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Formalizing Emphasis in Information Visualization

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Abstract

We provide a fresh look at the use and prevalence of emphasis effects in Infovis. Through a survey of existing emphasis frameworks, we extract a set-based approach that uses visual prominence to link visually and algorithmically diverse emphasis effects. Visual prominence provides a basis for describing, comparing and generating emphasis effects when combined with a set of general features of emphasis effects. Therefore, we use visual prominence and these general features to construct a new mathematical Framework for Information Visualization Emphasis, FIVE. The concepts we introduce to describe FIVE unite the emphasis literature and point to several new research directions for emphasis in information visualization.

1. Introduction & Motivation

Emphasis is an essential component of Infovis, and encompasses, for example:

- Highlighting regions of interest, e.g., coloring data points when brushing and linking to emphasize relationships;
- Animating data points using motion [BWC03, WB04] and flickering [WLMB*14], which are efficient for catching a viewer's attention; and
- Altering the size of data points to provide more detail or to increase their legibility relative to other data points, e.g., the many space-distortion techniques in the literature including overview+detail and zooming (see [CKB09] for a review).

The commonality between these diverse techniques is that all of them make some data points more prominent than others. For example, when a visualization exploits highlighting to emphasize some data points, differences in the prominence of the data points arise from variations in color, or more specifically hue, a powerful visual variable. While emphasis effects in visualization can be created using any visual variable [CM84, Ber83, Mac86], Infovis researchers have often focused on distortion and magnification techniques, e.g., [CM01, LA94, Kea98, PCS95, SA82]. These techniques create emphasis effects by manipulating magnification (i.e., by simultaneously manipulating the visual variables size and position) where differences in the prominence of data points arise from variations in magnification. Recently, researchers have explored new emphasis effects using, e.g., blur [KMH02, Hau06], transparency [Hau06], halos [OJS*11], motion [BW02, HR07], and flicker [WLMB*14]. This continued emergence of new emphasis effects has moved visualization research beyond existing emphasis frameworks. Given the usefulness of previous frameworks, it is important to develop a new, more complete framework for emphasis in information visualization, i.e., a unifying description of emphasis that captures the breadth of the new and existing emphasis effects. To address this challenge, we explore emphasis effects in five steps:

A review of existing emphasis frameworks
In this review, we introduce visual prominence as a means of dividing the data points within a visualization into subsets. This emerges from our analysis of previous frameworks. We use these emphasis subsets constructed on visual prominence to describe emphasis effects in visualizations and conceptually unify the diverse emphasis effects in the literature.

A survey of classes of emphasis effects in visualization
In this discussion, we extract general features of emphasis effects. For example, we elaborate on the often overlooked role of time in emphasis effects. We also introduce the concepts of: 1) *intrinsic emphasis effects* – changes in the prominence of data points resulting from the initial visual mapping process when creating a visualization (e.g., coloring water and land differently on a map), and 2) *extrinsic emphasis effects* – changes in the prominence of data points resulting from applying visual effects on top of existing visualizations (e.g., applying a lens to a map).

An approach to generating emphasis effects
We show how visual prominence subsets and related general features of emphasis effects are a conceptual basis for generating emphasis effects for visualizations.

A formal framework: FIVE
We provide a Framework for Information Visualization Emphasis (FIVE) that captures all previous emphasis frameworks, and expands on this work. FIVE is consistent with describing and generating emphasis effects using visual prominence subsets and our extracted general features of emphasis effects.

This is the authors' version of the work.
The definitive version is available at http://diglib.eg.org/ and http://onlinelibrary.wiley.com/ .

Opportunities for using FIVE

Using FIVE and its related concepts, we provide an initial exploration of new opportunities and future directions in emphasis research. This outlook highlights many research challenges, and this STAR can support researchers as they undertake this work.

