Bentley University

HF700: Foundation in Human Factors

Pattern Perception

Pre-attentive Processing &
COVID-19 Dashboard Case Review

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Introduction

This product review explores the importance of pre-attentive processing and pattern perception as it relates to the field of design. Pre-attentive processing automatically registers the features in our visual field as patterns (A. Treisman, 1985). Pattern recognition has proven critical to our survival and human evolution because it enabled us to respond to threats and opportunities quickly and efficiently in our environment (Öhman, 1997). For example, pattern detection enabled us as hunter gatherers to identify the camouflaged spotted leopard in sun dappled areas of the wild and escape its attack. While we are no longer hunter gatherers today, pattern perception is still important in our everyday lives because it allows us to see visually distinct components in our visual field. For interaction design specifically, pattern perception is useful for data displays because information can be understood "at a glance" when it efficiently gets processed in pre-attentive ways. (A. Treisman, 1985; A. Treisman & Gormican, 1988). This paper will describe and apply the science of pre-attentive processing and pattern perception to a Massachusetts COVID-19 dashboard case study.

Pre-attentive Processing

Pre-attentive processing is the neurological process by which humans register stimulus features in parallel and group these shared perceptual qualities and characteristics with high capacity and speed (A. Treisman, 1985). In hundreds of psychophysical experiments, participants have been asked if a certain shape emerges among a pattern of other shapes that are flashed in front of their eyes quickly. These studies underpin the concept of pre-attentive processing, which is the foundation for our understanding of visual distinctiveness (A. Treisman, 1985). Attributes such as orientation, size, motion, and color are all pre-attentively processed (Wolfe & Horowitz, 2004).

Redundant Coding vs. Conjunctive Search

Easily detected patterns that are visually distinct make the search query faster and more efficient (Wolfe, Butcher, Lee, & Hyle, 2003; Wolfe & Gray, 2007). Items can appear distinct by the design of a single feature, such as color, or by the design of multiple features, such as color and size. Using multiple dimensions to make an item distinct is called redundant coding (Monnier, 2003). When optimum redundancy is accomplished, there is almost always a benefit to coding with redundant properties (Egeth & Pachella, 1969; Eriksen & Hake, 1955). While redundant coding includes a parallel search that can be executed on one property *or* another, conjunction searches are serial and require searching for conjoined properties one *after* the other. For example, searching for a blue triangle involves searching for the specific attributes of color (blue) *and* shape (triangle) (A. M. Treisman & Gelade, 1980). Conjunction searches are not considered to be pre-attentive except for a few key exceptions that conjoin spatial information and a second attribute (D'Zmura, Lennie, & Tiana, 1997; Driver, McLeod, & Dienes, 1992;

Nakayama & Silverman, 1986; Theeuwes & Kooi, 1994; A. Treisman & Gormican, 1988). While redundant coding and some conjunctive searches guide pre-attentive processing, neurological mechanisms along the cortical chain are responsible for implementing these methods on a physiological level.

The Cortical Chain

The Lateral Geniculate Nucleus (LGN)

Light travels through the three retinal layers of the eye: (1) the ganglion cells, (2) the amacrine, bipolar, and horizontal cells, and (3) the rods and cones at the back of the retina. The rods and cones then transduce this light and fire back electrical impulses to the ganglion cells, which then transmit the information from the retina through the optic nerve to the visual cortex (Hubel, 1995). Along the optic nerve, these electrical impulses pass through a neural “way station” called the lateral geniculate nucleus (LGN) (Goard & Dan, 2009). The LGN is a “nucleus” (collection of nerve cells) in the thalamus. The thalamus is an area of the brain located below the cortex, closer to the brainstem. It is responsible for transmitting sensory information from the outside world to the brain. The thalamus has many different “nuclei” each responsible for a different sense, but the LGN is the specific thalamic nucleus corresponding to vision (O'Connor, Fukui, Pinsk, & Kastner, 2002).

