Chapter 11
Perspectives and Good Practices in Visualization of Knowledge About Public Entities

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ABSTRACT

Visualization of knowledge in public entities is becoming more and more popular due to the development of information technology tools, the demand for solutions allowing for reduction of information overload (IO), and new approaches to local government, including citizen participation. The chapter presents some case study examples of knowledge visualization in public entities with some conclusions and recommendations for policy makers. Additionally, it presents a complete map of certain Polish counties prepared by the authors. The authors applied, apart from the visualization in the form a map, the "Chernoff Faces" method (invented by Herman Chernoff in 1973). This method displays multivariate data on Polish counties in the shape of a human face. The individual parts, such as eyes, ears, mouth, and nose, represent values of the variables by their shape, size, placement, and orientation. The idea behind using faces is that humans easily recognize faces and notice small changes without difficulty. Chernoff Faces handle each variable differently.

DOI: 10.4018/978-1-5225-4990-1.ch011

INTRODUCTION

The inventor of the “Chernoffs Faces” method of visualization of knowledge is Hermann Chernoff (now Professor Emeritus of Applied Mathematics, Department of Statistics at Harvard University). He created the method in 1973 for the graphic representation of statistical data, to represent specific multivariate data using only one symbol (a human face) changing its features. In the late 1970’s Chernoff faces began to be popular outside of the USA. Today, the processing of data using Chernoff faces is a common feature of statistical software (e.g. Statistica, S-PLUS or Systat). The underlying motive for using Chernoff faces is that humans possess an innate ability easily recognize distinct faces and notice small, even subtle changes in facial features.

Creating visualizations of data is becoming more and popular as a method of communicating and sharing knowledge. In a world where complexity is growing at an accelerating rate and where time is increasingly the scarce resource, traditional ways of exchanging knowledge are perceived as insufficiently efficient. Text and numbers are yielding to visualization as a tool for exchanging knowledge. But a wide variety of visualization techniques have been developed; choosing the technique that is best suited for the nature and details of the knowledge the researcher desires to convey is thus a critical research task (Meyer, n.d.)

The visualization technique used should also take into consideration the audience for which the information is intended. Remo Aslak Burkhard noted in his doctoral thesis that architects presenting information about the same object (a skyscraper) used different complementary visualization techniques in addressing various target groups (e.g., lawyers, engineers, clients and workers) with diverse knowledge backgrounds and a need to understand different levels of detail (Burkhard, 2005).

Visual descriptions of data provide meaning to information which may be especially useful in intercultural communication, as well as an answer to the IO challenge. Through knowledge visualization, complex sets of data are displayed in a graphical interface – for example, in a chart or on a map – which allows the viewer to gain deeper insight into patterns and trends. Visualized knowledge is highly sharable on social media channels and social networks. Visualization of knowledge is very useful to communicate science to lay audiences. Thus, knowledge visualization serves educational purposes.

Knowledge visualization is a relatively new field of research that focuses on the creation and transfer of knowledge by visualizations with and without the help of computers. It has the possibility to be a mediator between many different disciplines. Knowledge visualization (and modeling) is a term used to describe the use of visual representations to transfer knowledge between a minimum of two people. Its purpose is to improve the transfer of knowledge by using a mix of computer and non-computer-based visualization methods.

During the process of learning and problem solving, visualization can help the learner overcome problems. Combining computer-based information systems with human cognitive capabilities, while using visualization as the link between the two, is seen to be far more powerful than just using human cognitive processes. In an educational context, learner visualizations may foster constructive cognitive processing and visual/spatial strategies (Burkhard, 2005).

KNOWLEDGE VISUALIZATION VS. INFORMATION VISUALIZATION

Knowledge visualization and information visualization are related techniques, as they both assist in visualizing different abstraction levels of data (Burkhard, 2005). Robert Meyer distinguishes among:

- *Data*, which are symbols or facts that are isolated and have not yet been interpreted;
- *Information*

. . . is more sophisticated. It is data that has been interpreted or processed and therefore contains some meaning and can give answers to questions like 'who?', 'what?', 'where?', 'why?' or 'when?' For those who do not comprehend the meaning it still stays data.

- *Knowledge* is a step further, being information that has been processed and integrated into someone's existing knowledge structure. While information is outside the brain, knowledge is inside.

Thus, the content and process of information- and knowledge visualization differ. While both are based upon the abilities of the human perception system, information visualization is much more linked to computer-based visualizations; it cannot process non-computer-based visualizations and knowledge types (Meyer, 2008-2009). Burkhard argues, however, that as a new field, knowledge visualization lacks a theoretical basis and an interdisciplinary mediating framework; while information visualization researchers have succeeded in creating new insights based upon abstract data, they have not been able to develop a means of transmitting this information to the recipients, which Burkhard hopes will result from the recognition and pursuit of knowledge visualization as a new field of research (Meyer, 2008-2009).

To this end, Burkhard proposes a knowledge visualization model, developed around the principle that knowledge cannot be transferred directly from one person to another; the recipients must integrate the transferred knowledge (which to them is initially information) into their own knowledge base developed from their individual background and experience. The vehicle for this transfer is the use of complementary visualizations for the successive steps in the knowledge transfer process from sender to receiver. Burkhard's proposed model seeks to answer five questions:

- What is the aim and the effect of externalizing knowledge into visual representations?
- What is relevant and should be visualized?
- Which audience should be addressed?
- What is the interest of the recipient?
- What is the most efficient way to visualize the knowledge?" (Meyer, n.d.).

