Clustering algorithms in the touristic sector:

Case study on travel agency data

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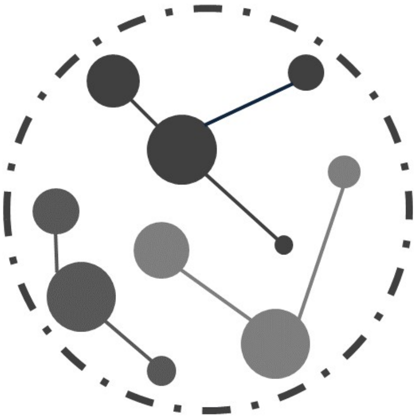

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Clustering algorithms in the touristic sector

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Abstract

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INTRODUCTION

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BACKGROUND

2.1 Overview

2.1.1 Machine Learning

Machine learning is the field of study that focuses on training machines (e.g., computers) to identify patterns and derive logical conclusions (Bishop, 2006). It is technically an imitation of the human learning process and can be divided into different types based on the approach it uses to train the algorithm (Marsland, 2004, p. 5). The two main types are supervised and unsupervised learning (Dunham, 2002, p. 43):

- Supervised learning is used to classify instances to already known categories based on their characteristics. Algorithms that belong to this type are first trained on an already labeled with the possible categories dataset and, afterward, use their gained knowledge to classify new unlabeled datasets (Han et al., 2011, p. 24). Technically it is like a human trying to learn by first looking at all the correct answers and then, based on them, try to classify new ones (Marsland, 2004, p. 5). For example, a supervised learning problem would be images, each one containing one hand-written digit, and its label the number to which it corresponds. After training the algorithm with a labeled set, the algorithm would be capable of recognizing digits on images.

- Unsupervised learning, on the other side, is used to group data without knowing the labels beforehand and without any training proceeding. This type of learning allows the model to learn by itself. Usually, a person with knowledge in the sector is needed to interpret and extract the knowledge from the created groups (Han et al., 2011, p. 25). In this case, a human would only know whether or not his answer is correct, but nothing about the way to the right answer (Marsland, 2004, p. 5). The above example using unsupervised learning would be giving as input the images to the algorithm without labeling the digits. The expected output would be ten clusters, each one corresponding to one of the digits from zero to nine. A person inspecting the results would be in the position to recognize which is the digit shown on the images of each cluster.

Apart from those two main categories, two additional categories are worth mentioning, semi-supervised learning, and reinforcement learning.

- Semi-supervised learning falls between the above two types. It consists of a small amount of labeled data and a large amount of unlabeled data. The labeled data serve as initial training, and the results are using the unlabeled data to improve the process and, on many occasions, spot outliers (Han et al., 2011, p. 25). Following Marsland (2004)'s ratiocination, in real life, it would look like a person given a few correct answers as a starting point to solve more complex questions. Using the digits example, let us suppose that labeling all the pictures would be a very costly procedure, therefore someone would label a small amount of the images to use as the training set, and afterward apply the algorithm to the rest of the images to improve the model.

- Reinforcement learning is a more interactive method, as opposed to the previous ones. It uses unlabeled data and requires rewards or penalties based on its behavior. This type of machine learning takes decisions that lead to the maximization of the reward taken (e.g., a numerical value) (Sutton & Barto, 2015, pp. 2–3). Similarly to unsupervised learning, it is like giving feedback to a person, but not by telling it whether the answer is correct or not, but by grading its performance. Then that person using its sought knowledge would try to improve itself (Marsland, 2004, p. 5). Therefore, the digits paradigm would be similar to the one of unsupervised learning. However, instead of trying to discover hidden patterns, it would try to find the output with the maximized reward (or minimized penalty), making different decisions based on its previous experience.

