What for: classification of visual paradigms

Ph.D. Franklin Hernandez-Castro
Instituto Tecnológico de Costa Rica - Hochschule für Gestaltung Schwäbisch Gmünd
Costa Rica, franhernandez@itcr.ac.cr

Ph.D. Jorge Monge-Fallas
Instituto Tecnológico de Costa Rica
Costa Rica, jomonge@itcr.ac.cr

Abstract

During the past 20 years, taxonomies have been defined to classify visualization paradigms. However, none of these taxonomies have been based on what the visualization wants to emphasize. This article proposes a classification based on data relationships and appropriate visualization paradigms to emphasize specific types of goals.

Keywords

Data Visualization, Data Relationships, Taxonomy, Information Visualization, Data Interpretation, Visualization Paradigms

1. Introduction

Defining taxonomies to classify visualizations to best describe one scenario versus another was first studied in 1996 with the classic Schneiderman focus (Shneiderman, B., 1996).

Continued and modified by many others (L. Tweedie, et. al. 1997, Chi, E. H. 2000, Hernandez-Castro, et.al., J. 2007, Gleicher,M. , et. al., 2011, Zoss, A., 2014, Landsberger et al. 2011), such classifications have been extended to incorporate other types of interactions (Yi, J. S., et al. 2007, Beck, F. et al. 2014).

As a result of these classic taxonomies, a classification trend developed based on the topological characteristics of the visualizations, such as 1-, 2-, 3-dimensional data, temporal, multi-dimensional data, tree and network data, as proposed by Shneiderman.

However, intra data relationships have hardly been explored, resulting in a classification when attempting to describe the needs for visualizations. This, in turn, is based on analysis of internal relationships among data and the potential desired results. For this, answers to questions like:

What is the purpose of this visualization?

What is the question that needs to be answered?

What types of data relationships need to be presented and made evident to the user?

We classified four characteristics: location, attributes, relationships and time. We made a classification with the aim of choosing a paradigm according to the features you want to be displayed.

This paper summarizes such a classification system that we have been using with Information Design and Computer Science students for various years to address this gap.

This paper is grouped as follows: Section 2 Definitions of used concepts, terminology and classification edges; Section 3 Describes our classification and methodology; Section 4 Conclusions.

2. Definitions

2.1 Graphs and Bipartite Graph

A graph is an ordered pair G = [V,A] defined as a set of vertices V and a set of arcs $A \subseteq V \times V$.

A bipartite graph (or bigraph) is a graph whose vertices can be divided into two disjoint sets (U & V) such that every edge connects a vertex in U to one vertex in V. Also, a bipartite graph is a graph that does not contain any cycles.

2.2. Hierarchical (Trees)

A tree is a connected graph without any cycles; it is said to be a connected acyclic graph. A tree has to be a simple graph, because of lacks self-loops and parallel edges.

We difference between a tree (Acyclic Graph Connected) and general graphs (Graphs and Bipartite Graph), considering that hierarchical structures (Trees) are often present in data.

2.3. Location, Attributes, Relationships and Time

After years doing visualization projects, we believe that these four data characteristics are the most used when it comes to visualizing, and based on them one should choose the visualization paradigm.

2.3.1 Location: these are cases where the position of data in the structure, is what is be shown on the visualization (if are they neighbors of someone and, if so, in which neighborhoods they are, if they are hierarchical: in what position in the hierarchy they are). Typical examples are species distribution in taxonomies (Hernandez-Castro et al. 2009), business structures, social networks, etc.

2.3.2 Attributes: these are cases in which some attribute in data is more important than position, and this attribute are what you want to make manifest. Cases such files on a hard disk, in which the attribute weight (MB) is crucial or cases where an attribute as "education" or "economic position" are important in an area affected by a particular disease are classic examples of this type.

2.3.3. Relationships: These are cases where the relationships between the data are more important than their position or their attributes. In these cases, one wants to know first what data are "associated" with what other, presence of mutations in genes, or types of diseases in human groups, are examples of this type of visualisations.

2.3.4 Time: as last characteristic we have the time, cases in which the way the data behave over time is most important and what you want to display on the visualization.

2.4. Types of data visualization

It has been written a lot about data visualization (Heer, J.,et al., 2014, Hernandez-Castro, et al., 2007,, Zoss, A.2014, Pettersson, R.2009, Lima, M.,2011, Gleicher,M.,2011, Schulz, et al. 2006) etc.) and interesting paradigm classifications are online as treevis.net or Dynamic Graph Visualization.

For example, Noik, E. (1994), classifies data in six dimensions, while Lee, B. (2006) classifies them by levels of tasks. In the case of Von Landesberger (2009) classification, it has very varied topics such as interaction, representation, and analysis.

However, most visualization types fall into four main categories: node-link, adjacency, enclosure, and networks.