Burkhard proposes a staged substructure that does not rely upon a single knowledge visualization technique for the knowledge transfer process but rather complementary visualizations for different purposes. Burkhard suggests the following stages:

- The first stage involves catching the *attention* of the recipient – for example, by a provoking image;
- In the second stage, the sender must:

    - Illustrate the *context* of the knowledge to make the recipient aware of the importance of the knowledge to him;
    - Provide an *overview* of the information, showing the "big picture" of the topic;
    - Offer some *options to act*, enabling the recipient to focus his interest;
- In the third stage, the sender presents the *details* of the knowledge to be transferred.

Burkhard notes as a caveat, however, the limitations of the model due to different abilities of all humans to interpret visual stimuli, while suggesting that the model can provide general guidelines for using knowledge visualization.

ADVANTAGES OF KNOWLEDGE VISUALIZATION

Knowledge visualization offers many benefits. Burkhard (2005) identified the following functions of knowledge visualization:

- Coordination: Visual representations (VRs) help to coordinate individuals in the communication process.
- Attention: VRs help to get and keep the viewer's attention by addressing emotions.
- Understanding: VRs help to identify patterns, outliers, and trends.
- Recall: VRs improve memorability, remembrance, and recall.
- Motivation: VRs inspire, motivate, energize, and activate viewers.
- Elaboration: VRs foster the elaboration of knowledge in teams.
- New insights: VRs support the creation of new insights by embedding details in context, showing relationships between objects, and leading to "ah-ha" effects.

The attention function overlaps with that used in the AIDA model — "Attention, Interest, Desire, and Action," developed by E. St. Elmo Lewis in 1898 (Vakratis, 1999) — where drawing the attention of the recipient of information is a prerequisite for successful communication.

These functions are part of an overall Knowledge Visualization Framework that includes the following additional elements:

- Knowledge type:
    - Know-what;
    - Know-how;
    - Know-why;
    - Know-where; and
    - Know-who.
- Recipient type
    - Individual;
    - Group;
    - Organization; and
    - Network.
- Visualization type (see discussion in the next section, "Tools of knowledge visualization").

Other functions of knowledge visualization can be achieved through:

- **Stress Reduction:** Uncertainty is one of the main causes of stress and the subsequent decrease in the ability to process information (Rock, 2009). A simplified version of the reality presented in a visual representation of knowledge is conducive for stress reduction and, as a consequence, may improve learning outcomes.
- **Metaphor:** A metaphor consists in giving a thing a name that belongs to something else (Sontag, 1988). In visualizing knowledge, different commonly known objects such as a tree, an iceberg, a mountain, a pyramid, a ladder, and dice, are frequently used to describe a process or a phenomenon. Morgan (1998) used metaphors to describe the complexity of organizations. Metaphors enable understanding reality through sense making (Weick, 1995).

Visualization of knowledge is often used in strategic management. Strategy visualization is defined as the systematic use of complementary visual representations to improve the analysis, development, formulation, communication, and implementation of strategies in organizations (Burkhard 2005). Barrett (1994) distinguishes between *business visions* (the organization's values, philosophy, or beliefs) and the *process visualization* (which tells how to do those things right and focus, motivate, and engage individuals). La Rooy (2000) emphasizes the importance of visualization as a *visual motivation*, which involves employees in the implementation of many small improvements by using photographs of "before and after" situations tagged with ideas and findings of the improvement ideas.

TOOLS OF KNOWLEDGE VISUALIZATION

Burkhard (2005) has developed a taxonomy of seven tools that can be used in knowledge visualization that researchers can use to achieve "knowledge communication", which Martin Eppler defines as an "...activity of interactively conveying and co-constructing insights, assessments, experiences or skills through verbal and non-verbal means" (Eppler, 2004). The seven are:

- *Sketches* (simple designs helping to visualize key features and the main idea quickly);
- *Diagrams* (abstract, schematic representations used to display, explore and explain relationships);
- *Maps* (plans that present entities on a different scale and allow two-dimensional representations of three-dimensional objects);
- *Images* (renderings, photographs or paintings);
- *Objects* (physical models to show projects from different perspectives);
- *Interactive visualization* (visualizations allowing the recipient to access, combine, control, explore, and manipulate different types of complex data); and
- *Visions/stories* (non-physical, imaginary visualizations that transfer knowledge across time and space).

Some complex formats of knowledge visualization are theory-drive conceptual maps, concept maps, interactive visual metaphors, or knowledge maps (Meyer, 2016).

Another tool for visualization of knowledge is difficult to classify. It is based on humans' innate ability to process visual information related to face recognition. Inspired by this unique feature of the human brain, Hermann Chernoff developed a unique type of knowledge visualization tool now commonly called "Chernoff Faces". Chernoff created Chernoff Faces as a method for multiple variables data presentation method in 1973 (Chernoff, 1973). Its underlying principle is the use of the human face (especially its features) to show the intensity or level of different variables.

