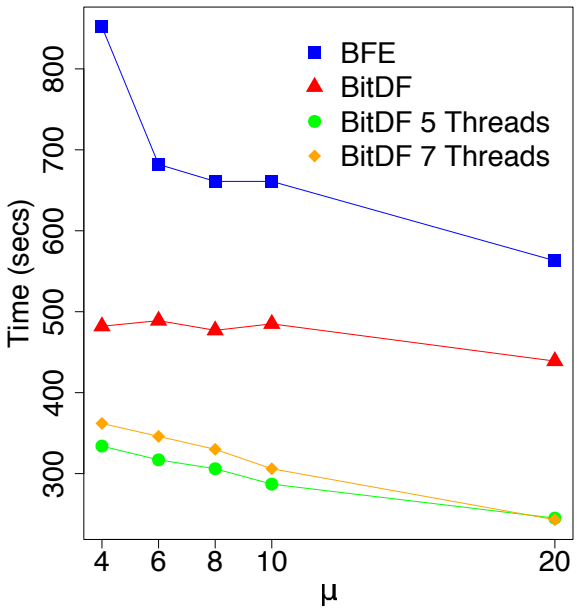


(b) $\mu = 4$, $\delta = 8$ and ε varying



Source: Made by the author.

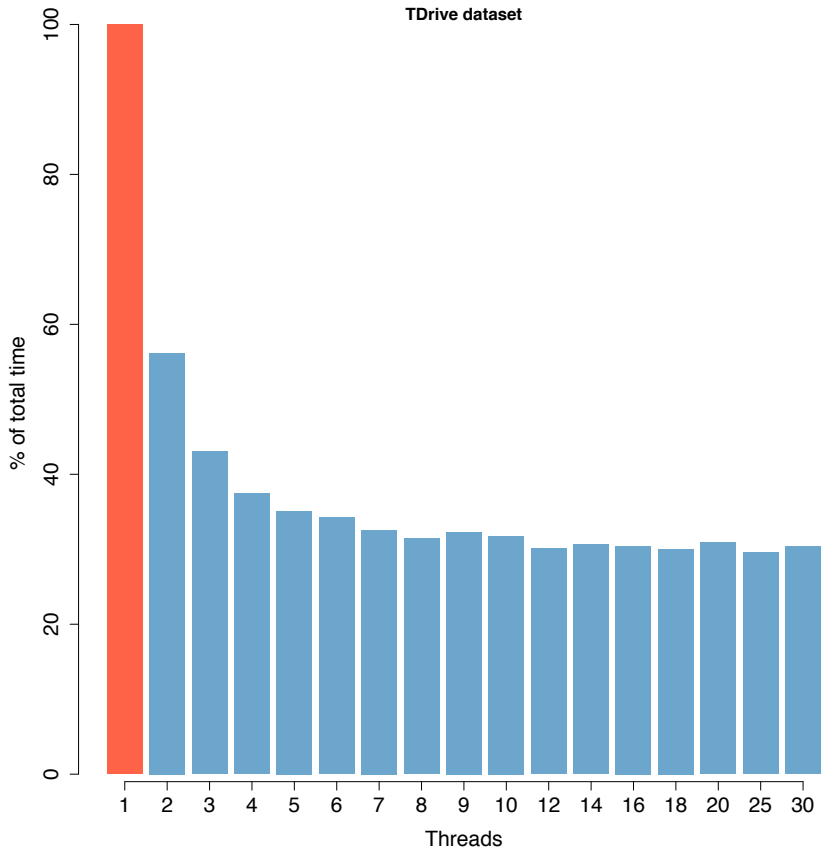
Figure 5.16: Results having $\delta = 8$, $\varepsilon = 100$ and μ varying for the BerlinMOD dataset



Source: Made by the author.

Last, but definitely not least, we can se in Figure 5.15b that BitDF MT improved the running time of BitDF by 70%, with both 5 and 7 worker threads.