Within these categories, there are many styles of representation as sunburst, treemaps, conetrees, chords, etc.

Some of these types of representations are more suitable than others, depending on what you want to expose in the data. Our proposal emphasis in the relationship between the characteristics cited below (Location, Attributes, Relationships and Time), and the most useful visualization types in each case.

3. Classification and Methodology

3.1. On Selecting Paradigms

In his famous article, Graphs in Statistical Analysis (Anscombe, F. J. 1973), author Francis Anscombe demonstrated that the type of visualization could reveal unexpected conclusions depending on how it is graphically interpreted. Thus, selecting the correct type of visualization is critical for its success, “*The challenge is to create effective and engaging visualizations* ***that are appropriate to the data****… Creating a visualization requires a number of nuanced judgments.* ***One must determine which questions to ask****, identify the appropriate data, and select effective visual encodings to map data values to graphical features such as position, size, shape, and color*.” (Heer, J.et al., 2014)”.

Types of visualizations are generally referred to as “visualization paradigms” ranging from conventional pie charts to complex visualization systems such as Treemaps, Chord Diagrams or Sunbursts. Obviously, the selecting the right paradigm is even more critical today than in the time of Anscombe, given the increased complexity and the array of paradigms.

The key to selecting the right paradigm may lie in asking the right question. It may seem too obvious. But, when one begins to design visualizations, designers do not spend enough time on asking simple questions such as, What is the purpose for this visualization? What is the question that needs to be answered? What types of data relationships need to be presented and made obvious to the user? Based on the answers, the final question would be – What is the visualization paradigm that is most adequate for this specific case?

Although "building knowledge through computers is a classic principle" (Jonassen, D., et al. 1998), basic questions about nature of information is practically nonexistent in visualization design. In Knowledge Management, Santo emphasizes that that knowledge (and not only data) can be captured through specialized tools. However, to achieve this objective, it is of utmost importance to concentrate on reducing the cognitive load of visualization and focus all attention on one specific problem (or question) instead of simultaneously addressing simultaneous problems, which is commonplace. If our objective lies in conveying information since "information must be interpreted by individuals to become knowledge" (Santo, Brown & Duguid, 2000)" then it would be useful to go through these steps and visualize the problem specifically to attain the best results.

The crux of the visualization must be the message conveyed (Pettersson, R., 2009) and not its topology. Without this consideration, it is impossible for the user to learn from it. (Kozma, 1994, or Lee, H. 2013). The most successful method for understanding this phenomenon is based on the observe-imagine relationship (Henriksen et al. 2014), which must be incorporated to determine the correct paradigm for each case and the subsequent taxonomy to develop.

3.2 Classification of Data Relationships for Visualizations

The objective of the proposed classification is to observe data and its relationships and emphasize those relationships that must be most obvious to the user and, ultimately, based on that premise, establish the ideal paradigm for each specific case.

To achieve a more efficient use of data and their conditions, we propose a classification in two dimensions. On one hand it should be clear which of these features (location, attributes, relationships and time) is the most important to answer the research question: What is the purpose of this visualization? What is the question that needs to be answered?

On the other hand, the nature of data, divided into hierarchical (trees o connected acyclic graph) and general graphs (Graphs and Bipartite Graph o simple Networks)

Table 1. The two dimensions of our classification

	Location	Attributes	Relationships	Time
Trees				
Networks				

3.2.1 Trees (Hierarchical Data o Connected Acyclic Graphs)

In our proposed classification, divides data is, initially, divided into two types – hierarchical and non-hierarchical, which mathematicians refer to as simple graphs and connected acyclic graphs.

The following question must then be considered:
¿Is hierarchy a critical aspect of what I want the user to visualize?

Having determined that, one must next consider what should be arranged first - the position of the elements in the structure (Location) or certain attributes of the structure (Attributes). Sometimes, as is the case with taxonomies of animal species, it is important to understand how the “family” of one particular animal species is related to another animal species “family”. Thus, the position of the node in the structure is extremely significant. In other cases, such as analyzing files on a hard drive, the size of the file is important and is considered to be an attribute. Consequently, visualization must take these factors into account.

In the case of trees, note that the relationships between data are also the position, i.e., hierarchical relationships between them determine where they fit in the structure. For this reason, our classification topic "Relationships”, does not apply to this data type (hierarchical/trees), as is already implicit in the structure or position.

Let's start by analyzing the cases where the hierarchy/position is important.

3.2.1.1. Trees: Emphasis on Structure (Where is it Located?) (TL)

From now, we will use this table to show which case of our classification we are using in each headland.

	L	A	R	T
T				
N				

In this case, for example, we are using "Trees" (T) with the feature "Location" (L).

The most appropriate paradigms for such cases involving hierarchical data where nodes must be located within the structure are Node-Link Diagrams. These diagrams respond to the question "Where is it located?" The most frequently used node-link diagrams are lineal, circular and hyperbolic diagrams.