THE BACKGROUND OF THE CHERNOFF FACE METHOD

Chernoff used the human face because the face is the easiest way for humans to determine differences; people recognize others thanks to differences in, for example, the shape of the head, the nose and the mouth. Chernoff wasn't the first person using shapes to represent k-dimensional variables. Anderson in 1957 was using glyphs, a "graphical object whose properties represent data values" (e.g., Anderson in 1957 was using glyphs, a "graphical object whose properties represent data values" (Anderson, 1957) (e.g., circles with fixed diameters and rays that have different angles and lengths), but the glyph method was not as intuitive as Chernoff's idea of faces. Some researchers were using triangles (up to 4 variables - three lengths of sides and position). Chernoff wrote that he was using profiles with series of n bars (n = number of variable), but the use of such bars was not intuitive — a bar graph with more than 3 - 4 variables is difficult to examine, especially when searching for similarities. Standardization of data puts numbers into a range between -3 and 3 (with the mean = 0) and helps to compare relations between objects. For example, without standardization the importance of variables counted in billions would be higher than others counted in tens - because differences are counted in billions, not in tens. The data must be standardized (to range from 0 to 1, with standardization using a z-score) to have identical/nearing range. In 1970, he concluded that using bars was a very promising method of representation multivariate data, but it is highly vulnerable to noise in one group of variables overspreading differences between others.[1] Among other methods used nowadays, the most common still are polygons (stars, stars presentations, star coordinate systems and similar representations), classic bar-charts, and lines (Chambers, 1983). Chernoff claims that it is possible to show up to 18 different variables. Statistical packages offer over 40 different face features.

Chernoff Faces are used in many field of science – for example, in mechanics (Zhang, 2017), chemistry (Kim, 2012), geographical information systems, and cartography. Using Chernoff Faces and other specific diagrams in showing differences and similarities between areas is the most popular use of Chernoff Faces. The method was first used publicly by Eugene Turner in the map "Life in Los Angeles, 1970". In the 90's, Chernoff Faces were used to show differences in spatial structures of British electors (Dorling, 1991), feature salience and the election results in the United States of America - one of the most popular and most often-cited diagrams (Fabrikant, 2000) - in its most popular form, it uses the face, but in a simplified carto-diagram.

In 1997, a team of researchers from San Diego State University tested which features are the easiest and most efficient to detect within Chernoff Faces in a cartographic setting (Nelson, 1997). They concluded that subjects were the fastest and most accurate in determining changes in head size, with the greatest difficulty in detecting changes in mouth orientation; in between were eye size and nose size. While they did not use color in their study, they suggested that using color could be very effective in emphasizing one of many variables.

According to Hungarian and Argentine researchers, Chernoff Faces are a perfect base and concept for creating multivariable diagrams - instead of faces, researchers can use pictures of factory, mine, car, tank/artillery units and many other objects (Nuñez, 2011). Reyes and others (including Turner) proposed using additional features (filling in the head) and changing some parameters to make the diagrams more understandable (Reyes, 2009).

CRITICSM OF THE CHERNOFF FACES METHOD

Most of the criticism of the Chernoff Face method comes from the very different way that humans react to faces compared with other glyphs or symbols. Martin Elmer notes,

…human beings have ridiculously strong hard wiring for identifying faces. We sport an entire part of our brain dedicated to process images of faces, which snaps on faster than you can blink when a face comes into view. Our ability to recognize faces is famously overzealous . Chernoff was curious if he could co-opt our powerful face-spotting abilities to help humanity deal with something our brains are notoriously bad at comprehending: numbers. Thus, the Chernoff face: a face-like symbol where the various proportions of the facial features each correspond to some sort of data item (Elmer, 2013).

This innate human face-recognition capability raises a number of issues. One such issue is *pareidolia,* or the phenomenon of seeing faces in inanimate objects (e.g., the "man in the moon"). The Merriam-Webster defines pareidolia as:

The tendency to perceive a specific, often meaningful, image in a random or ambiguous visual pattern. The human brain is optimized to recognize faces, which could also explain why we are so good at picking out meaningful shapes in random patterns (Pareidolia, 2017).

A perhaps even clearer example is the use of aligned punctuation symbols to convey emotions. Examples include the following (Kosara, 2007):