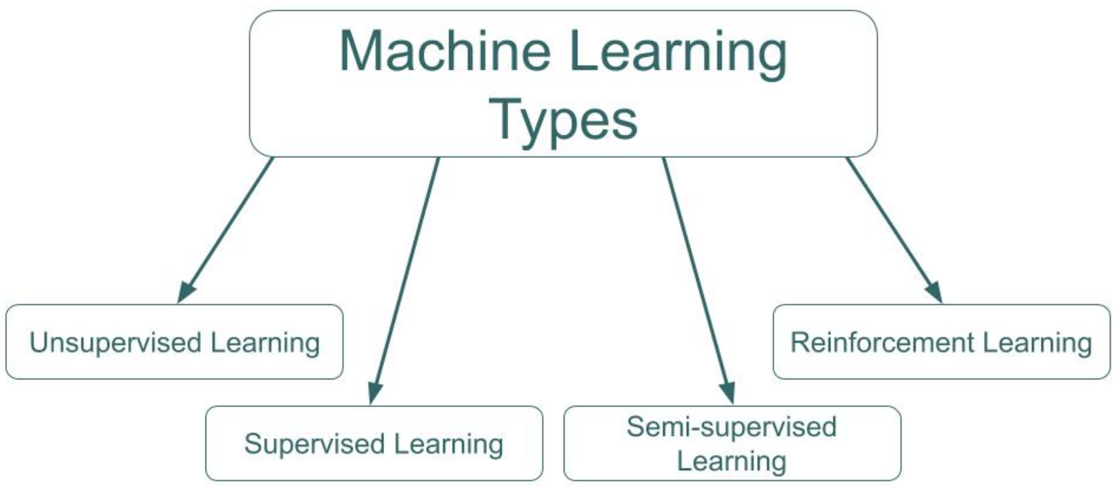

Figure 2.1.1: Types of machine learning.

2.1.2 Clustering

As indicated by the definitions given by Dunham (2002) and Tan et al. (2005), clustering or cluster analysis is a type of unsupervised machine learning. It groups instances to create coherent sets based on their similarities and dissimilarities. The aim is that instances that belong to the same sets are as much alike and as much different from the instances of the other sets as possible (Dunham, 2002; Tan et al., 2005).

As Kantardzic (2011) claims, humans are capable of detecting natural clusters from given data and compete with the clusters created by algorithms up until three-dimensional data. In real life, though, the dimensionality of the data examined is usually much higher than that, and therefore, if the cluster analysis were possible to be done by a human, it would not be as efficient (Kantardzic, 2011, p. 250). Since it is not humans that perform clustering, but algorithms, unexpected groups, and patterns can be discovered (Han et al., 2011, p. 444).

The usefulness of cluster analysis can be confirmed from its numerous applications in various fields of study. Some of them are mentioned by Everitt et al. (2011). Some of them briefly described are the following:

- Market research. A market researcher may want to use clustering to segment its audience and form its target groups. Furthermore, it can be useful to find the correlations between the financial measures of a company to its stock performance. Chakrapani (2015) describes an example in the market of sports cars. Whether a person will buy a sports car is not affected by demographics, but by its lifestyle, clustering can help to spot those lifestyles that lead to such a purchase (Everitt et al., 2011, p. 9).

- Astronomy. Astronomers need to discover distinct groups out of large data sets. For example, on Celeux and Govaert (1992)'s application, stars could be divided into groups differentiated by their volume and size based on their velocities (Everitt et al., 2011, p. 10).

- Psychiatry. Cluster analysis can group mental illnesses, detect patterns in people that commit suicide, investigate parasuicidal patients, and classify eating disorders. By further research on the results, new approaches can be proposed. Paykel and Rassaby (1978) found three different types of people that attempt suicide. They differ mainly on the cruelty of the methods they chose and their motivation behind the attempt (Everitt et al., 2011, p. 10).

- Bioinformatics and genetics. As Everitt et al. (2011) explain, the genetic code is complex, and its variations are responsible for the differences between organisms. In each cell, different genes are expressed, resulting in the production of several proteins. Combining different cell types makes an organism functional. In the case of alterations in the genetic code or malfunctions in those processes, diseases occur. Through clustering, it is possible to study the cause of a disease, investigate inheritance, discover the functionality of new gene sequences, and make research more efficient and affordable (Everitt et al., 2011, pp. 12–13). Ben-Dor et al. (1999) used clustering in their article to group genes that follow similar expression patterns in order to decrypt a gene's functionalities and regulative mechanisms (Ben-Dor et al., 1999).

Additional applications of clustering in the touristic sector will be analyzed more in-depth in section 2.4.