As we examine emphasis through each of the above steps, we focus on visual variables as a way to explore emphasis techniques because visual variables are integral to information visualization. In addition, we focus on the mechanics of emphasis using visual variables, rather than the details of *how* visual variables create emphasis for the viewer. Through focusing on the mechanics, we show how FIVE can use set-based mathematics to incorporate and extend previous function-based frameworks, providing new ways to decide both *what* to emphasize and *how* to achieve this emphasis. In addition, FIVE offers a basis for studying the details of how emphasis is connected to perception (see section 7.4). For example, some techniques (e.g., visual links [GR15, SWS*11]) point to how emphasis can arise not just from varying visual variables, but also by leveraging Gestalt concepts (e.g., connectedness in the case of visual links).

Frameworks that describe families of techniques have proven useful, e.g., [Fur86, LA94, CM01], in particular when they are *descriptive*, *comparative*, and *generative* [BL04, BL00]. Therefore, one of our goals when we set out to analyze the emphasis literature was to create a unifying emphasis framework that would be descriptive, comparative, and generative. FIVE is a new mathematical description of emphasis that exhibits these properties. FIVE incorporates several conceptual elements:

1. A set-based notation to describe visual prominence.
2. *Time* as a key part of describing emphasis effects (e.g., time variant and invariant methods).
3. The data duplication present in some emphasis effects.
4. The variable degree of continuity in emphasis effects.
5. The co-existence of intrinsic and extrinsic emphasis effects.

FIVE opens up new ways of thinking about emphasis while also being compatible with previous frameworks.

2. Reviewing Previous Frameworks

To understand emphasis effects, we first examine existing frameworks that describe emphasis effects in information visualization. We include three types of papers in this review:

1. Papers that define and review concepts related to emphasis as opposed to papers that introduce a single emphasis effect. Papers in this category are [CKB09, Fur86, Fur06, Hau06, Kea98, SA82].
2. Papers that provide a taxonomy of emphasis related effects, i.e., [KMH02, PCS95]. Note that we include the taxonomy in [KMH02] for completeness, although it is brief.
3. Papers that provide mathematical frameworks that describe emphasis effects. This category includes [CM01, LA94].

All these frameworks provide ways to systematically create emphasis effects and describe relationships between various emphasis effects. There are other papers that provide significant overviews of emphasis techniques [LH10, LM10, Rob11, TGK*14]; however, these have different contributions. Liang and Huang [LH10] take a very focused look at one aspect of emphasis (i.e., highlighting), and provide a list of how objects have been highlighted in visualizations. Lam and Munzner [LM10] discuss empirical considerations when deciding on the number of views and the relationships between these views for a particular interface. Robinson [Rob11] considers a large range of visual variables as starting points for creating highlighting effects and proposes design criteria to qualitatively compare these highlighting effects. However, Robinson [Rob11] focuses on highlighting related elements across multiple views in the context of geovisualization, a particular emphasis use case. Finally, Tominski et al. [TGK*14] have a partially overlapping survey in that they look at existing lenses, which have often been used for emphasis. However, they focus on using the perspective of Magic Lenses [BSP*94] to discuss different types of variations such as changes in representation. Therefore, though these additional papers contribute to the emphasis literature, we confine our review of previous emphasis frameworks to [CM01, CKB09, Fur86, Fur06, Hau06, Kea98, KMH02, LA94, PCS95, SA82].

2.1. Introducing A Set-Based Emphasis Language

Each of the previous frameworks covers a broad range of emphasis effects. However, as a collection, the frameworks are disparate in their descriptions of emphasis. Therefore, to enable our survey of these frameworks, we first establish a simple set-based language. While the generative aspects of the previous frameworks all rely on functions, the discussions in the papers frequently use set-based terminology. Hauser uses the word "subset" over fifteen times [Hau06] to describe emphasis effects. Furnas uses the word seven and twenty-six times in his two papers on fisheye views, [Fur86] and [Fur06]. In both of his papers [Fur86, Fur06], Furnas focused on how to establish which *subset* of a dataset to represent through use of a *Degree Of Interest* (*DOI*) function. Other previous frameworks also provide ways of emphasizing subsets of a dataset using function-based mathematics e.g., [CM01, Kea98, LA94, Hau06]. This prevalence of set-based ideas was one of our first clues to investigate a set-based framework. In this paper, we embrace the already established vocabulary of sets to describe emphasis effects.