;) : (>: P : ^ D

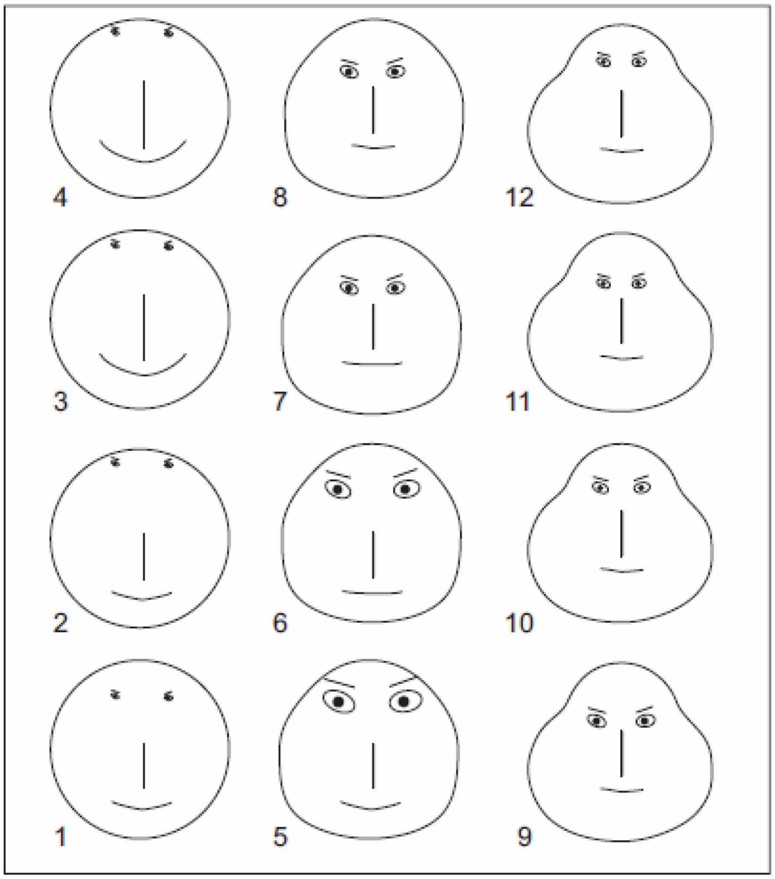
This tendency of humans to ascribe emotions to inanimate objects or sets of typographical characters suggests how faces as an analytical tool can confuse or mislead an audience. As Elmer notes, the academic term for this problem is "*correspondence*", which he defines as "simply how intuitive the relationship is between any given symbol and the thing it is symbolizing" (Elmer, 2013). Elmer criticizes Chernoff's use of human faces in his original 1973 article to represent the characteristics of various minerals. He provides examples of faces that Chernoff used to represent such characteristics (Figure 1).

As Elmer notes,

… we don't associate human faces with anything other than, well, human faces, so using them for numerical data seems silly. . . It makes a lot more sense to see a human face stand in for actual humans (Elmer, 2013).

Since Chernoff's 1973 articles, most authors have used Chernoff Faces for socio-economic data – i.e., data that involves human beings (and not, as in the original Chernoff article, inanimate items such as

Figure 1. Examples of Chernoff faces.
Source: Meyer, op. cit., citing Chernoff, op. cit., footnote 9



minerals). Thus, the most effective uses of Chernoff Faces have been where the data represented in the faces corresponds to the emotions that the faces derived from the data evoke in the intended audience.

Elmer cites as a famous example of an appropriate use of Chernoff Faces (i.e., "good correspondence") Eugene Turner's map showing socio-economic conditions in various parts of the City of Los Angeles. In this study, Turner mapped four variables over sixteen different regions of the City:

- "Affluence" (based upon various income, education and housing factors);
- Unemployment rate;
- "Urban stresses" (bsed upon various health, crime and transportation factors); and
- Racial composition (defined as the percentage of whites in the total population).

Here Turner used

- Rounder faces (compared with gaunt, emaciated faces) to show greater affluence;
- Smiles/frowns to show lower/higher levels of unemployment, respectively;
- Relaxed/tense eyes to show lower/higher levels of urban stress), and

- Different shades of beige/brown to show racial composition.

The correspondence works, because the more fortunate data results in happier-looking, more relaxed faces, while the less fortunate data produces unhappier, angrier-looking expressions. As a result, readers have a relatively intuitive understanding of the differences in socio-economic conditions within the City.

The problem with using Chernoff Faces is that good correspondence is hard to achieve. Elmer cites another example, using the data described in Figure 3.

In the example presented in Figure 3, lower unemployment rates generate a smile, while higher rates create a frown – all well and good. But higher divorce rates are represented by longer noses. While higher divorce rates are generally considered socio-economically less desirable, it's not intuitive that a face with a longer nose is less desirable than one with a shorter nose. Similarly, higher crime rates are represented by longer ears. While higher crime rates are clearly socio-economically negative, longer ears do not, at least for the authors of this study, generate either a positive or negative response. Perhaps the most glaring example of bad correspondence, however, (particularly in the politically correct environment of 2017; the example used dates from 2004) is the use of angry eyes to denote a higher percentage of women

Figure 2. Life in Los Angeles.
Source: Eugene Turner - Life in Los Angeles (1977)