2.1.3 Types of Clustering

Clustering algorithms can be categorized based on two criterions. The first one is the relationships between the produced clusters of one iteration with the ones of a previous iteration. The second one is the number of clusters an instance can be a part of.
Based on the first criterion, Tan et al. (2005) describe the following types:

- Partitional clustering is a type of clustering which allows no overlapping between two or more sets of clusters, hence partitions the initial set to independent sets. This means that each instance can be part of exactly one cluster (Tan et al., 2005, p. 492). Therefore, it could be described as:

$$C_i \neq \emptyset,\ i = \{1, .., K\}$$
$$\bigcup_{i=1}^{K} C_i = X$$
$$C_i \cap Cj = \emptyset,\ i, j = \{1, ..., K\}\ and\ i \neq j$$

  where X is the initial set, K the number of partitions, and C_i, Cj the i^{th}, j^{th} clusters (Xu & Wunsch, 2005, p. 645).

- Hierarchical clustering produces clusters in each iteration, which are subsets of a cluster of the previous iteration. This can occur by starting from one cluster, which contains all instances, and repeatedly partition the available clusters to even smaller ones (Tan et al., 2005, p. 492). Therefore, it could be described as:

$$\begin{array}{c} C_i \in H_m, C_j \in H_l \\ m > l \end{array} \Rightarrow \left\{ \begin{array}{c} C_i \subset C_j \\ or \\ C_i \cap C_j = \emptyset \end{array} \right. ,\ i \neq j\ and\ m, l = 1, ..., Q$$

where H_m, H_l partitions of the original set X, Q is the number of partitions, and C_i, C_j subsets of any of the Q partitions (Xu & Wunsch, 2005, p. 646).
Tan et al. (2005) mention three more types of clustering in their book, which are formed based on the second criterion and are the following:

- Exclusive clustering signifies that an instance can only be a part of only one cluster (Tan et al., 2005, p. 492). Let us define the binary variables x_i for each instance $x \in X$, where X are all the instances. If an instance x belongs to the i^{th} cluster x_i is set equal to 1, otherwise to 0. Then, if the number of clusters is n, we can describe each cluster by the function:

$$C_i = \{(x, x_i) | x \in X\}$$

  where C_i is the i^{th} cluster, and which has the following restrictions:

$$\sum_{i=0}^{n} x_i = 1, x_i \in \{0, 1\}$$

- Overlapping or non-exclusive clustering signifies that an instance can be part of more than one cluster (Tan et al., 2005, p. 492). We can describe each cluster the same way we did in exclusive clustering, just by adjusting the restrictions:

$$C_i = \{(x, x_i)|x \in X\}$$
$$\sum_{i=0}^{n} x_i \geq 1, x_i \in \{0, 1\}$$

  where C_i is the i^{th} cluster, x is a specific instance, x_i is the binary variable that describes x in the i^{th} cluster, X are all the instances and n is the number of clusters.

- Fuzzy clustering signifies that every instance belongs to all the clusters (Tan et al., 2005, p. 492). As Kantardzic (2011) explains, the function that shows the membership of an element inside a cluster is called membership function (MF). The value of the MF that describes a given instance is a number between [0,1]. Each cluster can be described as follows:

$$C_i = \{(x, \mu_C[x])|x \in X\}$$

  where C_i is the i^{th} cluster, x is a specific instance, μ is the MF function, and X is the set that contains all the instances (Kantardzic, 2011, p. 416).

2.2 K-means

K-means is a prototype-based, iterative algorithm in which instances are assigned to a cluster in each iteration. The basic algorithm requires as input K points, called centroids, where K is the number of the desired clusters. To define the cluster to which one instance belongs to, the algorithm calculates its distance from all the centroids and assigns it to the closest one. Finally, using the produced clusters calculates the new centroids and repeats until it reaches the desired set. Each cluster's mean needs to be defined and recalculated in each iteration to redefine the new centroids (Dunham, 2002; Tan et al., 2005).

Basu et al. (2002) explain that K-means is practically a minimization problem. The objective function (the function to be minimized) is the function that calculates the distances between one instance and its cluster's centroid. The smallest the sum of the distances of one cluster's centroid to its instances, the highest the homogeneity of the cluster (Basu et al., 2002, p. 2).