Figure 5.17: Execution time reduction by number of threads for the TDrive dataset

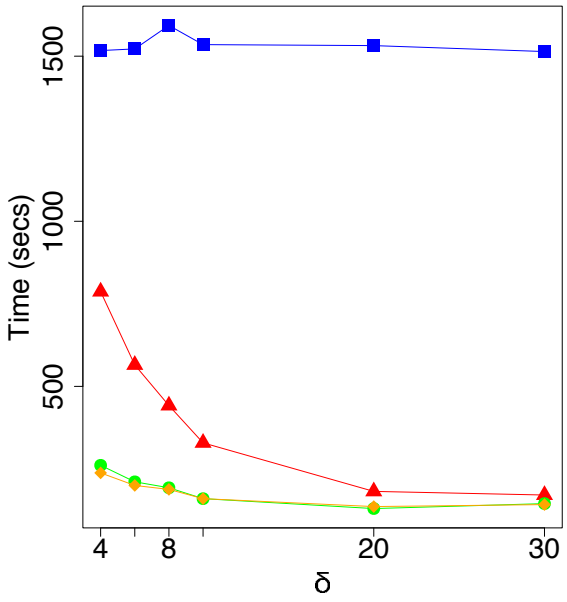


Source: Made by the author.

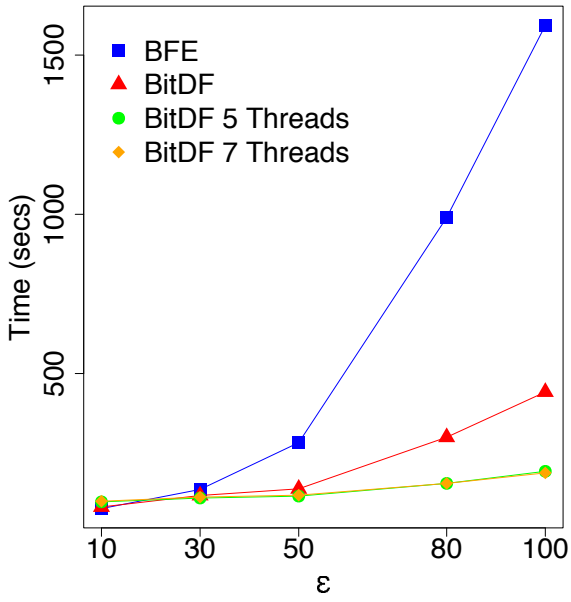
Another large dataset that we evaluate was the TDrive dataset, in which BitDF showed great results when analzing it. Based on the results presented in Section 5.3, we chose the parameter values that led to the longest execution time (around 600 seconds): $\mu = 4$, $\delta = 4$ and $\varepsilon = 100$. Figure 5.17 shows that the results follow the same pattern that we have been seeing in the previous analyses: great improvements in the beginning, but stabilizing as we exceed the number of processing units in the machine. We can also see some slight improvements even when we evaluate with more than 5 worker threads. It is also depicted in Figure 5.17 that we were able to reduce the running time as much as 70%, when compared to the single threaded model, which is a huge improvement added to those already achieved in Section 5.3

Figure 5.18: Results varying δ and ε for TDrive dataset

(a) $\mu = 4$, $\varepsilon = 100$ and δ varying



(b) $\mu = 4$, $\delta = 8$ and ε varying

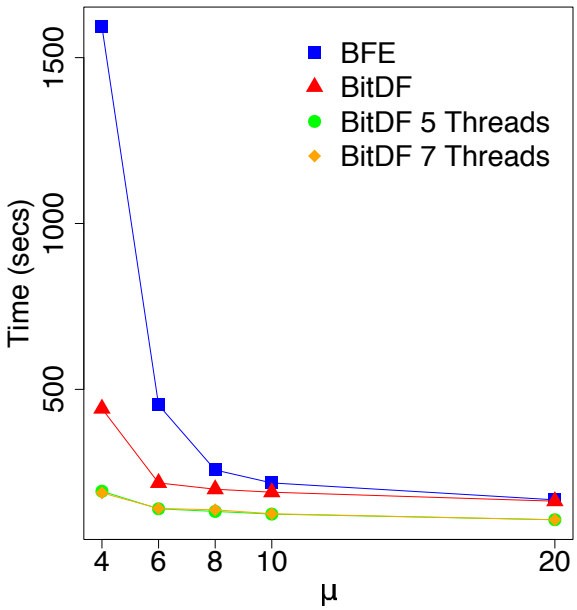


Source: Made by the author.