When light comes into the LGN via the retinal ganglion cells, the LGN layers on additional information to that raw light signal by encoding where motion, color, light, etc. are all occurring in the visual environment. The LGN primes these important spatial features of the visual field before they are fed forward to the rest of the cortical chain for further processing (Atkinson, 1992). The LGN encodes the nerve signals with two different, alternating cell types: M-cells and P-cells. M-cells respond to rapidly changing or moving stimuli, but do not register most color details. P-cells register static features of the visual field and have a greater capacity to pick up fine details, such as colors, edges, etc. (Hendry & Calkins, 1998; Yücel, Zhang, Weinreb, Kaufman, & Gupta, 2003). Once the M-cells and P-cells preprocess the light signals, this information is sent to visual area 1 (V1) and visual area 2 (V2) (Gegenfurtner, 2003).

Visual Cortex

The first areas in the cortex to receive visual inputs from the LGN are V1 and V2. These two visual areas comprise more than 40% of vision processing (Lennie, 1998). According to visual channel theory, the information processed in V1 and V2 flows through visual “channels”. The visual branch is divided into subchannels of form, color, and motion. Each of these can even be further divided into subchannels (Horiguchi, Nakadomari, Misaki, & Wandell, 2009).

Several billion neurons in V1 and V2 analyze signals from only two million nerve fibers coming from both optic nerves, so there is plenty of neural processing power to support the massive parallel retinal mapping of the entire visual field for incoming features of color, motion, texture, and form (Gegenfurtner, 2003). V1 and V2 contain key cells that are differentially tuned to the local elements of form, color, stereoscopic depth, and motion. These cells process the encoded features coming from the LGN by registering them in parallel so that every part of the visual field is spatially co-registered as discrete, semi-independent feature maps (Li, 2002). Feature integration theory states that features are "registered early, automatically, and in parallel" (A. M. Treisman & Gelade, 1980). For example, there is a map for blue, a map for horizontal orientation, a map for vertical motion, etc. When we conduct a visual query, a target set of features is defined for the visual search (Eckstein, Beutter, Pham, Shimozaki, & Stone, 2007). Saccades, rapid and frequent eye movements, are then programmed to scan regions of the visual field that best match the target set of features in line with prior feature maps. Saccadic eye movements are ballistic, meaning the muscles are preprogrammed once the brain decides where to pay attention and the movement cannot be altered mid-cycle (Liversedge & Findlay, 2000).

The Gabor Function

Several psychophysical experiments proved that V1 and V2 contain many neurons that filter for orientation and size. This information forms the basis for both shape and texture perception (Willmore, Prenger, & Gallant, 2010). The mathematical model that describes the receptive fields of this large array of neurons is called the Gabor function (Barlow, 1972; Daugman, 1984). Barlow developed a set of principles central to perceptual processing, one famously known as the “second dogma”, which was mathematically proven by Daugman in 1984. The “second dogma” claims the visual system is simultaneously optimized by Gabor detectors (tuned neurons for orientation and size) that preserve a combination of spatial location and frequency information. Many things about low-level perception can be explained by this model. First, Gabor detectors are used in theories of the detection of form, texture, stereoscopic depth, and motion (Fogel & Sagi, 1989; Grigorescu, Petkov, & Kruizinga, 2002). Secondly, Gabor detectors lay a foundation for a basic set of properties upon which more complex patterns are built (Jain, Ratha, & Lakshmanan, 1997). Some of the fundamental groupings that distinguish patterns at all succeeding levels of processing are established at this stage of visual processing.

