

## EXPLORATION OF URBAN PATTERNS AND RELATIONS THROUGH COMPUTATIONAL TECHNIQUES IN THE TRADITIONAL URBAN TISSUE: AN AMASYA CASE

PINAR ÇALIŞIR<sup>1</sup>, GÜLEN ÇAĞDAŞ<sup>2</sup>

### ABSTRACT

This paper presents an on-going study of a hybrid method that can be used in exploration of urban patterns in an existing historic city. A city is a complex system which has many forms and structures affecting each other spontaneously. Through time, it reorganizes its parts and formation with bottom-up forces and top-down planning decisions. While designing new spaces, designers must understand the inner nature of the city in order to protect the urban history and culture by designing coherent structures with city's existing culture, social-economic structure as well as its architectural tissue. In this context, this paper proposes a hybrid method to investigate urban patterns and their relations by utilizing environmental and urban data in the scope of sustainable design in an existing historic city. Throughout the study various Data Mining techniques and GIS tools will be used for compiling, collecting and analyzing different sources of information from the city. For a case study, the sample city, Amasya, and the selected part of it, the Hatuniye Neighborhood will be identified. After explaining methods used in this study, the case area will be presented. In the case study, the raw urban data is provided as various data types by different government institutions and translated into GIS software. Also, Attribute Table for buildings is prepared for Data Mining software which has different clustering and frequent pattern mining tools in order to reveal hidden patterns and relationships in the neighborhood. In the final section, the results coming from Data Mining studies are interpreted in order to discuss the potentials of this hybrid method in terms of investigating urban patterns and defining their relations to each other for urban design studies embracing locality and enhancing urban memory.

**Keywords:** Urban Pattern, Data Mining, Historic Urban Tissue, Pattern Exploration

### 1. INTRODUCTION

The city is a complex system like a living organism evolving through time with bottom-up forces and top-down planning decisions. Also, it creates spaces for people to encounter and produces activities across places. Through these places, every day a huge amount of local decisions and behaviors are emerged in the city and data exchange connects spaces and people

---

<sup>1</sup> PhD Student, ITU Department of Informatics, Architectural Design Computing Graduate Program, ISTANBUL

<sup>2</sup> Prof. Dr., ITU, Department of Architecture, ISTANBUL

to each other. As a result, the city produces large amounts of data every day in order to survive and reconstruct itself. The data produced by the city is a driving force to create its formation and reconstruction. Nothing remains the same in the city. Every city structure is affected, deformed and changed by the time in terms of form and function. Therefore, we can clearly see the history of the formation in urban strata. As Boyer stated, physical structure of the city carries 'memory traces of earlier architectural forms, city plans and public monuments' (Boyer, 1994, p.31). Thus, while designing for the city, creating coherent structures with the existing urban fabric is an important issue in order to embrace locality and enhancing urban memory. According to Rossi (1984) cities remember through its buildings and buildings reflect day-to-day lives of its residents. Not just buildings but all physical and social structure of the city are shaped and developed by lives and culture. Especially in historic towns this reciprocal relationship is very clear in the city form. Therefore, it is very important to sustain the pattern of the city and design new areas harmonized with old parts for the continuation of the past in the living city. In order to do this, designers must understand the data coming from the city and turn it into useful knowledge in order to reveal the inner nature and memory traces of the city formation and the relations between city's components. To achieve that a design area and surroundings need to be analyzed with both qualitative and quantitative research methods. After, designers can clearly see repetitive patterns, random behaviors and different factors affecting each other in the structure of the city. Also by doing this, we can reveal the different time periods and formation stages hiding in the city structure and sustain the cultural identity and urban history.