Fig 1. Basic concepts of Node-Link Diagrams (tree, tree circular and hyperbolic)

Another common visualization paradigm for this kind of hierarchical data organization is the use of conetrees, three-dimensional trees grouped together in cones.

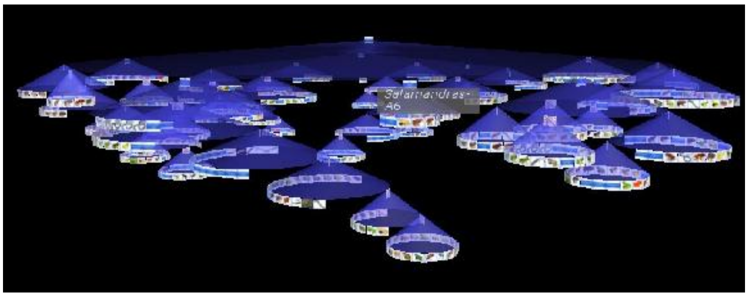

Fig 2. Conetree developed by Franklin Hernández-Castro and Jorge Monge-Fallas for the National Institute on Biodiversity of Costa Rica (InBio). (Hernandez-Castro et al. 2009)

3.2.1.2. Trees: Emphasis on Attributes (What is different?) (TA)

The following case exemplifies hierarchically/trees related data (T) for the purpose of comparing them with regards to a specific attribute (A).

	L	A	R	T
T				
N				

For such cases, the most adequate paradigms are referred to as Enclosure Diagrams since they underscore attributes through the size or color of the nodes.

The most frequently used Enclosure Diagrams are Treemaps that visualize hierarchies as orthogonal structures, effectively emphasizing their different. attributes.

Fig 3. Treemap of controlled microcircuit glitches for Intel®. Master Degree Students: Henry Rojas & Vittorio Capra, Costa Rica Institute of Technology, (TEC), Franklin Hernández-Castro, Ph.D.

This example shows how some elements cover a larger area of space than others, thereby showing those glitches that are most prevalent. Treemaps almost always include an indented hierarchy of the same data to better visualize the underlying structure.

Bubble trees are another paradigm used for emphasizing data attributes and are often combined with animation in order to show hierarchical data structures and their attributes according based on size variations.

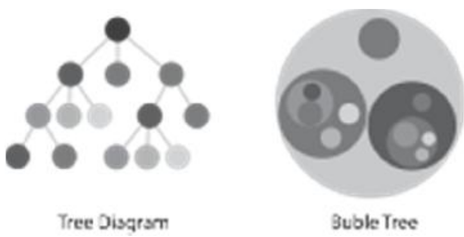

Fig 4. Basic Bubble Tree Concept.

3.2.1.3. Trees: Emphasis on both, Structure and Attributes (TLA)

Another type of visualization, which balances focus on attributes and structure are referred to as Adjacency Diagrams.

	L	A	R	T
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These diagrams are used when emphasis is sought both on the node position as well as certain attributes. Sunbursts are often used for these cases.

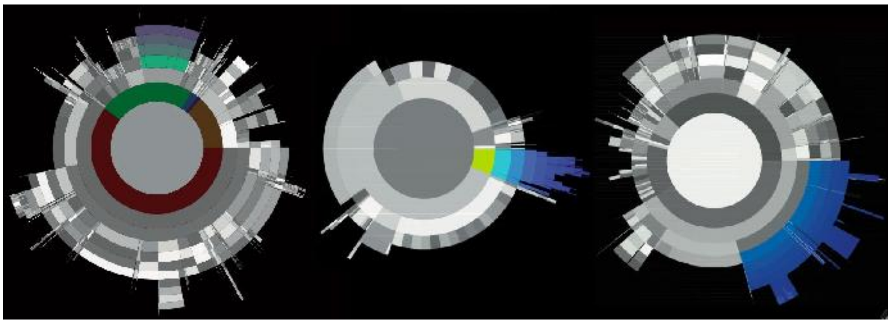

Fig 5. Data structure, attributes, classes and size on a hard drive visualized through a Sunburst Diagram. Graduate Students: Stephan Beyer, Felix Hohl & Alexander Mergenthaler (2008), University of Design Schwaebisch Gmuend, Germany, Franklin Hernández-Castro, Ph.D.

Icicle Diagrams are paradigms that are also used to present both structures and attributes in a proportional manner. Although this type of paradigm is not as compact as Sunbursts, its visualizations have a lower cognitive load.