While there are many means by which one can emphasize some data points in a visualization, the visual commonality between various emphasis effects is that some data points are made visually more *prominent* than other data points. For example, magnification, highlighting, and motion create emphasis on certain data points by making these data points more prominent than others (e.g., bigger, brighter, and moving). In particular, the data points in a visualization that has emphasis form groups or sets of differing visual prominence.

We define the foreground set of data points, F, as the data points that are most prominent in a visualization. The background set, B, is the set of data points that are least prominent in a visualization. Depending on the nature of the visualization and emphasis effect, there can be data points of intermediate prominence between F and B, and these data points form the midground set of data points, M. These sets of data points need not be mutually exclusive since a visualization can represent some data points multiple times. As an example of this, consider the overview+detail interface in Figure 1.

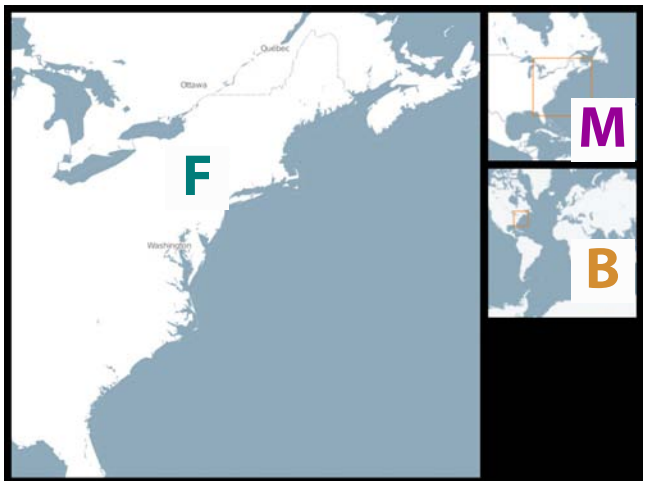

Figure 1: *F, M, and B characterize an overview+detail interface for a map (from www.unfoldingmaps.org). Here, F, M and B partially overlap as some data points are visible in more than one view. The most prominent visualized data points are in F, the least prominent ones in B, and the ones with intermediate prominence are in M.*

In Figure 1, some data points visible in F are also visible in M, and some data points visible in M are also visible in B. The data points common to multiple subsets (e.g., F and M) have multiple prominences. If there was no overlap between the three represented subsets of data (F, M and B), there would be no information in common between the three views. Therefore, F, M and B can be, but need not be, mutually exclusive.

We use this set-based terminology of F, M, and B to analyze visualizations from previous emphasis frameworks according to differences in data point prominence. The other factors we use for comparing previous frameworks are: 1) visual variables, and 2) the use of data suppression. Manipulating visual variables [Ber83,CM84,Mac86] can be used to create emphasis effects. Data suppression, i.e., choosing to not show certain data points in a visualization, can also create emphasis effects since data points that are not represented have no visual prominence and are consequently less prominent than the represented data. Therefore, we analyze the previous framework papers using the perspective of sets (F, M, and B), visual variables and data suppression. We summarize our analysis of previous frameworks and highlight the coverage of each framework in Figure 2. Figure 2 shows that 1) previous frameworks mostly focus on the visual variables *size* and *position*, and 2) only a few visual variables are discussed while some visual variables are never mentioned (e.g., motion and orientation). We group previous framework papers into three categories:

Magnification Papers that describe magnification emphasis effects, i.e., [CM01, LA94, Kea98, PCS95, SA82].

Beyond Magnification Papers that describe non-magnification emphasis effects, i.e., [CKB09, KMH02, Hau06].

Data Suppression Papers that focus on the creation of emphasis effects through data suppression, i.e., [Fur86, Fur06].