## 2. COMPLEXITY THEORY AND CITIES

What is the connection between cities, ant colonies and neurons (Johnson 2001)? In all these systems global form and behavior are generated by local interactions spreading through networks. They have components with self-similar characteristics and organized by self-organization rules. In this context, a city is a complex system which has many forms and structures affecting each other spontaneously. Even if, we shape certain areas of cities with laws and planning decisions, through time, it reorganizes its parts and formation with bottom-up forces. In 1965, Christopher Alexander published an article named "A city is not a tree" in which he made a distinction between artificial and natural cities. According to Alexander (1965), a city is a semi-lattice system which is not the hierarchical city network like a tree but interconnected in multiple ways and complex like a lattice system. While we plan a new city which is artificial we only copy the appearance of the old one (the natural city) and forget the essence which gives life to the old city. According to Rossi (1984), this essence is history which is an underlying principle of urban structure and gives characteristics to all urban dynamics. Thus, to design coherent structures and sustain the urban memory, designers need to understand the structure of the city and its parts. The city consists of interdependent parts all working together unconsciously as a whole. In natural cities, parts of the whole usually overlap and fuse with each other and create a complex living system (Alexander 1965). Also, the natural city is a composed of different time periods and works like a palimpsest. Therefore, decomposing and realizing these parts are very important to reveal the inner nature and different layers of this complex system which gives a characteristic to the city. As Johnson (2001) mentioned, the complex networks of cities trigger the emergent behaviors. Information flows between small components of the city determines the both physical and economic as well as the social structure of the city. Sidewalks, for instance, are encounter places for people and let data exchange across spaces (Jacobs 1961). Similar point of view about cities also

appears in Batty’s works. Batty (2013) says that cities work like an organism more than a machine and urban spaces are connected to each other with activities generating them. Therefore, in this complex structure, designers must understand the inner nature of the city in order to design coherent structures with existing culture, social-economic structure and architectural tissue of the city.

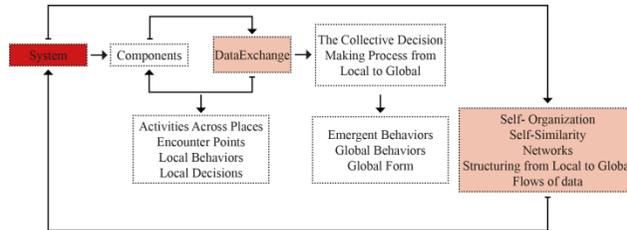


Figure 1. Complex Nature of Cities

### 3. METHODOLOGY

As we mentioned above, for sustainable design in an urban environment and enhance the collective memory in the city, designers must have strong ideas about architectural, social and economic dynamics of the city in addition to its history and local values. Therefore, the design area and surroundings need to be deeply analyzed. The results coming from these analyses may help designers to reveal systems of cities. In order to do this, we have to collect as much as information from cities. Then, we need to find appropriate methods and techniques which can resolve the complex structure of urban systems. In this context, we propose a hybrid method for exploration of urban patterns with computational tools. Throughout the study, in order to compile and visualize different sources of information from cities GIS software will be used and in an analysis phase of this information, we will benefit from various Data Mining techniques (Table 1). For Data Mining studies, Rapid Miner –open-source software- was used. Collecting data for Data Mining was carried out in ArcMap/ESRI and cleaning digital data was done in AutoCAD/Autodesk.

Table 1. Methods and Tools Used in This Study

Phase	First Phase	Second Phase
Method	Producing Urban Data	Transforming the Raw Urban Data into the Useful Knowledge
Tool	Geographic Information Systems	Data Mining Techniques
Input	the Raw Urban Data	Attribute Tables
Operation	Collecting the Data Storin-Cleaning the Data Visualizing the Data Spatial Analysis Preliminary Evaluations	Frequent Pattern Mining Clustering Interpretation of the Results
Output	Attribute Tables/ Maps	Useful Urban Knowledge