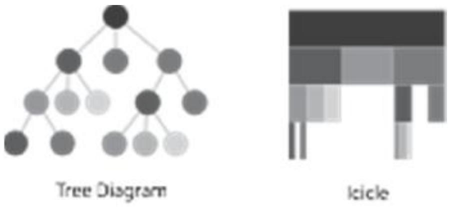

Fig 6. Basic structure of an Icicle Paradigm

3.2.1.4. Trees: Emphasis on Relationships (TR=TL)

	L	A	R	T
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As is already said, relationships inside trees are implicit in structure, that to say, in position as well. For this reason, in our classification, in this case (Trees): “Locations” and “Relationships” are the same features (TA=TL)

3.2.1.5. Trees: Emphasis on Time (When?) (TT)

In these cases, we want to show changes in structure through time. A lot of work have been made about this topic (Beck, F., et al., 2014), some better than others.

	L	A	R	T
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For such cases, most adequate paradigms are referred to as Juxtaposed Node-Link Diagrams since they underscore attributes that change by time.

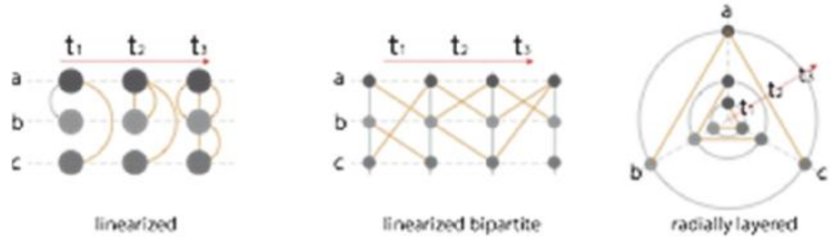

Fig 7. Juxtaposed node-link approaches on a timeline (Beck, F., et al., 2014)

3.2.2 Non-Hierarchical Data (Graphs and Bipartite Graph)

Non-hierarchical data is more broadly known as Networks or simple Graphs and comprises the major category of our classification.

This category applies to two types of scenarios, (1) one where different data groups are interrelated, but are not related within each group, such as specific gene mutations present in a gene pool (Bipartite Graph), (2) another scenario consist of a single data group that is interrelated, such as a visualization showing text messages among a group of people (simple graph).

3.2.2.1 Networks: Emphasis on Structure/Locations (Where?) (NL)

In this case, we are talking about simple Graphs, where the feature we want to show, is Location of elements in relation their neighbours. It is to say; we are in "Networks-Location" (NL) in our classification.

	L	A	R	T
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The free layout is the most obvious representation of node-link diagrams in a network, where nodes are "points" and arcs are "lines" and they are freely distributed.

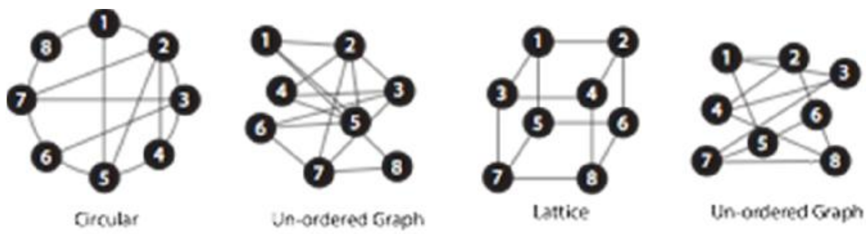

Fig 8. Examples for styled network layouts

This paradigm, of course, works only for small data amounts, in other cases, when we have more data, we have to use Constraints Techniques on Network Visualizations.

Three-dimensional visualisations for networks – also referred to as Force -Directed Layouts – , for example, are used for this purpose. Figure below shows how a group of “forces” are distributed along nodes to provide better exposure to those parameters that need to be emphasized.

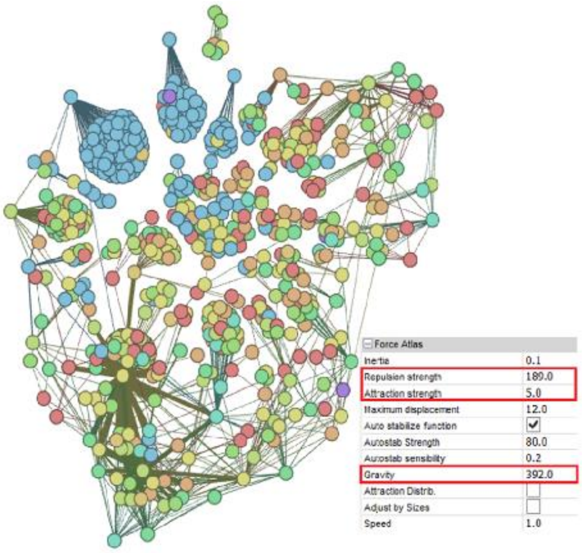

Fig 9. Proof of Concept of a Force-Directed Layout Master Degree Student Alvarado-Brenes and Franklin Hernández-Castro Professor (Alvarado-Brenes B., 2014)

3.2.2.2 Networks: Emphasis on Attributes (What is different?) (NA)

Perhaps, the most form of non-hierarchical data is a single class that has many similar attributes. This type of data is generally represented in bar graphs.