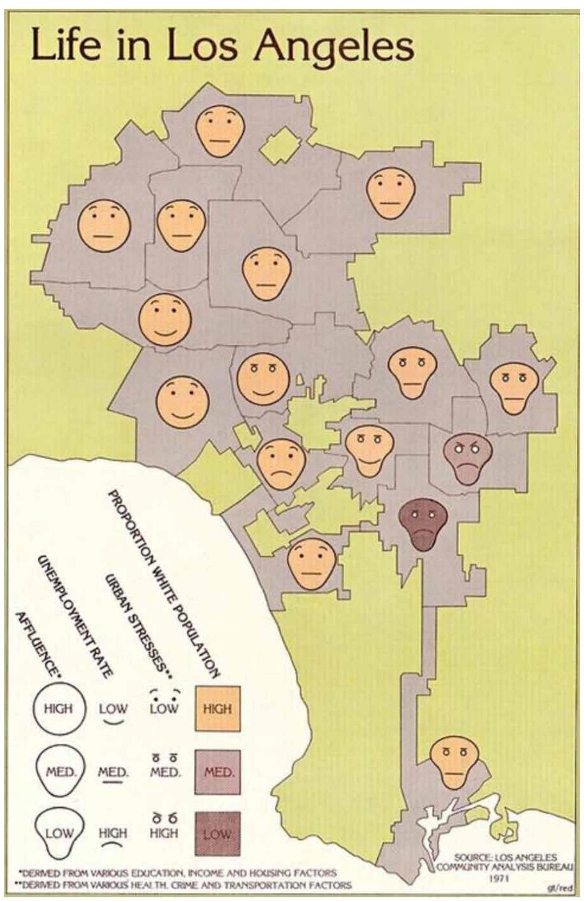
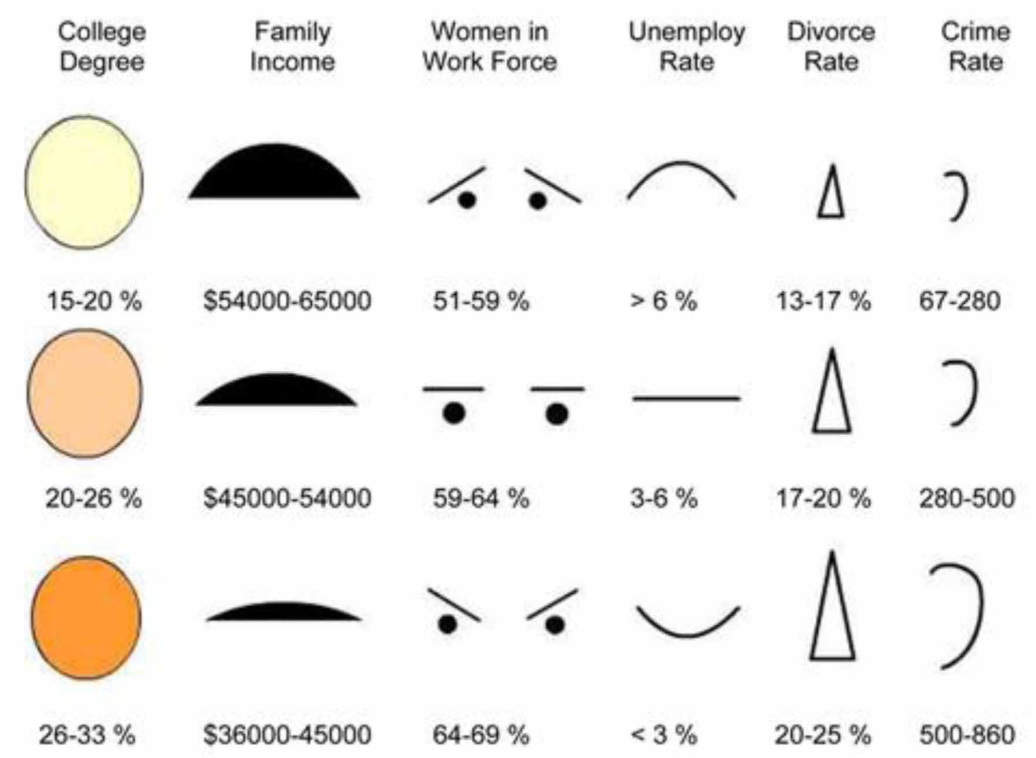


Figure 3. Examples of unintuitive correspondence.
Source: From Joseph Spinelli and Yu Zhou (2004)



in the workforce. This choice of symbolism seems clearly counter-intuitive, as a higher percentage of women in the workforce (again, for the authors of this article) seems as if it should generate a positive emotion rather than the increasing anger that the symbol for the eyes evokes.

Elmer suggests two fundamental difficulties with using faces to depict multivariate data symbolization:

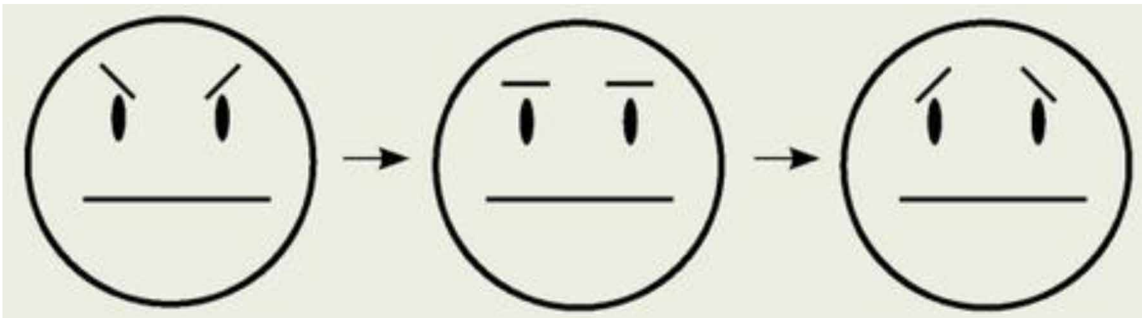
1. *Facial features are not generally ordinal.*
2. *Humans treat faces as more than the sum of their parts.*

Re. 1: In data theory, data is ordinal if it can be arranged in groups with a meaningful order. Elmer contrasts two different types of data:

- Crime figures (which can be meaningfully order, as high crime rates are more than medium and low crime rates); and
- Nationality (American, British, German, etc. cannot be meaningfully ordered).

While some types of data can be meaningfully ordered, many facial features (e.g., eyes and eyebrows) cannot. Maps using Chernoff Faces often use the position of eyebrows as a data representation, with the angle of the eyebrows varying depending on a data value (see Figure 4).