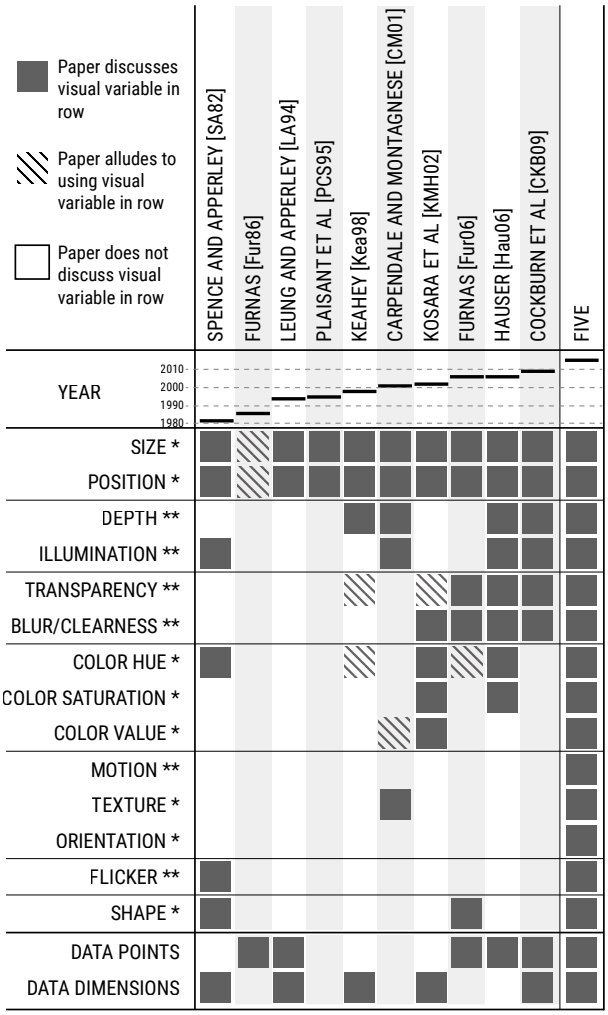

Figure 2: *Analysis of existing emphasis framework papers according to early and recent visual variables, chronologically ordered and grouped by similarities (using Bertifier [PDF14]) in terms of which visual variables the papers consider for creating emphasis effects. We demonstrate in this paper how FIVE can encompass any of these visual variables. Figure Legend: * early visual variables [CM84, Ber83, Mac86]; ** recent visual variables [War12]. Note that we interpret what Spence and Apperley referred to as pulsed illumination [SA82] as flicker.*

2.2. Magnification

The literature is full of work concerned with creating emphasis using magnification and distortion techniques. Therefore, instead of detailing all the specific techniques, we focus on the frameworks that encompass these techniques. Magnification and distortion techniques (e.g., polyfocal projections [KS78], Spence and Apperley's BiFocal Displays [SA82], Furnas' work [Fur86], or the Elastic Presentation Framework [CM01]) have generally been created to provide people with views (usually magnified) that assist in some data-oriented task in a visualization. This has led to many magnification techniques, such as constrained lenses [CCF95, KR96, SG07], Sigma Lenses [PA08] (which combine constrained lenses

with Magic Lenses [BSP*94]), Melange [EHRF08] (which makes use of compressing regions), and JellyLens [PPCP12] (which fits the lens to data regions). All of these techniques create expanded focal regions by compressing other regions, generating distortion. This strategy has been applied to many datasets and visualizations, such as trees [LRP95,MGT*03], graphs [GKN05,TAvHS06], tabular visualizations [RC94], calendars [BCCR04], text documents [RM93], flow visualizations [DHGK06], collaborative visualizations [VLS02], and lens-based approaches – see [TGK*14] for a review of interactive lenses in visualization.

Magnification is the result of varying the visual variables size and position in an interrelated manner to create an emphasis effect. F is the most magnified data subset, B is the least magnified subset, and M is the set of subsets of varying magnification between the magnifications of F and B. Magnification does not necessarily decrease monotonically as a function of increasing distances from F as is exemplified by polyfocal displays (e.g., see Fig. 5a in [LA94]). Figure 3 shows a magnification-based emphasis effect in the style of the Elastic Presentation Framework (EPF) [CM01]. Despite their visual similarities, researchers can approach magnification techniques from a variety of algorithmic perspectives. We briefly summarize the perspective from each framework that focuses on magnification: [LA94, PCS95, Kea98, CM01].