When it comes to comparing the running time of BitDF MT against BitDF and BFE, we can see that BitDF MT was able to improve the running time even more than we have seen in Section 5.3. When varying the parameter μ we could reduce the execution time by 60%, as one can see in Figure 5.19. Figure 5.18b also shows improvements of 60%, when compared against BitDF, when varying the parameter ε. The best result though is when we varied the parameter δ, in which we could improve the BitDF running time by 70% when executing BitDF MT with both 5 and 7 worker threads, as depicted in Figure 5.18a.

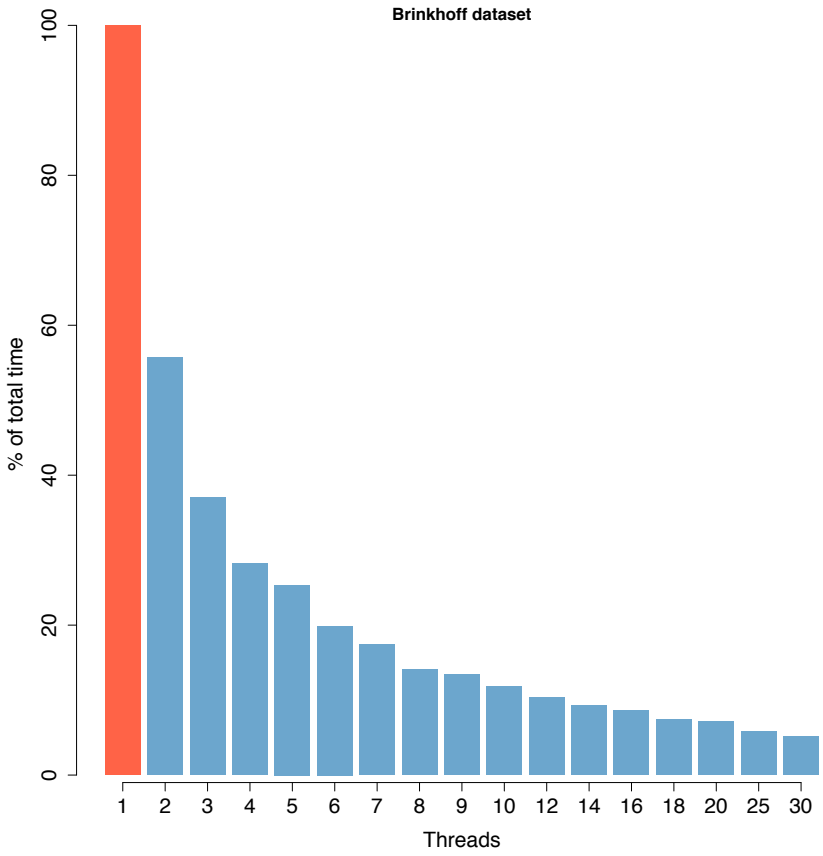
Our last dataset to evaluate is the Brinkhoff synthetic dataset. We were already able to achieve huge running time improvements with BitDF, but we could achieve even more with BitDF MT. Based on the dataset results (Section 5.4), we chose the running parameters as follows: $\mu = 4$, $\delta = 4$ and $\varepsilon = 1200$. Figure 5.20 shows that we were always able to reduce the BitDF running time even with the number of worker threads being way higher than the number of available processing units in the machine. That is a result that is completely different from

Figure 5.19: Results having $\delta = 8$, $\varepsilon = 100$ and μ varying for the TDrive dataset



Source: Made by the author.

Figure 5.20: Execution time reduction by number of threads for the Brinkhof dataset