#### 3.1. The First Phase: GIS Studies

Geographic Information System (GIS) provides visual and non-visual information of spatial locations. GIS tools can collect, store, process and visualize geo-spatial data. In this study, the main point of using GIS software is to collect, store and visualize geo-spatial data. Through a database made by GIS software, collected information becomes unique to the neighborhood. In this study, we can create a database through GIS software, preprocess the data and visualize this data for Data Mining techniques. In the first phase, we gather information from the city

through city councils, municipalities and governmental institutions. This information may be in any format such as vector map, portable document format, excel sheet, etc. Additionally, most of the time, the collected information from these institutions is not enough for deeper and reliable operations; therefore, we have to create a building info form in order to complete missing data. After collecting and completed the data, we start visualizing the city information in GIS software and match the data with actual buildings. In the GIS tool, we can create our own vector map from scratch, but usually institutions may provide vector maps in AutoCAD format. Thus, in the AutoCAD file we may clean our data and export it into the GIS tool by turning our lines into polygon format. By doing so, we can behave our buildings/parcels like polygons and match them with data as much as possible. GIS tool helps us not only visualizing the data in actual space but also it develops our data by its spatial analyst tools such as slope and aspect operations. Moreover, it stores all the data matched with polygons in the Attribute Table and we can export this table in excel format in order to use in Data Mining process. From Table 2, we can see that headlines in the attribute table vary in a wide range of data; such as architectural features, building location, dimensional features, landuse information, topography, etc. Throughout the study, additional attributes can be added or unnecessary data can be extracted from the table due to selection of designers.

**Table 2. Data Attributes**

Type	Attribute Name	Type	Attribute Name
nominal	Building Status	nominal	Additional Building
nominal	Construction System	nominal	Courtyard Entrance Orientation
nominal	Construction Material	nominal	Building Entrance Orientation
nominal	Building Form	nominal	View
nominal	Plan Type	nominal	Entrance Type
nominal	Roof Form	nominal	Entrance Qualification
numeric	Facade Number	nominal	Building Position
nominal	Facade Details (front-back-oriel)	nominal	Privacy Situation
nominal	Balcony Existence	numeric	Slope (Percentage)
nominal	Basement Existence	nominal	Aspect
numeric	Parcel Area	numeric	Distance to Landmarks
numeric	Building Base Area	numeric	Distance to Railway
numeric	Base_Parcel Ratio	numeric	Distance to River
nominal	Front Face Direction	numeric	Distance to Neighborhood Square
numeric	Ground Floor Access	numeric	Distance to City Square
numeric	Hall Type	numeric	Number of Floors
nominal	Courtyard Existence	nominal	Landuse Basement
nominal	Courtyard Location	nominal	Landuse Ground Floor
nominal	Landuse Third Floor	nominal	Landuse First Floor
nominal	Landuse Fourth+ Floor	nominal	Landuse Second Floor

### 3.2. The Second Phase: Data Mining Studies

Data Mining is an important part of the process called Knowledge Discovery in Databases (KDD). KDD process "makes sense of the data (Fayyad et al. 1996, p.37)" stored in digital Databases. Every day, heavy load of information is uploaded into Databases and this raw data cannot be analyzed with manual methods. KDD gives us computational techniques and tools to evaluate, interpret this data and construct meaningful hypotheses according to our interest. This process of transformation from raw data to knowledge helps us to analyze the current situations, make predictions and decisions for the future. Data Mining is the main part of this process which is "the application of specific algorithms for extracting patterns from data (Fayyad et al. 1996, p.39)". In Data Mining studies, it is very important to choose appropriate algorithms for data type and data scale in order to gain meaningful and reliable results. Data Mining contains different mathematical techniques for producing patterns from transformed data in databases for further interpretation and evaluation. If we consider the city as a large database collecting raw data, we can use Data Mining techniques in order to produce useful knowledge by collecting, selecting and evaluating data focusing on our design problems in

cities. In this study, Data Mining phase consists of two consecutive steps. In the first step, clustering algorithms will be used to find subsets in target data and in the second step, urban data is processed in order to find frequent patterns in the dataset. In RapidMiner –open source software, different Data Mining tools mentioned above are used in order to reveal hidden patterns and relationships in the neighborhood.