In 1994, Leung and Apperley [LA94] created a taxonomy for distortion-oriented presentation techniques. This taxonomy is for two-dimensional distorted images that are produced by applying a transformation function to an undistorted image. The transformation functions enlarge focal information compared to contextual information, but do not remove the context entirely (as would occur in a simple zoomed view). Instead, both the enlarged focal region and the reduced contextual region appear concurrently. The taxonomy is based on descriptions of the magnification functions for various distortion techniques.

Plaisant et al. [PCS95] provided presentational and operational taxonomies for browsing images. They focused on presenting an image at different magnifications, e.g., using an overview+detail display or zooming. This presentational taxonomy is divided into the static and dynamic aspects of presenting images. The dynamic aspects relate to ways of altering the magnification of the image, e.g., fixed zoom increments or continuous zooming. The static aspects of the taxonomy relate to spatial and temporal relations between the magnification levels provided to the viewer, e.g., the number of views and their coordination in an overview+detail interface. Fisheye views in this taxonomy are the result of using what Leung and Apperley [LA94] refer to as distortion-oriented techniques.

Keahey [Kea98] discussed the "generalized detail-in-context problem". He applied nonlinear magnification fields [KR97] to two dimensional data representations and discussed how designers can use the resulting increased space dedicated to magnified regions.

In 2001, Carpendale and Montagnese [CM01] introduced the EPF as a means of applying magnification to two-dimensional data representations. The EPF considers placing the data representation on a pliable sheet that can be deformed in three-dimensional space with respect to the viewpoint. This approach encompassed all previous magnification approaches and frameworks except those based

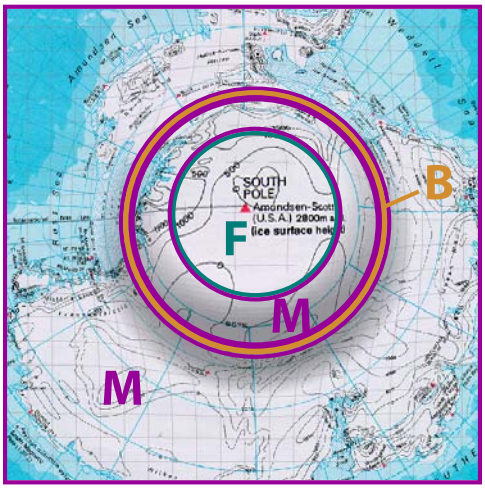

Figure 3: *F, M, and B regions in a lens-based magnification visualization of a map. The lens uses a Gaussian drop-off function in the style of the EPF [CM01]. The visualization uses a deformation of two visual variable (size and position) to make the data points in F more prominent than the ones in M and B. For this example, B is spatially between M regions, and corresponds to the inflection point in the Gaussian drop-off function. This example highlights how magnification need not decrease monotonically as a function of spatial distance from F. That is to say, there is not a strict spatial constraint on the relationship between F, M, and B.*

on Spence and Apperley's 1982 work [SA82] and some variations covered in Furnas' 1986 paper [Fur86]. EPF focused on the inclusion of multiple focal regions of varying shapes, and the drop-off functions used to create the transition, M, between the focal regions F, and the context B. Carpendale and Montagnese also incorporated lighting, shading, depth, and grid-based textures, to create more readable variations in magnification. Therefore, there are a variety of ways to create magnification emphasis effects, but all of them exhibit F, M, B.

2.3. Beyond Magnification

A few papers describe emphasis effects beyond magnification, i.e., emphasis effects using visual variables other than size and position (see Figure 2).