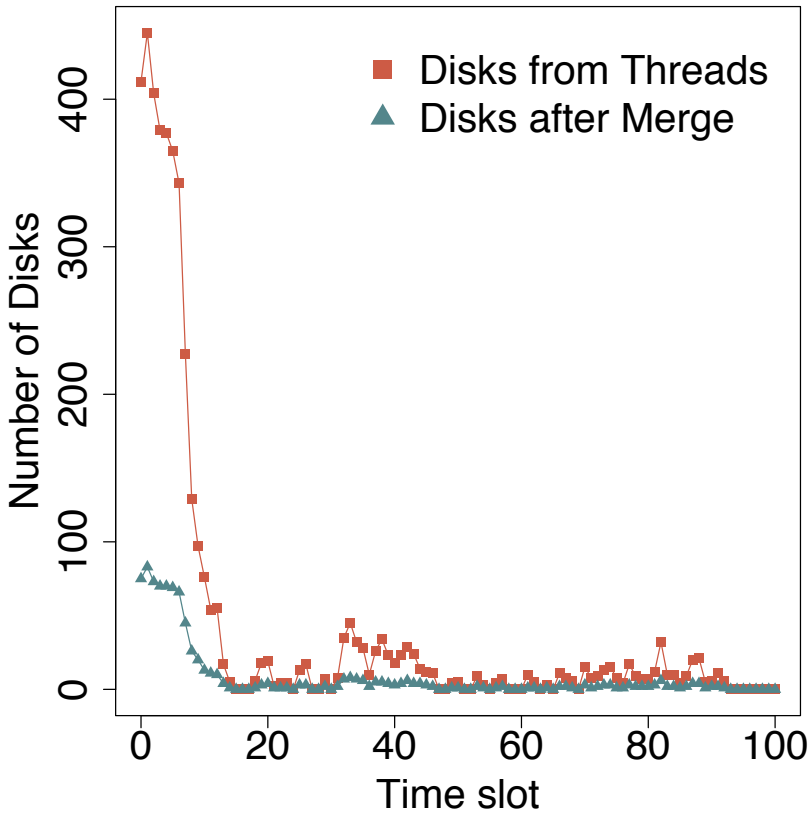


Source: Made by the author.

those that we saw with the previous datasets. Compared with the BitDF run, we could reduce the running time by 96%, being that highest cutback achieved with 30 worker threads (60 in total). Given that different behavior from the other datasets, we took a closer look on it when running

with a high number of threads, in order to try to find out the reason that BitDF MT runs better as the number of worker threads grow. As one can see in Figure 5.21, the number of disks that are being generated by the disk threads (t_d) are very close to the final number of disks that are being inserted in the global disk set. That means that the each disk thread is able to eliminate a lot of repeated and superset disks before returning them to be merged in the global set. Another thing that is important to note is that the number of disks being generated is really small as time advances, meaning that the points are more scattered over time, causing less disks to be generated and then less synchronization between shared queues for each executing thread. Because of that, threads could spend less time blocked waiting for shared data to become available.

Figure 5.21: Sum of disks generated by the disk threads (red) and number of disks that were inserted in the global disk set after subset/superset check (blue), by time slot



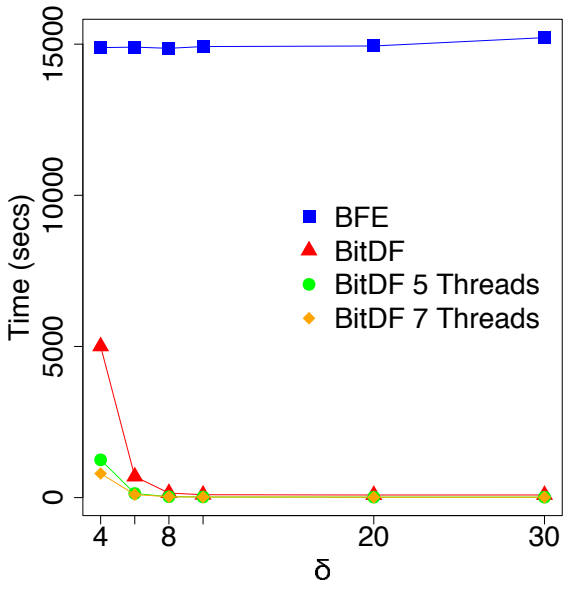
Source: Made by the author.