Figure 4. Examples of faces showing non-ordinal emotions.
Source: Eugene Turner - Life in Los Angeles (1977)



Elmer describes (accurately in the authors' view) the emotions generated by these faces as angry, bored/indifferent and sad. He notes:

These emotions aren't orderable: an angry person is not "more bored" than a sad person. A sad person is not "less angry" then a person with a blank expression. These emotions don't fit along a sliding scale, so pairing them with data that does (e.g., the high/medium/low urban stresses in Turner's map) is inappropriate at best and misleading at worst (Elmer, 2013).

Re. 2: Elmer provides an example of the following face (which could have, but did not, occur in the Turner study, as it would imply high urban stress but low unemployment) (Figure 5).

Using the Chernoff criteria, this face would be happy but angry. Elmer asserts:

Figure 5. A mixed-attribute face. Source: Eugene Turner - Life in Los Angeles (1977), cited in Elmer, op. cit.

… facial expressions are, visually, more than the sum of their parts. Place a happy grin and angry eyebrows onto a face, and the result is not "both happy and angry", but rather an entirely new emotion (impishness) that is not relatable to the components that created it. This creates problems in the context of the map, because mixed-up facial expressions like these A) just plain look silly and B) obscures the actual goings-on of the data (Elmer, 2013).

Elmer notes a fundamental distinction between facial features that convey emotion and those that do not. He cites a cartoonist asserting that the facial features that convey emotion are:

- Eyes;
- Eyebrows;
- Mouth shape; and
- Cheeks.

He adds that the text-based emoticons (see, e.g., the examples above) always display the eyes and mouth; they do not include noses, ears or hairlines, which generally do not provide information about how a person is feeling. When a facial feature does not convey emotion, it's hard to convey any meaningful information by differences in that features. While such differences may be perceptible, responses to those differences will not be intuitive.

Elmer offers the following criteria for effective use of Chernoff Faces, the data should be:

- Socio-economic in nature;
- Devoid of mixed attributes (as in the smiling/angry face above); and
- "Plottable" to emotion-linked facial features (he adds head-silhouette – as the use by Turner in the City of Los Angeles data suggests – as a possible emotion-linked feature).

He concludes:

That's a lot of barriers to be overcome, and even if they are, the product is still going to have to tangle with all the emotional and cultural and biological baggage that humans have when it comes to looking at faces. I honestly don't know if truly good Chernoff faces can ever be pulled off (Elmer, 2013).

THE RELIABILITY OF THE CHERNOFF FACES METHOD

Data used in creating Chernoff Faces must be standardized and assigned to different features of the face. Researchers should avoid using data with low variation coefficients. The process of assignment is the most difficult part of creating the diagram. While popular statistical software (i.e. STATISTICA, R, STATGRAPHICS) assigns data and standardizes it automatically, we do not recommend this practice.

The most popular features used in analysis are length of the nose and mouth, curvature of the mouth, slant of the eyebrows, size of the eyes and ears, eccentricity of the upper- and lower-face, visibility of the eyeballs and many other features (filling the eyes and face with gradients). Study designers should assign features in a logical way, correlating stimulant variables with positive images, while using negative images for depressants (i.e., higher incomes should relate to a more curved/bigger smile; a higher unemployment rate shouldn't). Connecting face features with variables is the most important and most difficult issue.

Researchers can encounter many problems, raised both by critics and followers of Chernoff Faces, including:

- Hiding interesting patterns by using the wrong feature connected with a variable (for example, the face shape or nose length can change the perception of the mouth);
- Using the wrong feature for more important variables;
- Encountering pareidolia;
- Finding different perceptions of the human face (there are more and less important features) – which can result in over-emphasizing or understating some variable (intentionally or by accident); and
- Recognizing the human face not by analyzing every feature and connecting it; people just recognize a person, or judge her/his character, personality, mood, etc.

Followers would say that Chernoff Faces, despite these disadvantages, are the best way to find patterns and similarities in multivariate objects, because careful researchers can avoid most of the disadvantages. Additionally, intuitive analysis of the same sets of faces by different analyst would give similar (but not identical) results.

THE APPLICATION OF THE CHERNOFF METHOD TO VISUALIZE KNOWLEDGE ABOUT POLISH COUNTIES

The applications of the methods are multifarious. Gifford (1997) conducted an interesting research study using the Chernoff method to test its reliability. He used Chernoff Faces to depict certain financial indicators (e.g., working capital, profitability) in periodic reports. Gifford asked two groups of professionals to provide their financial forecasts of the analyzed companies. One group was using traditional numerical data; the other was using Chernoff Faces to analyze the financial standing of the same companies' historical data. Those analysts who based their forecasts on visual information were more accurate in predicting the financial future.

In this study, we endeavored to use the Chernoff Faces method to visualize certain socio-economic indicators, establishing a set of variables describing some selected statistical information about Polish counties. We chose the features of a face listed below and matched with the variables indicated Table 1).

An extended list of 15 variables the differentiation among faces/counties is higher:

1. Width of the face: cultural accessibility
2. Level of ears: employment rate
3. Mid-face: long-term unemployment
4. Shape of the upper part of face: migration balance
5. Shape of the lower part of face: number of divorces
6. Length of nose: average salary
7. Mid-mouth: number of areas covered by local development plans (MPZ[2])
8. Curvature of mouth: value of completed projects

Table 1. Features of a face matched with the variables.