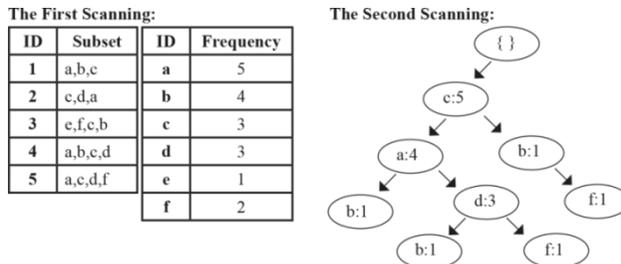
### 3.2.1. Finding Frequent Patterns

Frequent Pattern Mining tries to find frequent subsets in the given database. Therefore, it is very helpful tool for revealing useful and meaningful patterns in the dataset. The main objective of these algorithms is displaying relationships between objects and their attributes in the database by finding hidden trends and behaviors (Zaki and Meira Jr. 2014). From the results coming from the algorithms we can define Association Rules for target objects and their attributes. In order to do that, we need two values to consider: first one is the Support value and the second one is the Confidence value. The evaluation of the results and Association Rules can be constituted by considering these two values. From Tablo 3, we can see an example of an association rule and how it is defined by the Support and the Confidence values.

**Table 3.** An Example of the Association Rule (Han, et al., 2012)

<b>Association Rule</b>	buy (customer_X, "computer") => buy (customer_X, "software")	{ support = 1%, confidence = 50%}
<b>Meaning</b>	1% of ALL customers shopping in the store buy a computer and a software together; 50% of customers PURCHASING COMPUTERS buy also a software from the store.	

In this study, we use FP-Growth (Frequent Pattern-Growth) Algorithm. This algorithm works on an itemset by dividing and editing its elements according to a frequency value. The Frequency value determines how often an element occurs in an itemset. The algorithm creates a tree structure in order to keep track of subsets and by doing so it prevents repeating objects from being held in the memory (Figure 2).



**Figure 2.** FP-Growth Process (Han et al. 2012)

### 3.2.2. Clustering

The second Data Mining technique used in this study is Clustering. Clustering is a technique for sparing a dataset into subsets or clusters. Classification and clustering methods work on similar tasks however clustering techniques do not need any previously known class for training. Therefore, clustering techniques automatically divides objects in the data according to their similarity measures. The main goal of the clustering is to collect similar objects in the same cluster and put different objects in the separate clusters as much as possible (Han et al. 2011). Clustering techniques are highly used in image pattern recognition studies, web search

techniques, fraud detection and biology disciplines. It is basically “a discovery of previously unknown groups within the data” (Han et al. 2011, p.444). There are various clustering algorithms according to data scale and data type. In this study, mixed nature of our dataset leads us to use Hierarchical Clustering methods because; the basic hierarchical clustering methods can handle both numeric and categorical data (Huang 1998). These methods can be run in two different ways. First one is the agglomerative way which is a bottom-up approach starting with each object in a separate group and the other one is the divisive way that is a top-down approach and starts with all objects in the same cluster. In the end of the clustering process we have a connectivity-based hierarchy of clusters for our dataset [url 1]. After having large collection of information about this neighborhood, we can use Data Mining techniques in order to see a complex structure of this part of the city. We can detect interesting or dominant patterns, relationships between city elements and evaluate these results to find the essence of the city which gives form to it.

#### 4. THE EXPLORATION OF URBAN PATTERNS: AN AMASYA CASE

For the evaluation of the proposed method we chose the historic Hatuniye Neighborhood in Amasya/Turkey and started creating database for this neighborhood with GIS software. Hatuniye Neighborhood is situated along the river and leans its back to the Kırklar Mountain. At the peak of the mountain, Harşena castle, above it 5 pontic tombs and the urban structure of the neighborhood with the river create "a poetic urban experience (Bechhoeffer and Yalçın 1991, p.24)". The neighborhood has 4 bridges and two of them draw the periphery of the neighborhood (Figure 3).