Disimalirites between data objects are their distance (Tan et al., 2005, p. 69), though there are many different methods of calculating the distance between two instances, the most common one used is the Euclidean distance (Xu & Wunsch, 2005, p. 648). Using the Euclidean distance to calculate the distances between the centroid of a cluster, and the rest of the cluster's instances, for a one-dimensional dataset, the model is as follows:

$$d_{ij} = \sqrt{(c_i - x_j)^2}$$

where d_{ij} is the distance of the j^{th} element from the i^{th} cluster, c_i is the i^{th} centroid, and x_j is the j^{th} element (Tan et al., 2005, p. 69).

In the simple case where there is only one numerical value describing each instance the cluster mean can use the basic mean definition from statistics as follows:

$$m_i = \frac{1}{m}\sum_{j=1}^{m}(x_{ij})$$

where m_i is the mean of the i^{th} cluster, m is the number of instances that belong to the i^{th} cluster, and x_{ij} is the j^{th} instance of the i^{th} cluster (Dunham, 2002, p. 140). As Dunham (2002) describes, the termination techniques of the algorithm may vary. It could be that the clusters of each iteration are the same or almost the same or that the algorithm terminates after a fixed number of iterations (Dunham, 2002, p. 140).

Algorithm 2.1: K-means

```
Input: D = {x_1, x_2, ..., x_n}
       K initial centroids
Output: K cluster sets
while termination condition is not reached do
    Assign each element to the cluster of the closest centroid.
    Recompute the new centroids.
end
```

Algorithm 2.1 shows the K-means' basic steps (Dunham, 2002; Tan et al., 2005). The algorithm's time complexity is O(tkn), where t is the number of iterations, n the number of elements, and k the number of clusters. (Dunham, 2002, p. 141). It is considered to produce good results and handles better storage and noise compared to some hierarchical agglomerative algorithms (Tan et al., 2005, p. 526). On the other side, it is not very scalable and time-efficient (Dunham, 2002, p. 141). Furthermore, outliers need to be handled exclusively in order for the clusters to be representative (Tan et al., 2005, p. 506).Finally, since K-means bases on the euclidean measure, it works well with globular data, but not that well with other geometrical shapes nor with multi-dimensional (categorical) data (Xu & Wunsch, 2005, pp. 647, 649).

2.3 Agglomerative Clustering

2.4 Applications in the touristic sector

As Dolnicar (2008) states, companies all around the globe use market segmentation to target their audiences more effectively and consume their resources more efficiently. Cluster analysis is a useful tool for the creation of those segments to create groups of people that seek similar benefits from their travel experiences. These groups not only help in the formation of marketing strategies but also to products that offer higher fulfillment to their consumers (Dolnicar, 2008, p. 17). This type of segmentation was introduced by Haley (1968) in 1968 and is called benefit segmentation. The need for the creation of a new way of grouping target groups arose from the fact that tourists' behavior is mainly determined by the benefits they seek to satisfy and not by descriptive factors (Haley, 1968, p. 31).

2.4.1 Benefit segmentation of potential wellbeing tourists

A sample application of benefit segmentation using cluster analysis describe Pesonen et al. (2011) in their article. Data about tourists were gathered in the region of Savonlinna, Finland, during the period with the highest footfall of the year through electronic questionnaires. The research aims to find the different segments of tourists based on the benefits they seek and then examine the interest of each segment on wellness holidays.

For the segment formulation, they used two algorithms, one hierarchical to find the best number of clusters, and K-means to create the clusters. The solution they proposed contained four distinct clusters. From the four clusters, two of them seemed to have a higher preference for wellness services, as designated by Pesonen et al. (2011) 'Culturals' and 'Sightseers'. Both clusters portrayed people that seem to favor attractions and also have a tendency to go back to the same destination for their vacation. Additionally, the 'Culturals' show a preference for cultural activities, where 'Sightseers' show a preference for sightseeing activities. The illustrated interpretation of the results is that the previous approach, which promoted wellbeing products based on nature, might not be the most appropriate. The suggested alternative claims that combining wellbeing with history, culture, diverse experiences, and attractions could be more efficient (Pesonen et al., 2011, pp. 308–312).