Feature	Variable
Face width	Accessibility of cultural goods (the wider the face, the more accessible cultural goods)
Ear positioning	Unemployment rate (low ears = low unemployment rate)
Length of nose	Number of square meters of living space per inhabitant
Mouth position	Foreign capital invested per employment age inhabitant
Mouth gesture	Number of businesses (high number = smiling mouth)
Length of mouth	Accessibility through transportation network (rail, plane, road)
Upper face shape	Divorces per 1000 inhabitants (higher divorce rate = more rounded face)
Lower face shape	Average gross salary in divorces (higher salary = more rounded face)
Mid-face shape	Migration balance among communes in the county

Source: own elaboration

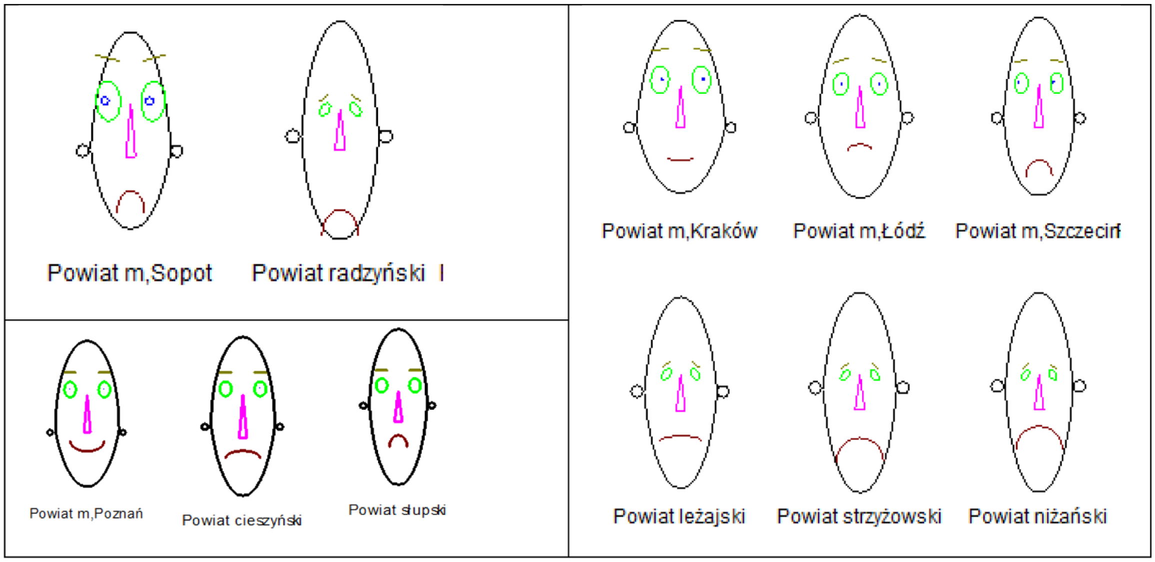
9. Length of mouth: number of square meters of living area per inhabitant
10. Height of ears: amount of foreign capital
11. Distance between eyes: number of businesses
12. Slant of eyes: businesses per 1,000 inhabitants in production age
13. Eyes’ slant: number of entrepreneurs.
14. Eyes’ length: NGOs per 1,000 inhabitants
15. Level of pupils in eyes: communication accessibility

As we look at such counties as Sopot, Łódź and Kraków and compare them with Leżajsk county, one can see that in urban counties, the number of divorces is higher (the face is more rounded). The size of the eyes indicates that Sopot and Krakow have the highest number of registered businesses and NGO’s. A comparison of Legionowo (in the northwestern Warsaw suburbs) and Debica (in rural southeastern Poland) demonstrates how quickly and dramatically viewers can perceive differences in variables such as average salary (length of nose), value of completed projects (mouth curvature) and foreign (height of ears). Similarly, comparing two counties from the same Polish region (Upper Silesia) quickly shows the vast differences between an industrial (Katowice) and a rural county (Rybnik) in terms of various business statistics (eye-related features) and unemployment (mouth-related features).

First, we created three sets of faces by using a large number of variables – a list of variables from 2014 was mentioned above; in 2012 it was the same (except one additional variable: the number of square meters of an average flat. The differences between the three faces are easy to notice: “Perfect county” face has big, round eyes; a long nose; a smile; horizontal eyebrows, etc. There are only a few problems in recognizing the differences – the perfect county has a smaller size and a different shape for the lower part of the face; one can believe that the bigger face is better, so it should have been changed. The next issue is the shape of the mouth; it is one of the most popular and visible features of the face, so there is a risk that the weight of mouth shape would be too high. But generally it is easy to recognize similarity; almost everybody says, that “Powiat poznański” is closer to being perfect than to being the worst; there are some issues with the smile and nose length, but similarities are easy to recognize.

In the last case, where we applied only five variables -- the dynamic of changes in migration balance (level of ears), the dynamic of divorces ratio (mid-face shape), the dynamic of communication accessi-

Figure 6. "Faces" of selected Polish counties.



bility (lower part of face), average salary (upper part of face) -- the differences are harder to discern. All the faces are happy and have similar noses, eyes and mouth. The only differences apply to face shape, but it is not the perfect solution. That is why Chernoff Faces can be used both to finding similarities and showing multiple variables on one picture, but also to manipulate, showing the lack of differences or emphasizing less important things.