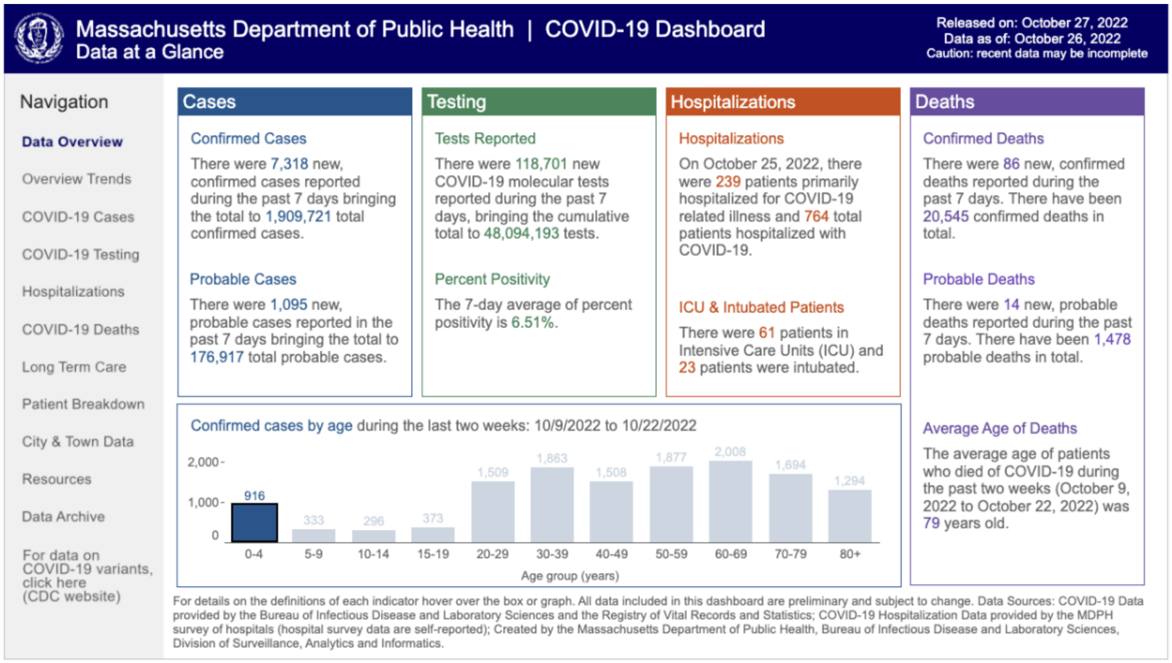
Groupings

Basic grouping principles were established by the pattern perception work of Gestalt psychologists in 1912 (Wertheimer, 1912). First, proximity is a powerful organizing principle as items close together are perceptually grouped together (Quinlan & Wilton, 1998). Furthermore, we perceptually group regions of similar element density, also known as the spatial concentration principle (Slocum, 1983). Second, similar elements tend to be grouped together as stated in the Law of Similarity, which proposes elements that are similar to each other tend to be perceived as a unified group (Graham, 2008). Similarity can refer any type of feature, such as size or color. Third, connectedness is a grouping that describes how lines connecting different objects suggest there is some relationship between them (Todorovic, 2008). Fourth, the continuity principle describes how we prefer visual elements that are smooth and continuous versus ones that contain abrupt changes in direction (Todorovic, 2008). Fifth, the principle of closure and common region (a region enclosed by a contour) suggest we are inclined to categorize parts of space as being "inside" or "outside" a closed contour, and this tends to be a stronger organizing principle than proximity (Palmer, 1992). Lastly, size is grouping principle as we have a strong perceptual tendency to group objects based on similar size (Wong, 2010).

Case Review

Context

This case review analyzes the Massachusetts COVID-19 data tracker. It is an interactive data dashboard updated on a weekly cadence every Thursday at 5PM EST. It is offered by the commonwealth’s Department of Public Health and the Executive Office of Health and Human services. The dashboard is rich in data and includes 11 tabs containing cumulative records of COVID-19 trends, cases, testing, hospitalizations, deaths, long-term care, patient demographics, city/town data, and other insights. The COVID-19 online dashboard is a flexible design offered in web, tablet, and mobile views. Users include the public and public health officials who are interested in carefully monitoring the state of the pandemic in Massachusetts.


Massachusetts Department of Public Health | COVID-19 Dashboard
Data at a Glance

Released on: October 27, 2022
Data as of: October 26, 2022
Caution: recent data may be incomplete

Cases

Confirmed Cases

There were 7,318 new, confirmed cases reported during the past 7 days bringing the total to 1,909,721 total confirmed cases.

Probable Cases

There were 1,095 new, probable cases reported in the past 7 days bringing the total to 176,917 total probable cases.