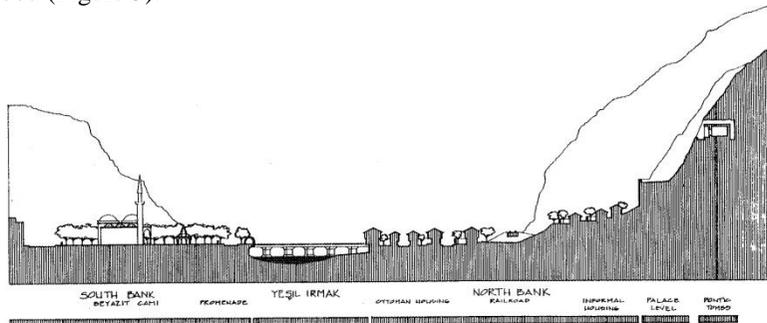
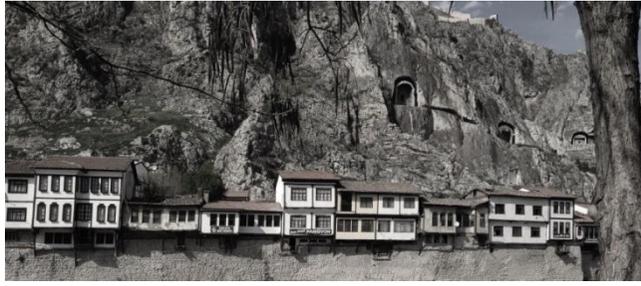


Figure 3. Hatuniye Neighborhood in Section (Bechhoeffer and Yalçın 1991)

We chose this neighborhood for the case study, because it has clear geographic borders and a unique urban form despite changing social, economic and cultural dynamics of the city. The neighborhood consists of 14 street blocks, 204 parcels, 165 main buildings and 41 additional buildings in total. Most of the waterfront houses in the Neighborhood are from the Ottomans in the 19th century. There are also few houses and monuments built in the 18th and the 17th century. Nowadays, this historic neighborhood is under the pressure of the high demand of tourism and construction activities. Thus, there is an urgent need for a method to understand the inner nature of the city in order to protect the city's self-evolved structure respecting local climate, topography and culture.



**Figure 4.** A View from Hatuniye Neighborhood

For GIS studies, digital maps are provided by Amasya Municipality and cleaned drawings are exported to ArcMap. Furthermore, Building Info Form -mentioned in the section 3.1- is prepared to complete missing information on digital maps.



**Figure 5.** Hatuniye Neighborhood in GIS Map



**Figure 6.** Hatuniye Neighborhood in GIS Map: Buildings in Pink and Courtyards in Green

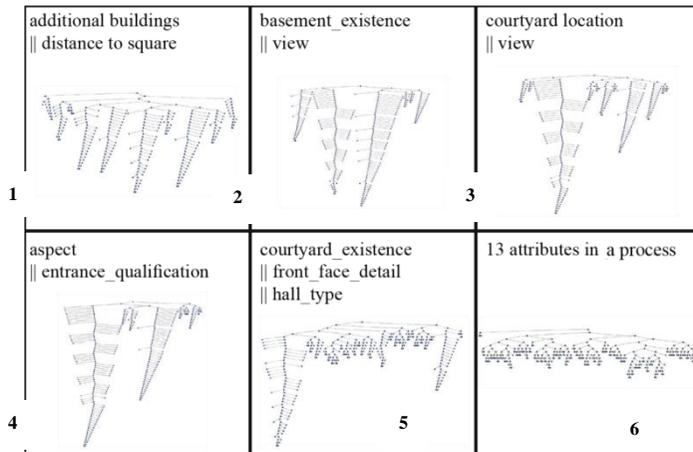


**Figure 7.** Hatuniye Neighborhood in GIS Map: Aspect Analysis.

#### 4.1. Data Mining Results

In this section, the results coming from RapidMiner operations are interpreted to discuss the potentials of this hybrid method in terms of investigating urban patterns and defining their