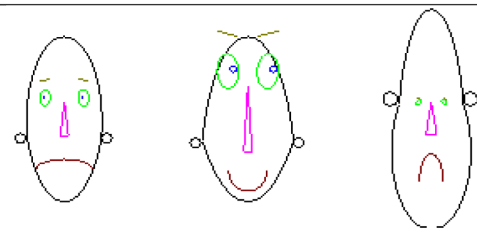
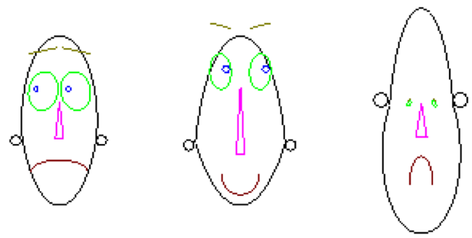
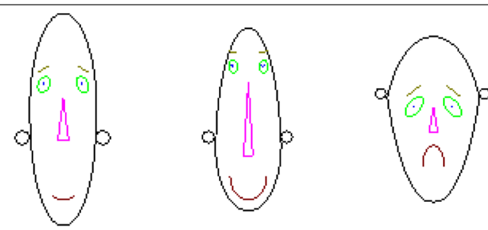
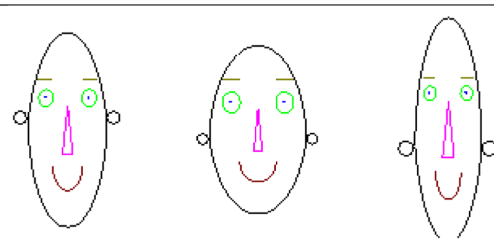
CONCLUSION

We have used the Chernoff Face knowledge visualization technique to analyze a complex set of 15 socio-economic variables shedding light on the lives and living conditions of citizens of various Polish counties (*powiats*). Our primary purpose is to demonstrate the utility of Chernoff Faces for researchers seeking to analyze these types of political/economic data. Secondarily, we wish to show how these results can be a tool for policy makers and their advisers in making decisions based upon this research.

Before providing the data analysis, we discuss why, in an increasingly data-rich (or data-cluttered) 21st-century context, knowledge visualization is becoming an increasingly attractive and significant research tool, particularly across cultures. We seek to distinguish knowledge information from information visualization and discuss the advantages that knowledge visualization offers and the variety of its uses in strategic management. We then consider the traditional tools used in knowledge visualization and suggest the unique features of Chernoff Faces that differentiate this technique from older knowledge visualization techniques.

We believe that the comparisons show that Chernoff Faces are a useful tool for comparing data between counties, and, using a finer measurement scale, for areas within counties. Among the subjects that we feel merit further research are:

Table 2.

Absolute values	Description	
2014, 14 variables	From left: Powiat poznański, perfect county, worst county	
2012, 16 variables	From left: Powiat poznański, perfect county, worst county	
2010, 13 variables	From left: Powiat poznański, perfect county, worst county	
Dynamics 2004 - 2014, 5 variables	From left: Powiat poznański, perfect county, worst county	

Source: Original creation.

- Whether the emotions conveyed by the face (happy, indifferent, sad) create a bias or distortion in the viewer's perception;
- How switching the assignment of specific data to certain features changes the perception of the face; and
- Whether recipients can glean useful information for analysis or policy making from the Chernoff Face depictions.

Finally, we believe that Chernoff faces will become an increasingly frequently used tool for 21st century socio-economic research.

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KEY TERMS AND DEFINITIONS

AIDA Model: Attention, interest, desire, and action. This model works under the assumption that drawing the attention of the recipient of information is a prerequisite for successful communication.

Business Visions: A for-profit organization's values, philosophy, and/or beliefs.

Chernoff Faces: A method of visualization of knowledge developed by Herman Chernoff using a graphical representation of statistical data to represent specific multivariate data using only one symbol—a human face—to represent e data in question.

Emoticons: A visual representation of a facial expression using only typed symbols, such as colons and parentheses.

Herman Chernoff: Professor Emeritus of Applied Mathematics from Harvard University's Department of Statistics, creator of Chernoff Faces.

Information Technology: Telecommunication technology used for storing, retrieving, and sending information data.

Information Visualization: Using visual mediums and methods to convey information and/or data to an audience.

Knowledge Base: An individual's lifelong collection of knowledge and wisdom.

Pareidolia: The phenomenon of seeing faces in inanimate objects.

Process Visualization: A visualization given to members of a team so that they may better understand the methods that are expected to be utilized to achieve a collective goal.

Socio-Economic: Pertaining to an individual or group's combination of social and economic factors which determine their social standing.

Unintuitive Correspondence: A situation in which the intuitive or presumed correspondence of a visual representation of knowledge and its underlying data and truth is skewed by poor design.

ENDNOTES

In the case of small differences between objects (in areas of one variable), it is not appropriate to use standardization, because differences would be strengthened (and thus would appear bigger than they are).

2 *Miejscowy Plan Zagospodarowania* (Local Development Plan): a strategy for local spatial development which defines what can be constructed and where in the area covered by the plan. These plans in Poland can be very controversial, as they often cause chaotic development and/or stall development and investment.