Despite the reduction in running time of more than 90% that BitDF was able to achieve, as seen in Section 5.4, we could reduce that number even more with BitDF MT. It is difficult to see the actual difference between the running time of BitDF and BitDF MT, due to the slowness of BFE in that dataset, which is causing the y axis range to be very wide. However, BitDF MT with 5 and 7 worker threads could reduce the time of BitDF by 82% when varying the μ parameters, as shown in Figure 5.23. When varying the ε parameter, BitDF MT with 5 and 7 worker threads could also decrease the BitDF running time by 82% (Figure 5.22b). Finally, by varying the δ parameter and running with 5 worker threads, BitDF MT could outperform BitDF

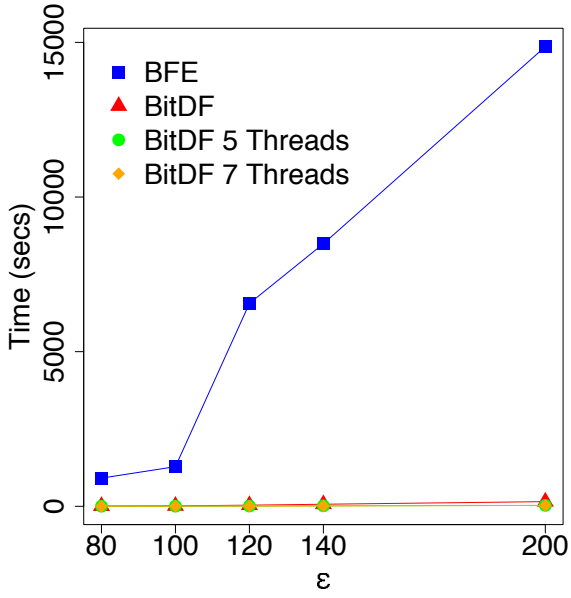
by 76%, whereas by running with 7 worker threads, BitDF MT could be better by 85%, as we can see in Figure 5.22a.

Figure 5.22: Results varying δ and ε for Brinkhoff dataset

(a) $\mu = 4$, $\varepsilon = 100$ and δ varying

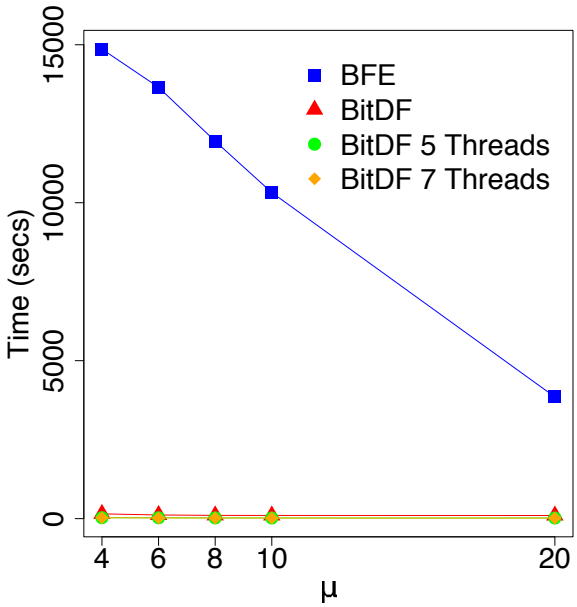


(b) $\mu = 4$, $\delta = 8$ and ε varying



Source: Made by the author.

Figure 5.23: Results having $\delta = 8$, $\varepsilon = 100$ and μ varying for the Brinkhoff dataset



Source: Made by the author.

In this section we could show that a simple remodeling in a system's architecture could lead to tremendous running time improvements, by taking advantage of the multi-core paradigm. Our results show that we could reduce the running time by as much as 96%, when choosing the correct number of worker threads and the correct separation of work that can be parallelized.

6

Conclusion

Pattern mining in spatio-temporal datasets is a really relevant subject in the academia and the industry nowadays, due to its wide applicability in helping to solve real-world problems. Many of them can be found in the context of Smart Cities, like Traffic Management, Surveillance and Security and City Planning, to name a few. Among the various spatio-temporal patterns that one can extract from a spatio-temporal dataset, the flock pattern is one that has gained a lot of attention. The reason for such attention it is because of its collective behavior properties, which are very applicable and are intrinsically related to the type of problems that we have just mentioned.

Throughout this dissertation, we could show that a lot of work has been done in the academia, in order to provide algorithms able to identify the flock pattern. However, none of them could perform that task efficiently nor be able to scale well when a large dataset was the analysis target. Additionally, we found that there was no system architecture proposal that could be simple and modular in order to address the problem of flock pattern detection in spatio-temporal datasets. Hence, since we are witnessing the rising of Smart Cities, helping to solve those aforementioned issues would be of tremendous importance and the flock pattern can be a valueable ally on that matter.