relations to each other for urban design studies embracing locality. The data table from ArcMap is imported in a data mining application software-Rapid Miner as an Excel sheet. For a preliminary action, software analyses numeric values, such as parcel and building areas, in terms of maximum, minimum and average values. According to this analysis, the smallest street block is 66,468 m<sup>2</sup> and the biggest one is 9144 m<sup>2</sup>. For the size of parcels, while the smallest one is 19,591 m<sup>2</sup>, the biggest one is 946,342 m<sup>2</sup> and the average value of parcels is 153,646 m<sup>2</sup>. Monumental buildings also added into the calculation, therefore, their influence on the average should be considered during the interpretation process. Similarly, the smallest building size is 21,196 m<sup>2</sup> while the biggest one is 336,655m<sup>2</sup> with average 86,634 m<sup>2</sup>. In this way, Rapid Miner can give us statistical results about maximum, minimum and average values for the building envelopes and open spaces for further design studies. Next, 165 main buildings were classified with k-means clustering algorithm according to the building area. K-means clustering was chosen because of the small size of our numeric data. 5 groups of buildings emerged due to building size: [1] 21-58 m<sup>2</sup> [2] 59-94 m<sup>2</sup> [3] 96-130 m<sup>2</sup> [4] 150-203 m<sup>2</sup> [5] 253-336 m<sup>2</sup>. The first group of buildings mainly contains additional structures and the fifth group contains monumental ones such as mosques and baths. In the data table, there are mainly nominal values for attributes. Therefore, as we mentioned before, hierarchical clustering method is used in order to see strong patterns and anomalies in the urban structure (Figure 8).



**Figure 8.** Different Cluster Trees with Various Attributes: The Hierarchical Clustering

In Figure 8, different clusters based on different attribute relations can be seen. According to this table, the first clustering process is based on ‘the additional building’ and ‘the building distance to the neighborhood square’ attribute gives us 12 important groups. From this grouping, we can say that only 12 out of 39 buildings which are 100 meters away from the center have an additional building. Similarly, only 9 out of 36 buildings which are 200 meters away from the center have an addition. This result shows that buildings closer to the neighborhood square usually don’t have any additional buildings because of their small parcels. The second clustering process works on ‘the basement existence’ and ‘the view’ attribute. From this process, we can say that the first obvious pattern in the urban fabric is ‘the buildings with the basement floor and the river view’. The second clear pattern is ‘the buildings

with no basement floor and the street view'. Only 6 out of the 22 buildings in the mountain area have basement floor and these buildings are mainly new buildings for accommodation. In the third clustering test, groups are revealed based on 'the courtyard location' and 'the view' attribute. From these results, some anomalies are detected in the urban fabric. The first anomalous structure which is unique to the area has 'an inner courtyard' and 'the street view'. Another unique structure is in 'the street area' and has 'a front and side courtyard'. The last one has 'a side and back courtyard' and also in 'the street area'. From the fourth clustering process, we can see a repetitive pattern which has 71 buildings in 'the south aspect' and with 'the entrance from the street to the courtyard'. Moreover, from this tree, we can detect some unique structures as well. First one is a building in 'the southeast aspect' which has 'an entrance from the additional building to the main one'. The two other structures in 'the southeast aspect' have two entrances at the same time and the last three unique buildings in the same aspect have entrances directly to the home from the street. The fifth clustering process gives us an idea about 'the hall type', 'courtyard existence' and 'the front face detail'. As clearly seen from the Figure 8, there are various clusters with similar sizes but the most important one is a rare cluster which has only 6 buildings with 'an external hall', 'a courtyard' and 'a console along the floor'. The open external hall concept was the main organization in the area during the Ottoman period. But changing life conditions and illegal interventions to the buildings caused the disappearance of this plan layout. Therefore, existence of the external hall plan layouts is very important to sustain the original morphology of the urban fabric. In the last clustering process, two obvious anomalies can be seen in the neighborhood according to number of floors. Although these two structures are highly similar with other buildings based on various other attributes in the neighborhood, they become very different due to their high number of floors. As a result of the clustering studies, we can propose that clustering techniques can help us to see repetitive patterns, anomalies or obvious structures in the urban fabric. The other Data Mining technique used in this study is the Frequent Pattern Mining which reveals attributes that are frequently used together and create some association rules according to mining results (Table 4).