	L	A	R	T
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An interesting paradigm for these cases consists of Tag Clouds, where the size of the name of the attribute is graphed according to its importance. Additionally, its spatial relationship defines its position or proximity to other attributes.

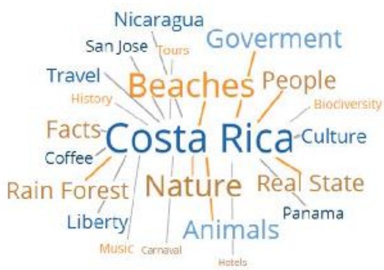

Fig 10. Tag Cloud for a Google Search on Costa Rica. Master Degree Students: Eduardo Ramírez and Laura Vásquez for Intel ®. Costa Rica Institute of Technology, Franklin Hernández-Castro, Ph.D.

3.2.2.3 Networks: Emphasis on Relationships (With whom?) (NR)

The next typology considered in our classification is a data group set that is interrelated. A typical example is in Communications, such as a text message visualization among individuals. Yet there are many types of data groups that with these characteristics, such as foreign trade among nations or authors who cite another author, etc.

	L	A	R	T
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The first aspect to consider in visualizing relationships among elements – is emphasizing with whom they are related. This is best demonstrated by Matrix Views, Arc Diagrams and Chord Diagrams visualization techniques.

A Matrix Views simply place elements on two planes and visualize their relationships by shape, color or size. The degree of the relationship defines the intensity of the color or shape of the elements between two data components.

The second paradigm that is appropriate for representing data relationships are Arc Diagrams. Through this method elements are observed on a line and connected to the arcs they are related to.

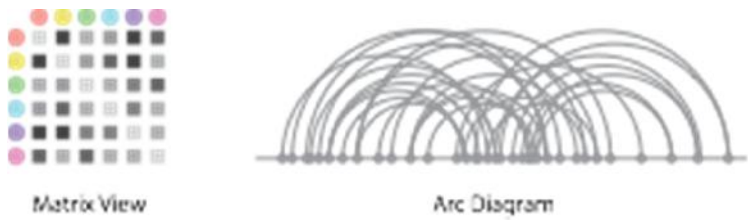

Fig 11. Basic concepts of Matrix View and Arc Diagram paradigms

The third paradigm that is useful in these cases is the Chord Diagram. Here the entire circumference of the graph is filled with elements of the same class given that, in this case, there is only one group of elements. As is shown in the example below, the chords represent a relationship, which, in this case are text messages among individuals from a corporation.

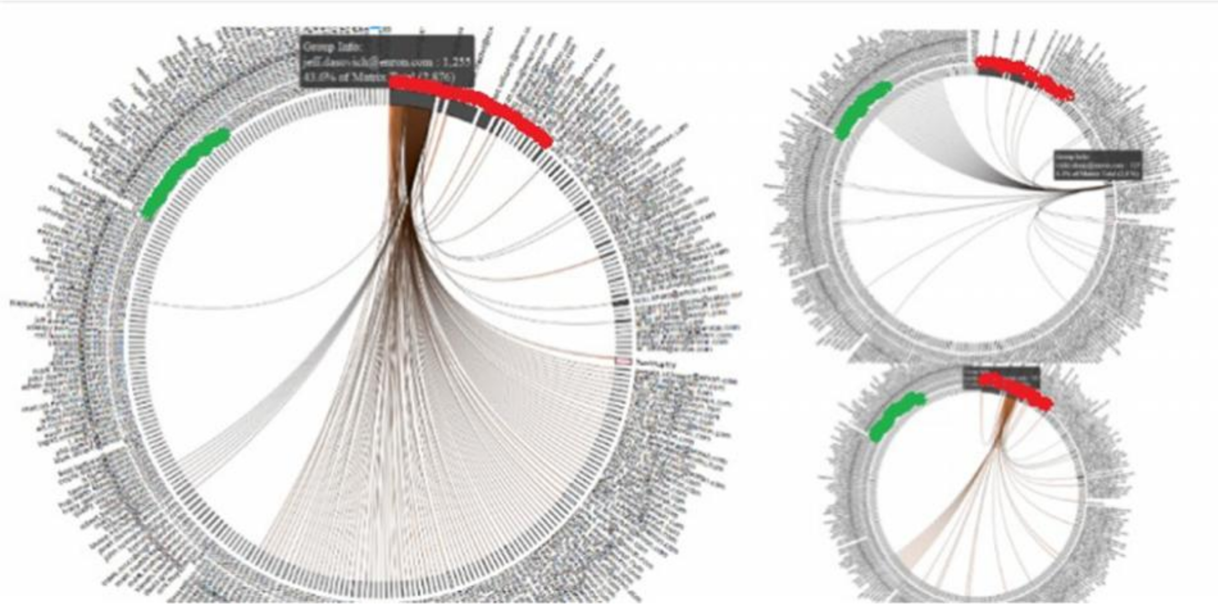

Fig 12. Circos plot used for visualizing intracompany emails at Enron Corporation. Mater degree Student: Berny Alvarado-Brenes. Costa Rica Institute of Technology, Franklin Hernández-Castro, Ph.D. (Alvarado-Brenes B., 2014)