Testing

Tests Reported

There were 118,701 new COVID-19 molecular tests reported during the past 7 days, bringing the cumulative total to 48,094,193 tests.

Percent Positivity

The 7-day average of percent positivity is 6.51%.

Hospitalizations

Hospitalizations

On October 25, 2022, there were 239 patients primarily hospitalized for COVID-19 related illness and 764 total patients hospitalized with COVID-19.

ICU & Intubated Patients

There were 61 patients in Intensive Care Units (ICU) and 23 patients were intubated.

Deaths

Confirmed Deaths

There were 86 new, confirmed deaths reported during the past 7 days. There have been 20,545 confirmed deaths in total.

Probable Deaths

There were 14 new, probable deaths reported during the past 7 days. There have been 1,478 probable deaths in total.

Average Age of Deaths

The average age of patients who died of COVID-19 during the past two weeks (October 9, 2022 to October 22, 2022) was 79 years old.

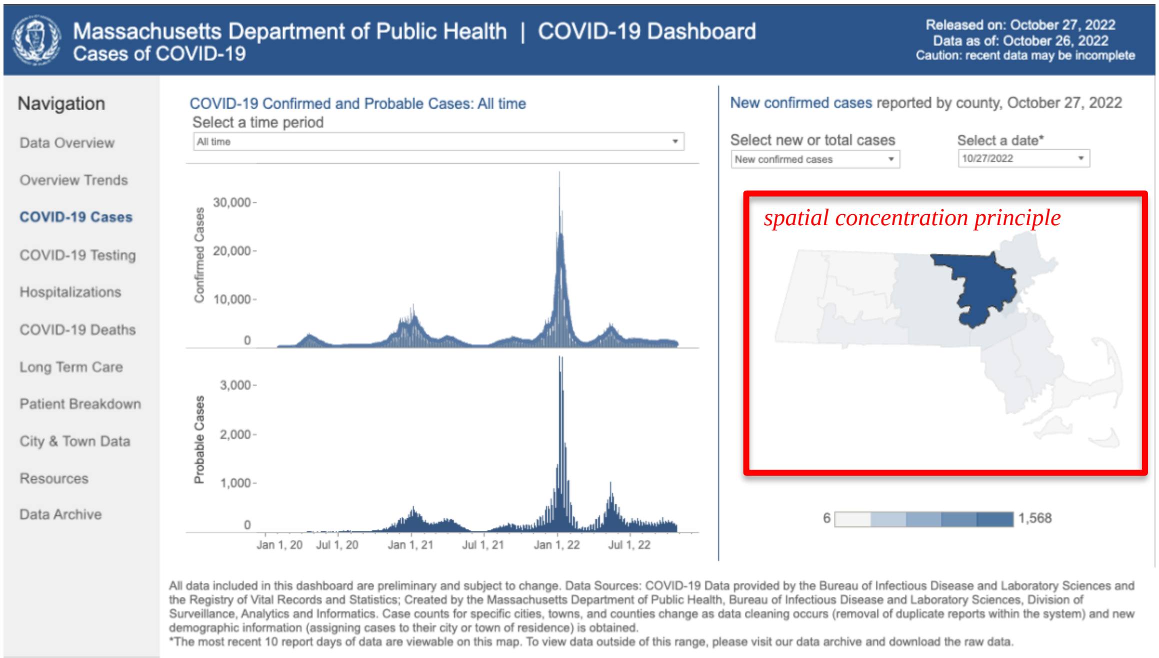
Confirmed cases by age during the last two weeks: 10/9/2022 to 10/22/2022

For details on the definitions of each indicator hover over the box or graph. All data included in this dashboard are preliminary and subject to change. Data Sources: COVID-19 Data provided by the Bureau of Infectious Disease and Laboratory Sciences and the Registry of Vital Records and Statistics; COVID-19 Hospitalization Data provided by the MDPH survey of hospitals (hospital survey data are self-reported); Created by the Massachusetts Department of Public Health, Bureau of Infectious Disease and Laboratory Sciences, Division of Surveillance, Analytics and Informatics.