Given the importance of efficiently discovering flock patterns, in order to enable decision makers to act fast, we proposed a simple, and modular system architecture that can fit in the flock pattern detection problem and possibly be used in other pattern mining scenarios as well. We then used that architecture to implement a novel flock pattern detection algorithm that was able to outperform the state-of-the-art solutions in more than 99%, with absolutely no impact in accuracy. Such impressive results were possible due to the filtering heuristic based on bitmaps that we proposed, which was able to reduce the generation of cluster disks in more than 96%, directly reducing the amount of data that needed to be processed by the algorithm. Despite the great results achieved with our solution, we realized that there was still more room for improvements, given the large availability of multi-core processors in today's computers. With that in mind, we remodeled our proposed solution to perform some critical and time consuming tasks in parallel, taking full advantage of the multi-core paradigm. Our performance benchmarks showed that we could outperform our own single threaded solution by 96% in some cases. Moreover, if we were

to show our performance gains in numbers of seconds spent to analyze a large dataset, we were able to reduce a running time of 15,000 seconds (state-of-the-art techniques) to only 13 seconds (BitDF MT). It is also important to mention that our experiments were performed using various datasets, both synthetic generated and collected from real-world experiments and all of them having a considerable number of entries.

6.1 Future Work

Even though we were able to present great contributions in this field, there are still some gaps that can be filled and points that need more work and can lead to important results as well. Here is a list with some of them:

1. The disk superset and duplicate check is very expensive and would need further investigation in order to make our proposed architecture even more efficient. Additionally, because it modifies the same disk set, it is really hard to parallelize it without causing performance degradation.

2. When investigating a grid cell, its extended grid might have cells that were previously processed by other extended grids. Thus, we could avoid paring the same points and generating the same disks again if we could keep some sort of disk cache and reuse those disks.

3. There is no study to see how different flocks relate to each other, like some MO that starts in one flock and later moves to a different one.

4. Make each module of the proposed architecture run in its own thread/process and then make them independent of the time spent in other modules.

In this dissertation we showed how BitDF and BitDF MT behaves when applied to datasets collected from vehicle mobility in road networks, or datasets that simulate that same scenario. There are still other mobility scenarios that can also take advantage of flock pattern detection:

1. See how BitDF performs in indoor flock detection.

2. Use BitDF in pedestrian mobility datasets.

3. Evaluate BitDF in animal mobility datasets, such as those from Movebank Database (MOVEBANK, 2015).

Finally, some other data handling techniques can be used to help in the clustering process of points, such as Voronoi Diagrams used in conjuntion with Delaunay Triangulation and data structures like K-D-Tress.

6.1.1 Deployment Challenges in Real World Scenarios

In order to be ready to be deployed and used as a data mining solution, some work is still needed. In our experiments, we noticed that, due to the nature of real-world datasets, one big challenge is still the time synchronization of the data stream, i.e. the discovery of the correct time slot size. As we said in Chapter 3, we cannot assume that the data entries in a spatio-temporal dataset are sampled in a fixed time rate, so there is still an effort needed in order to synchronize and group the entries in buckets of a pre-defined size, as we did with our σ parameter. Therefore, for online analysis, there is a need for an automatic process to detect the best value of that σ parameter according to the dataset being analyzed and also being able recalibrate it if the data behavior changes. Additionally, such automatic process should be smart enough to deal with abnormalities, such as outliers.

Another scenario that needs to be evaluated is when we have a high speed online stream of data. With high speed incoming data, we can face some data drop, because of a DSC component being busy processing the data or forwarding the data to other components and that taking too long. Some evaluation would need to be done in that scenario and mitigation solutions would need to be proposed. Some possible solutions to avoid data drop could be: implement some buffering mechanism of incoming data, data sampling, data hashing, etc.

GPS data is known to be very noisy and thus generate a lot of outliers. That said, it is very important to know how to deal with such problematic data without excluding good data entries. More importantly, when filtering bad data entries, such pre-processing should be done in a way that does not compromise the accuracy nor the efficiency of the solution proposed in this dissertation.

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