The same paradigm can be used to compare several groups (Bipartite Graph o Multipartite Graph). Groups are ordered into sections of the circumference and, again, it distributes data radially along a circle and shows their relationships as interconnecting lines. In our experience, this is the most used type of the classification.

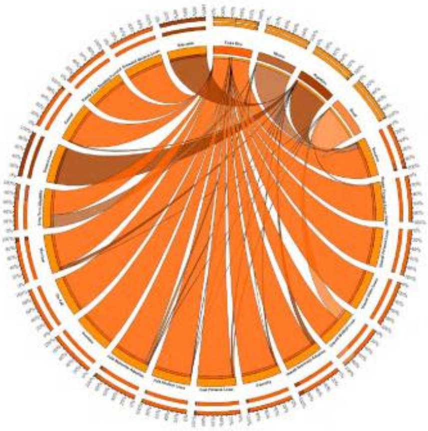

Fig 13. A Chord Diagram visualization showing a relationship among different countries and the different types of employee absence requests at Intel Corporation®. Master Degree Students: Ariel Araya & Melissa Espinoza from Intel ®, Costa Rica Institute of Technology, Franklin Hernández-Castro, Ph.D.

Another type of paradigm for these cases are Gmaps or maps which show “country” proximity and size based on the relationship of elements they have with their neighbours. Other elements (such as department affiliation), which can be visualised by the color or size of the typography. The end result is a visualization where understanding the relationships among the different elements becomes an intuitive process but with a clear understanding of their position.

Figure below shows Enron employee e-mails regarding the Enron Case selected according to keywords. The different colors represent the departments that the employees belonged to and the thickness of the lines the number of email traffic among them. It is seen that the vast majority of emails on this matter pertained to two or three individuals.

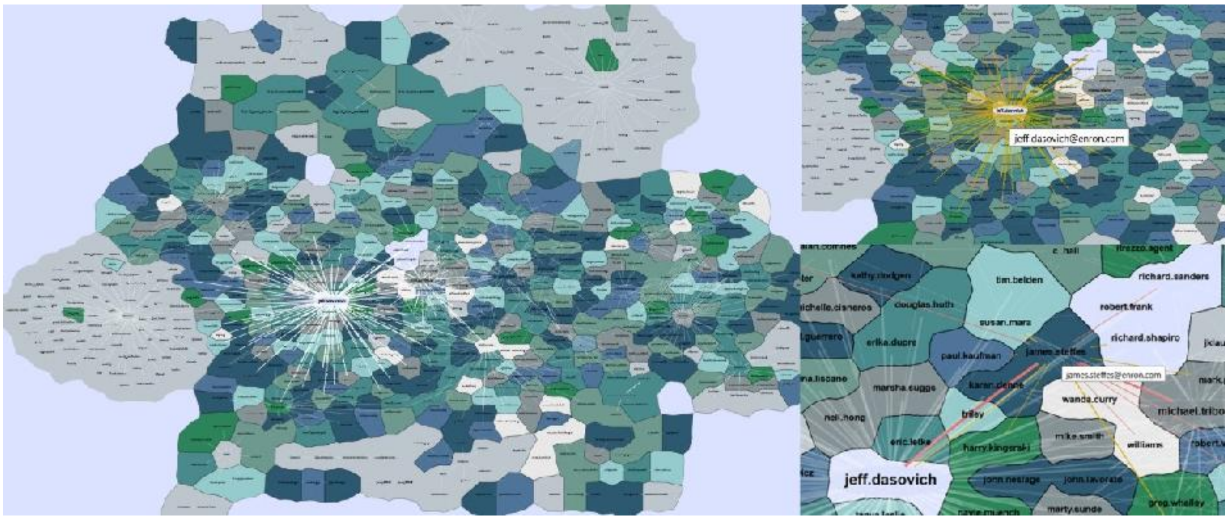

Fig 14. Gmap visualization for intracompany e/mails on the Enron Case. Master Degree Student Alvarado-Brenes B., Professor Franklin Hernández-Castro Ph.D. (Alvarado-Brenes B., 2014)

The following paradigm which is used, as well, to compare two, three or up to six exclusive groups (Bipartite Graph o Multipartite Graph) is referred to as “Hive Plots” and consists in visualizing different groups of attributes in axes that revolve around a common center.