Screenshot #1: ‘Data Overview’

Analysis

This dashboard adheres to many of the grouping principles consistent with pre-attentive processing and pattern perception. First, the ‘Data Overview’ (**screen shot #1**) tab excellently employs the use of the closure and common region principle. There are five “boxes” each enclosing a region with specific COVID-19 information. Furthermore, redundant coding is present in this "chunking" as each box is an enclosed region reinforced by a visually distinct color from the other boxes (e.g., 'Cases' is navy blue, 'Testing' is green, 'Hospitalizations' is orange, and 'Deaths' is purple). Secondly, the Law of Similarity applies to the case data because the two regions in navy blue are both covering case data (e.g., 'confirmed cases', 'probable cases', and a graph of 'confirmed cases by age over the last two weeks'). The use of navy blue to denote this category of case data enables the brain to preattentively process these two boxes as a unified group distinct from the other categories of COVID-19 data displayed. Moreover, a compact data display like this one, in which the five boxes are clustered together, enhances visual search because saccadic eye movements can travel shorter and faster between the compact information nodes of the COVID-19 data. The 'Covid-19 Cases' tab (**screen shot #2**) also applies the spatial concentration principle very well as the higher density / saturated counties on the MA map correspond to the grouping of higher number of confirmed cases.



All data included in this dashboard are preliminary and subject to change. Data Sources: COVID-19 Data provided by the Bureau of Infectious Disease and Laboratory Sciences and the Registry of Vital Records and Statistics; Created by the Massachusetts Department of Public Health, Bureau of Infectious Disease and Laboratory Sciences, Division of Surveillance, Analytics and Informatics. Case counts for specific cities, towns, and counties change as data cleaning occurs (removal of duplicate reports within the system) and new demographic information (assigning cases to their city or town of residence) is obtained.

*The most recent 10 report days of data are viewable on this map. To view data outside of this range, please visit our data archive and download the raw data.

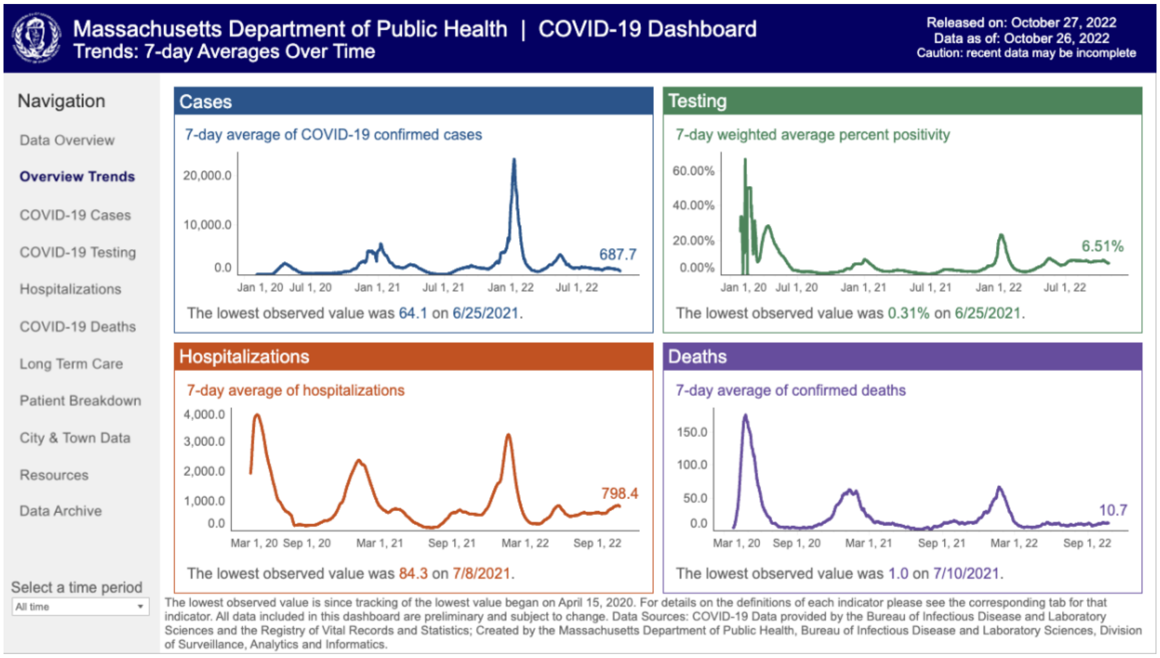
Screenshot #2: 'COVID-19 Cases'