Kosara et al.'s taxonomy [KMH02] focuses on ways to make the data points comprising F more prominent compared to those of M and B instead of considering the relationships between F, M, and B. Their brief taxonomy divides emphasis techniques into three categories. *Spatial* methods make use of magnification to create emphasis effects and fall into the previous section. For *dimensional* methods and *cue* methods, F corresponds to what Kosara et al. call the "focus" region, and B is the "context." For a specific emphasis effect, M may or may not be empty. Figure 4 uses our set-based terminology to describe Kosara et al.'s blur function, which they introduce alongside their taxonomy.

Hauser [Hau06] proposed that focus+context is the unequal utilization of graphical resources between the focus and the context, by using space, opacity, color, frequency (i.e., image crispness),

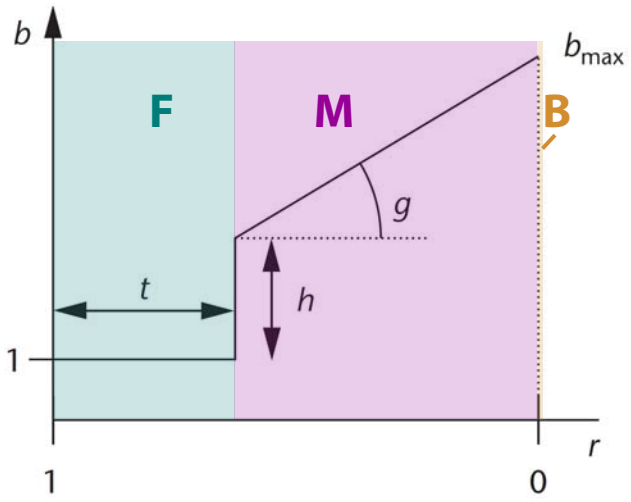

Figure 4: *Using our terminology to show how F, M, and B can be used to describe the blur function discussed in [KMH02]. The underlying graph is a facsimile that we have created to emulate Kosara et al.'s function [KMH02]. Here, $r \in [0,1]$ is the relevance value of a given data point. A data point is irrelevant if $r = 0$ and maximally relevant if $r = 1$. The blur value b is a function of r, and b depends on the threshold t, the step height h, the maximum blur diameter b_{max}, and the gradient g. In terms of sets, F consists of the data points with a relevance $r > t$; the most prominent data points in the visualization. B consists of the data point(s) with $r = 0$, the least prominent data points. M consists of the data points with a prominence between the most prominent ones and the least prominent ones, with decreasing prominence as r decreases.*

and rendering style. In this generalization of focus+context, Hauser suggests using a normalized *DOI* function that takes on a value of 1 for the focus and 0 for the context, with intermediate values in between. F corresponds to the data points with a *DOI* value of 1. B corresponds to displayed data points with the lowest *DOI* value – 0 if the entire dataset is shown. M is all of the displayed data points with a *DOI* value between that of B and 1. Hauser's generalization only uses of a subset of the possible visual variables to make F more prominent compared to M and B. There are additional ways to alter prominence, e.g., other visual variables, as Figure 2 shows.

Cockburn et al. reviewed overview+detail, zooming, focus+context, and cue-based techniques [CKB09]. The first three types of techniques are based predominantly on magnification. Cue-based techniques use differences in rendering styles (e.g., highlighting, blur, and visual proxies) instead of size to make some data points more prominent than others. This variation in rendering style provides a means by which the prominence of some data points can be altered. The most prominent data points are part of F, relative to other data points in the visualization, in M and B. To use blur as an example, when some data points are rendered crisply and others are blurry, the crisp data points are more readable than the blurry data points and the crisp data points form F. The most blurry data points form B, and depending on how the blur is varied across the visualization, M contains data points with intermediate blurriness, between that of F and B.