Fig 15. Basic Hive Plots Structure

The next paradigm consists of Parallel Coordinates, one of the most commonly used paradigms for these cases. This visualization strategy uses various vertical axes to visualize different group attributes.

The main advantage of Parallel Coordinates is that the axes can be moved to compare attributes and reveal they are interrelated.

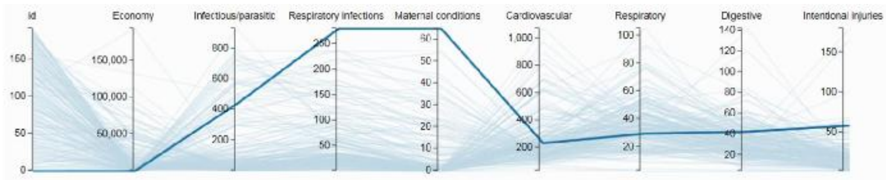

Fig 17. A Parallel Coordinate Visualization that represents attributes such as how the country´s economy affects burden of diseases. The least developed economies have a higher incidence of respiratory infections and lower incidence of cardiovascular disease. Master Degree Students Randall Arce & Randall Gonzales, Costa Rica Institute of Technology (TEC), Franklin Hernández-Castro Ph.D.

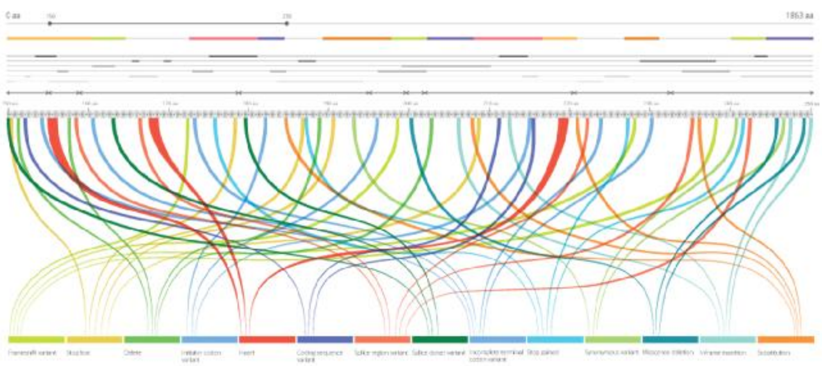

Fig 18. A Parallel Coordinate visualization showing gene mutations for a specific protein marker linked to breast cancer. Graduate Students: Veronica Alfaro & Antonio Solano, Costa Rica Institute of Technology, Franklin Hernández Castro, Ph.D. (http://skizata.com/variation-viewer.html)

3.2.2.4 Emphasis on time (When?) (NT)

Time is frequently a factor that is visualized on networks. We choose three appropriate paradigms can be used to visualize time through different classes and attributes. However, that is just a tiny part of the many paradigms available in these cases.

	L	A	R	T
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Simple paradigms, like Heatmaps, show a good representation of how data changes over time. Nevertheless, only small amounts of data, are possible to visualize with this paradigm without increasing cognitive load.

Fig 19. Heatmap showing routes with the highest traffic density in Costa Rica. Datos WAZE Connected Citizens. Graduate Students: Sofía González Villalobos & Evelyn Barquero Rodríguez, Costa Rica Institute of Technology, Franklin Hernández Castro, Ph.D. (http://skizata.com/variation-viewer.html)

The next paradigm, related Time, consists of Stacked Graphs, also referred to as Streamgraphs, these are visualizations designed to show how elements change through time.

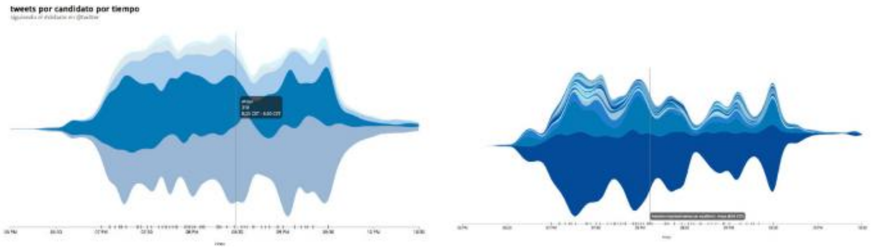

Fig 20. Stream Graph visualizing tweets on the Costa Rican Presidential Elections Debate on Sunday, January 19, 2014. Andrés Araya & Rodrigo Hernández from Hewlett Packard ®. Costa Rica Institute of Technology, Franklin Hernández-Castro, Ph.D. (http://visualizacion.aeongames.com/ index.php)

Another interesting paradigm to reflect how certain parameters change through time are Gapminders (http://www.gapminder.org) developed by Swedish statistician and physician, Hans Rosling.