2.4.2 A Clustering Method for Categorical Data in Tourism Market Segmentation Research

Another sample application that focuses more on the nature of the data to be analyzed describes Arimond and Elfessi (2001). Commonly, collected touristic data come from surveys, which, to a great extent, contain qualitative data. Furthermore, for the market segmentation to produce more representative results, many attributes should be used. Even so, most clustering methods used by marketers do not work well nor with multi-dimensional nor with categorical data (Arimond & Elfessi, 2001, p. 391).

Arimond and Elfessi (2001) used a Bed and Breakfast (B&B) survey in order to illustrate a more reliable way to deal with this type of data. First, they used multiple correspondence analysis (MCA) to produce some initial cluster groups, get a visualization of them, and understand them. Afterward, they performed cluster analysis, using the k-means algorithm, in order to find the market segments. They concluded in four clusters, from which the three of them seemed to be worthy of further analysis. The other cluster did not contain enough data to lead to meaningful interpretation. The first of the three segments contained respondents who were seeking a romantic experience and were less likely to return to the B&B. Also, they were not very concerned about the cost and amenities provided. Tourists of the second cluster were looking for cozier, more peaceful, nature-related options and were more likely to go back to the same place if they liked it. They also preferred to take part in energetic activities and, similarly to the first cluster, do not care so

much about price and amenities. The third cluster was technically a mixture of the two previous ones. The distinguishing factor was the eagerness of the people of the latter to socialize and the importance of price, value factors (Arimond & Elfessi, 2001, pp. 394–395).
Taking into consideration the results of the k-means Arimond and Elfessi (2001) used the geographical characteristics of each cluster and suggested the usage of different marketing approaches on each of the three regions that the respondents came from (Wisconsin, Minnesota, Illinois). The B&B owners made some changes based on the formed clusters to improve their customer satisfaction. For example, they decided to offer a private breakfast to the first cluster, add more activities to please the second cluster, and provide information about social events to the people of the last cluster. Furthermore, they were planning on changing their marketing strategy based on the demographics provided by the research to better target their audience (Arimond & Elfessi, 2001, pp. 395–396).

Chapter 3

CASE STUDY: CLUSTER ANALYSIS ON TRAVEL AGENCY'S DATA

3.1 Data

3.1.1 Description

The data used for clustering were drawn from the back office system of a travel agency in Parga, Greece. The majority of the data are about hotel reservations. The rest are about excursions and transfers. The back office uses a relational database to store its data. After thoroughly examining the available tables, only a few of them were kept for the analysis, the ones that seemed to have the most analytical value. Their relationships are shown in the following simplified diagram.

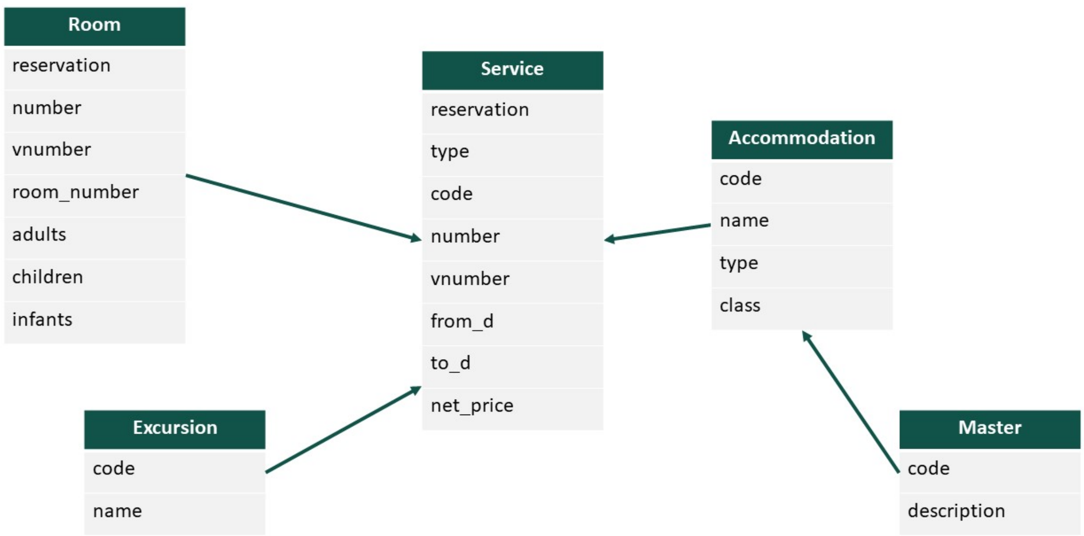

Figure 3.1.1: Relationships diagram.