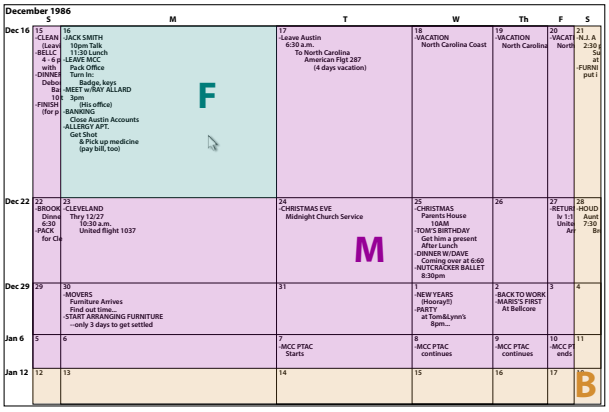

Figure 5: *This image is a facsimile that we have created to emulate Furnas' [Fur86] fisheye view of a calendar. F consists of the most prominent data point – Monday, December 16. B consists of the least prominent data points, and M consists of the data points with prominence between that of F and B.*

2.4. Data Suppression

In his seminal work on fisheye views [Fur86, Fur06], Furnas focused on which data points to represent rather than how to represent the chosen data points, and thus his work is more about data suppression. Furnas considers *DOI* functions as a way of deciding which data points a visualization should represent, i.e. *DOI* functions enable judicious choices about what data points to suppress. Data suppression relates to filtering, one of the earliest and most common emphasis effects in information visualization [Shn94, WS92].

Furnas explored the notion of fisheye views from the perspective of cognitive psychology. He came to the conclusion that an individual's recollections occur via the creation of emphasized subsets where individuals tend to recall items that are either of great *a priori* importance or of particular current relevance to them [Fur86]. Figure 5 shows Furnas' example of a fisheye calendar [Fur86] described using F, M, and B. Furnas defines the fisheye-DOI subset to be the set of points with a *DOI* greater than some cut-off value given the current focal point. The most general form of the fisheye-DOI is Equation 1 (in [Fur82] as cited by [Fur06]).

$$DOI_{FE}(x|.) = F(API(x), D(.,x)) \quad (1)$$

Here, the *DOI* of a point x (given the current focal point '.') is a function of the *a priori* importance of x, $API(x)$, and the distance between the focal point and x, $D(.,x)$. Furnas explains distorted views, zoom viewing, and multiple window views, i.e., view+overview or view+closeup, in terms of the fisheye-DOI subset [Fur06]. In particular, Furnas contends that such techniques show the same information, i.e., the fisheye-DOI subset, but in different manners. In this context, the fisheye-DOI subset is equivalent to $F \bigcup M \bigcup B$ and the different ways of representing the fisheye-DOI subset correspond to different ways of altering prominence to create F, M, and B.

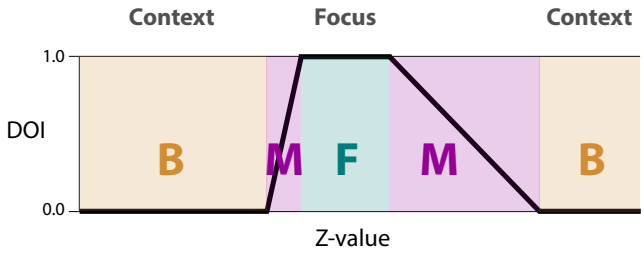

Figure 6: *This image is a facsimile that we have created to emulate the one-dimensional trapezoidal DOI function of Doleisch et al. [DHGK06]. The z values represent some attribute of the data points. Assuming that the visualization shows all of the data points, the z value of a data point determines whether it is part of the focus ($DOI = 1$) and therefore in F; part of the context ($DOI = 0$) and in B; or somewhere in between ($0 < DOI < 1$) and therefore in M.*

According to Hauser [Hau06], a *DOI* function is a function that returns a *DOI* value in $[0,1]$ for each data point, i, in a dataset. $DOI(i) = 1$ if i is part of the focus, $DOI(i) = 0$ if i is part of the context, and $0 < DOI(i) < 1$ if i is in between the focus and the context. As an example of this, Figure 6 shows the trapezoidal *DOI* function that Doleisch et al. describe [DHGK06]. *DOI* functions have also been combined within a single view and using fuzzy logic to create *DOI* functions describing features and sets of features [MKO*08].