Fig 21. Gapminder visualization of real time Incident Reports at the Hewlett Packard corporation®.Graduate Students: Jason Diaz & Ronny Ruiz. Costa Rica Institute of Technology, Franklin Hernández-Castro, Ph.D.

Another perspective to visualize change through time is the use of data animation (generally geolocalized). In Figure below, updated motor vehicle traffic is shown San Jose, the capital city of Costa Rica. Data animation allows minute-by-minute density of motor vehicle movement in a specific area.

Fig 22. Visualization of traffic in San Jose through reports from smart phone application WAZE. Dyer, Z., (2014, Oct. 2)

4. Conclusions

This article presents an example of a classication that emphasizes data relationships and highlights those relationships that are more preponderant than others.

The selection of a paradigm based on the visualization objectives is the one of the most effective and useful way of classifying visualizations as opposed to conventional taxonomies that are based on their own typological characteristics. The following chart summarizes the classification of visualizations as described in this article.

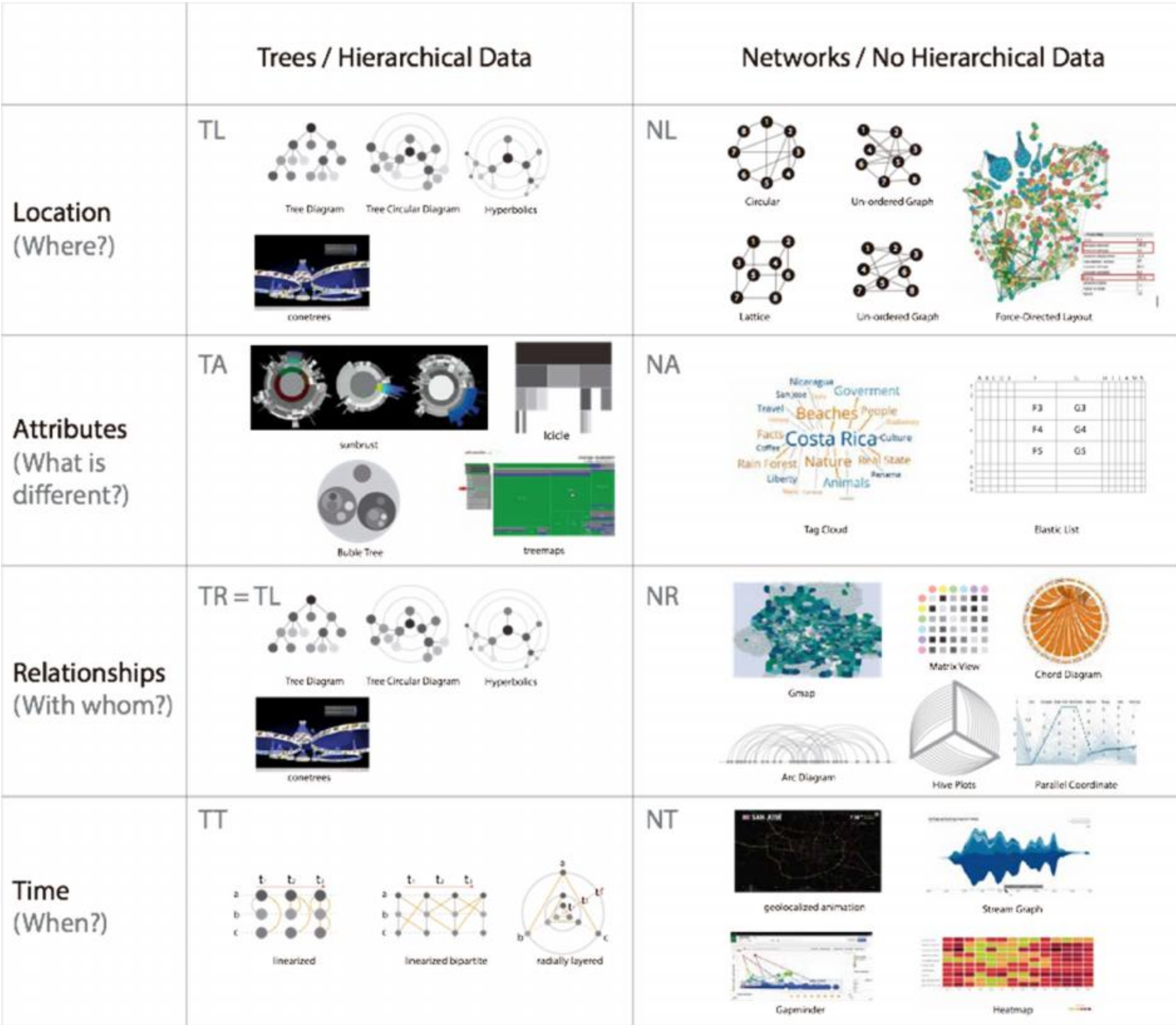

Fig 23. Example of a classification graph based on the content of this article.

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