**Table 4.** Association Rules for Hatuniye Neighborhood

[plan_type = single_sec, building_position = att_house] --> [buil_entrance_orientation = ns, roof_form = saddle_roof] ( <b>confidence: 0.800</b> )
[buil_entrance_orientation = ns] --> [aspect = s] ( <b>confidence: 0.803</b> )
[courtyard_location = front] --> [plan_type = single_sec, buil_entrance_orientation = ns, entrance_qualification = from_street_to_courtyard] ( <b>confidence: 0.809</b> )
[landuse_gorund = house] --> [buil_entrance_orientation = ns] ( <b>confidence: 0.811</b> )
[construction_sys = timber_frame, construction_mat = mudbrick] --> [buil_entrance_orientation = ns] ( <b>confidence: 0.812</b> )
[balcony_details = no_balcony] --> [plan_type = single_sec, aspect = s] ( <b>confidence: 0.815</b> )
[aspect = s, ground_f_access = ground_level] --> [balcony_details = no_balcony] ( <b>confidence: 0.815</b> )
[courtyard_location = front] --> [aspect = s] ( <b>confidence: 0.819</b> )
[courtyard_location = front] --> [buil_entrance_orientation = ns, entrance_qualification = from_street_to_courtyard] ( <b>confidence: 0.819</b> )
[ground_f_access = ground_level] --> [plan_type = single_sec, aspect=s] ( <b>confidence: 0.835</b> )
[landuse_1 = house] --> [plan_type = single_sec, landuse_gorund = house] ( <b>confidence: 0.848</b> )
[hall_type = no_hall] --> [aspect=s] ( <b>confidence: 0.854</b> )
[plan_type = single_sec, building_position = att_house] --> [roof_form = saddle_roof] ( <b>confidence: 0.842</b> )
[entrance_qualification = sokaktan_avluya] --> [plan_type = tek_bolumlu] ( <b>confidence: 0.989</b> )
[entrance_qualification = sokaktan_avluya] --> [courtyard_location = on] ( <b>confidence: 0.989</b> )

By changing support and confidence values we may create a high number of Association rules. In this study, our support value is 50% and confidence value is 80%. In Table 4, we can see attribute sets are frequently used together in the dataset. For instance, according to confidence values, we can say that 80% of all buildings in the neighborhood are north-south oriented-attached houses with no additional buildings, and saddle roofs. These houses are in the south aspect and have a front courtyard. Also, most of the buildings in the neighborhood are houses and made with the timber frame construction technique. Based on the results coming from Data Mining, we can say that the most important pattern emerged at the riverside contains attached houses oriented towards North-South with a front courtyard and a basement. Therefore, houses use a fortress wall for a base, create a semi-private area to protect privacy and have a river view from the South facade. Another finding is about additional buildings. Having an additional structure seems like an independent choice of users, however, far buildings from the neighborhood center are more likely to have an additional building due to larger parcels in that area. In the Street and Mountain area buildings usually don't have a basement and again, they turn their facade to the North-South orientation. Most of the buildings having a front courtyard don't need an extra entrance to the building. These results can be promising for understanding the nature of the neighborhood structure for a start, but still we need to collect more information and expand our data set to find more intricate relations between urban entities in the scope of further urban pattern explorations which can help us to reveal the inner nature of the city shaped by history.