Lastly, the proximity principle is applied very well to the side Navigation tab as the 11 tabs are vertically "chunked" together in the grey box away from the main data display.

However, there are some disadvantages of this dashboard. The layout of the 'Data Overview' (**screenshot #1**) tab violates the size grouping principle. We have a strong perceptual tendency to group objects based on similar size, which in this design should be grouping the 'Cases', 'Testing', 'Hospitalizations', and 'Deaths' boxes, as these are the four main categories of equal reporting importance. However, the Deaths box is ~1/3 larger than the other boxes for no significant reason. This is confirmed by the second tab, 'Overview Trends' (**screenshot #3**) where all four boxes are the same size. Additionally, the bottom alignment of the bar graph to the first three categories suggests there is a connection between the data shown in the bar chart and those three categories. However, the bar graph most closely supports a combination of information in the first and last box.

Recommendations

I recommend updating a few elements to better enable the understanding of certain features in this dashboard in pre-attentive ways. First, I would make the size of the Deaths box on the Data Overview tab (**screen shot #1**) the same size as the other three vertical boxes in order equate their importance, as consistent with the 'Overview Trends' tab below (**screen shot #3**).



Massachusetts Department of Public Health | COVID-19 Dashboard
Trends: 7-day Averages Over Time

Released on: October 27, 2022
Data as of: October 26, 2022
Caution: recent data may be incomplete

The lowest observed value was 64.1 on 6/25/2021.

The lowest observed value was 0.31% on 6/25/2021.

The lowest observed value was 84.3 on 7/8/2021.

The lowest observed value was 1.0 on 7/10/2021.

The lowest observed value is since tracking of the lowest value began on April 15, 2020. For details on the definitions of each indicator please see the corresponding tab for that indicator. All data included in this dashboard are preliminary and subject to change. Data Sources: COVID-19 Data provided by the Bureau of Infectious Disease and Laboratory Sciences and the Registry of Vital Records and Statistics; Created by the Massachusetts Department of Public Health, Bureau of Infectious Disease and Laboratory Sciences, Division of Surveillance, Analytics and Informatics.

Screenshot #3: 'Overview Trends'

Next, I would consider doing one of two options for the bar chart in the 'Data Overview' (**screenshot #1**). First, if the Deaths box is normalized to the size of the three others, the bar graph box should be bottom aligned to all four categories since it supports a combination of data contained across all of them. If the Deaths box remains larger in size compared to the others, then the principles of continuity and connectedness can be utilized to draw a smooth arrow pointing from the 'Average Age of Deaths' blurb contained in the Death box to the 'Confirmed cases by age' data in the bar graph box to underscore the quantitative connections. Updating these features are critical to the usability of this dashboard because it will more accurately reveal the relationships between each set of COVID-19 data. In general, adhering to these grouping principles for dashboard design will improve the larger user experience as it makes complicated data sets more digestible for users "at a glance".

<u>Conclusion</u>

With pre-attentive processing, our minds can detect and perceive patterns in a "split second". In just that short time frame, billions of neurons in our brain are sorting and organizing a myriad of features simultaneously so that we can efficiently thrive in our environments. As these patterns move through the cortical chain, subpopulations of cells are specifically tuned to pick up certain features and preserve the patterns. In “feed forward” fashion, the patterns are strengthened so higher-level cortical areas can eventually integrate them with conceptual knowledge (Gazzaley et al., 2007). Our understanding of preattentive processing is powerful because it enables us to create designs that yield a controlled, predictable, and desirable user response based on the science of pre-attentive processing, pattern perception, and grouping principles.

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