One reservation may consist of many services (e.g., hotel reservation, excursion activity). For each service booked, there is at least one corresponding row on the 'Service' table that contains its details in a total of sixty-seven columns. Eleven of them were used and are explained in table 3.1.

Column	Description
reservation	Service's reservation identifier.
type	Service type. Can be either hotel(HTL), excursion(EXC) or transfer(TRF).
code	Service code from either 'Excursion', 'Hotel', or 'Transfer' tables.
number	Service number. The service's identifier number per reservation.
vnumber	Service vnumber. A number starting from one for each service per reservation. Whenever the service is edited a new row is created with the updated details and vnumber incremented by one.
fromd	Service's starting date.
tod	Service's ending date.
net_price	The total price of the booked service.
status	Reservation status. Can be either canceled(CL) or confirmed(CF).
customer_id	Customer's identifier.

Table 3.1: Service table.

Whenever an accommodation service is booked, the "Accommodation"(3.2) table, holds the information that describes it. Using the service code set on the "Service" table the corresponding accommodation can be found.

Column	Description
code	Accommodation identifier.
name	Accommodation name.
type	Accommodation type identifier. Categorical value that shows the type of the accommodation.
class	Accommodation class identifier. Categorical value that shows the quality of the accommodation.

Table 3.2: Accommodation table.

The "Master"(3.3) table contains several codes, and its descriptions, that can be found on many tables of the database, including the accommodation class and type codes.

Furthermore, whenever an accommodation is booked, at least one new row is entered in 'Room' table. These rows contain the information of the booked rooms of the accommodation, as described in table 3.4.

Similarly to an accommodation booking, when an excurision is booked its details can be found through the service code of "Service" table in table 3.5.

Column	Description
code	A code.
description	Code's description.

Table 3.3: Master table.

Column	Description
reservation	Service's reservation identifier.
number	Service number. The service's identifier number per reservation.
vnumber	Service vnumber. A number starting from one for each service per reservation. Whenever the service is edited a new row is created with the updated details and vnumber incremented by one.
room_number	The number of rooms contained in this service booking with this specific composition.
adults	The number of adults in this room.
children	The number of children in this room.
infants	The number of infants in this room.

Table 3.4: Room table.

Column	Description
code	Excursion identifier.
name	Excursion name.

Table 3.5: Excursion table.

3.1.2 Processing and reforming

After cleaning the data and before performing the analysis, some additional preprocessing was done. This preprocessing contained the creation of new columns and tranformation of categorical data to numerical, ordinal whenever that was possible.Eventually, the tables were reformed to a flat structure. The additional data were used both for the analysis and the interpretation of the results.

First of all, the service booking dates were used in order to define the season status of the trip. The season status can either be low, medium or high, and is used to show whether, in a certain period, a small or a big number of reservations is expected. As defined from the travel agency, high season is during Christmas and Easter(in this case orthodox) holidays and from the 10th of July to the end of August. Medium season are considered September, June and from the 1st until the 9th of July. The rest of the year is considered low season. Furthermore, in order to keep each booked service only once, on its final state, only the maximum vnumber was kept for each service. Finally, for the accommodation services, to get a more representative value of the service, the price per person per night was calculated.

As shown in figure 'Relationships diagram' on page 15, the 'Room' table contains information with regard to its composition. Instead of just using the number of adults and children a composition tag was created. The terms used by the travel agency to describe the composition are family, couple, single, crew and group. For interpration purposes these tags were added to the room data.
As already mentioned, information about the type and class can be drawn from the 'Master' table. The descriptions of the codes by themeselves provide many verbal information that can be summarized to create universal tags for the accommodations. Therefore, using those descriptions, five type tags were created, hotel, studio, apartment, house and villa, and three class tags, A(high class), B(medium class) or C(low class). The class tags were represented by numerical values for the analysis.

3.2 Kmeans

3.3 Agglomerative Clustering

Chapter 4

CONCLUSIONS

4.1 Comparing Results

4.2 Restrictions

4.3 Future Work

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