## 6. CONCLUSION

This on-going study presented an approach for an exploration of urban patterns based on Data Mining techniques with the help of GIS tools. Experiments carried out in this paper are preliminary for further studies, therefore, a small part of the Hatuniye Neighborhood- was chosen for the application. In the framework of the study, first, a database was prepared in GIS tools. After, data set was used for Data Mining to investigate patterns and relationships among urban entities. Through this, we aimed to transform raw data in our data set into useful knowledge about urban characteristics. The process of construction the building database is still running, but obtained results in this paper showed that Data Mining presents various useful techniques to analyze raw urban information. For instance, numeric attributes can be classified according to its function and we can determine lower and upper size limits of urban entities. Also, the repetitive urban patterns can be revealed and used by designers in the pre-design phases. As Bechhoeffer (2001) mentioned, urban culture and history embodied and frozen especially in old cities. In order to sustain the continuity of the past, we must protect the physical and social character of the city. By this way, we can transfer the knowledge from the past and fuse the past, present and future of the city together in order to protect the urban culture and enhance local values which creates our lives in the first place. This study can help to build a rationale for the new design processes in traditional environments and also sustain the continuation of the collective memory and protect the urban characteristics in the city by revealing the frozen history and knowledge of the city form.

## REFERENCES

- Alexander, C. 1965. A City Is Not A Tree. in Larice, M. and Macdonald (eds.), The Urban Design Reader (2013), pp. 152-166, Routledge, New York.
- Batty, M. 2013. The New Science of Cities. The Mit Press, Cambridge, Massachusetts.

- Bechhoeffer, W. and Yalçın, A.K.1991. Amasya, Turkey: Lessons in Urbanity. Architect 40: Architecture in Development. September (1991), pp. 24-29, Concept Media Ltd., London.
- Bechhoeffer, W. 2001. Amasya: The Future of Tradition. In Turgut, H., Kellet, P. (Eds.), Traditional environments in a new millennium : defining principles and professional practice, 51-54. Yapı Endüstri Merkezi, Ankara.
- Boyer,C. 1994. The City of Collective Memory: Its Historical Imagery and Architectural Entertainments. MIT Press.
- Fayyad, U. Piatetsky-Shapiro, G. and Smyth, P. 1996. From Data Mining to Knowledge Discovery in Databases. American Assos. For Ai, Issue Fall, pp. 37-54, the American Association for Artificial Intelligence (AAAI).
- Han, J. Kamber, M. and Pei, J. 2011. Data Mining Concepts and Tecniques, Third Edition, Elsevier, Waltham.
- Huang, Z. 1998. Extensions to the *k*-Means Algorithm for Clustering Large Data Sets with Categorical Values. Data Mining and Knowledge Discovery 2, 283–304 (1998), Kluwer Academic Publishers, The Netherlands.
- Jacobs, J. 1961. The Death And Life Of Great American Cities. (trans.) Doğan, B. (2011), Metis Publishing, İstanbul.
- Johnson, S. 2001. Emergence: The Connected Lives Of Ants, Brains, Cities And Software. Scribner, New York.
- Rossi, A. (1984). The Architecture of the City. MIT Press.
- Zaki, M.J. and Meira Jr. W. 2014. Data Mining and Analysis: Fundamental Concepts and Algorithms. Cambridge University Press, Cambridge.
- Reference from Internet [Url 1]:  
[http://Docs.Rapidminer.Com/Studio/Operators/Modeling/Segmentation/Agglomerative\\_Clustering.Html](http://Docs.Rapidminer.Com/Studio/Operators/Modeling/Segmentation/Agglomerative_Clustering.Html) (date of connection: 25.02.2017)