In Furnas' work, the *DOI* function was not an end in itself. The *DOI* function was meant to be used with some threshold *DOI* value as a data filter to yield an appropriate fisheye-DOI subset [Fur06], i.e., a meaningful subset to be represented. Figure 7 is an annotated version of Furnas' example of viewing a list using a *DOI* function. This example makes it clear that deforming a representation is only one way to create an emphasis effect. Other ways to create emphasis effects include using visual cues and data suppression. The commonality between these possibilities is that they can all be described using F, M, and B.

In Figure 7, an original ordered list of letters (a) is viewed through different fisheye views (e–i) according to a *DOI* function (d) that is the sum of an A Priori Importance (API) function (b) and a distance (Dist) function (c).

In Figure 7(a), all the data points (elements of the list) are visible, and all data points have equal prominence as no data point is emphasized. In this case, all data points belong to F, with $M = B = \emptyset$.

Figure 7(e) is the subset of Figure 7(a) that shows only the elements of the list that have a fisheye-DOI value greater than a threshold; this threshold is indicated by the thin vertical line in Figure 7(d). In this first subset, the fisheye list is created using data suppression, i.e., elements in the list whose fisheye-DOI is lower than the threshold are suppressed from the visualization. Because all represented elements have the same prominence (in terms of font size), all visible elements belong to F. Since the visualization represents no elements with another level of prominence, $M = B = \emptyset$.

Figure 7(f) represents the same elements of the list as Figure 7(e), thus the same data suppression. However, in this case, the geometry is distorted, bringing all data points of F together. Again, $M = B = \emptyset$.

Figure 7(g) re-introduces information about the fact that data points in F are spatially distant. In this case, the elements in B are the letters between B and L and the letters between N and Y, which are represented using elision markers "...". In (f), we still have $M = \emptyset$.

Figure 7(h) differs from Figure 7(e,f,g) in that all data points are visible, but their sizes are distorted according to their *DOI* values. F consists of the biggest letters (simply, the letter M in this case). B consists of the smallest letters (letters D and V). M consists of all the remaining letters.

Figure 7(i) consists of the same F, M and B as in Figure 7(h), but in Figure 7(i) the data points are moved together. Note that most of the subsequent work based on Furnas' fisheye views has focused on presentations similar to that of 7(i), which distort data points rather than simply suppressing data.

2.5. Previous Frameworks Summary

All of the reviewed emphasis frameworks have proven useful in information visualization research, with each being the inspiration for more than one subsequent emphasis technique. However, while some of the frameworks describe overlapping types of emphasis, none successfully describe all current emphasis variations. For example, while EPF [CM01] describes most magnification or distortion approaches, it does not encompass Spence and Apperley's original work [SA82]. Similarly, Hauser's approach, based on Furnas' *DOI* function, includes a large part of the spatial and cue based approaches, but does not cover some of the possibilities in EPF. Despite the algorithmic and visual diversity of the emphasis effects found in previous frameworks, visual prominence and subsets (F, M and B) are a common language for describing these effects as Figure 7 accentuates.

3. Describing Classes of Emphasis Effects

We now expand on our analysis of previous frameworks by describing F, M and B for classes of emphasis effects. To reasonably cover the extensive emphasis literature, we select pertinent examples to illustrate that visual prominence provides a conceptual bridge between emphasis effects. For example, it is a common descriptive language for the visually distinct emphasis effects of zooming and highlighting.

Before proceeding, we introduce time variation as a new descriptor of emphasis. For example, time variation is a key difference between zooming and highlighting. Zooming and motion-based animations are emphasis effects that are based on time variation in the appearance of the visualization, e.g., items get bigger or smaller depending on the current level of zoom. In contrast, traditional highlighting is a static emphasis effect since the appearances of both the highlighted and non-highlighted data points do not change with time – interactively changing the highlighting results in a new emphasis effect. Therefore, we introduce the terms *time invariant emphasis effect* for an emphasis effect that does not use temporal variations in visual representations to achieve emphasis, and *time variant emphasis effect* to refer to emphasis effects that do leverage temporal variations in visual representations to achieve emphasis.

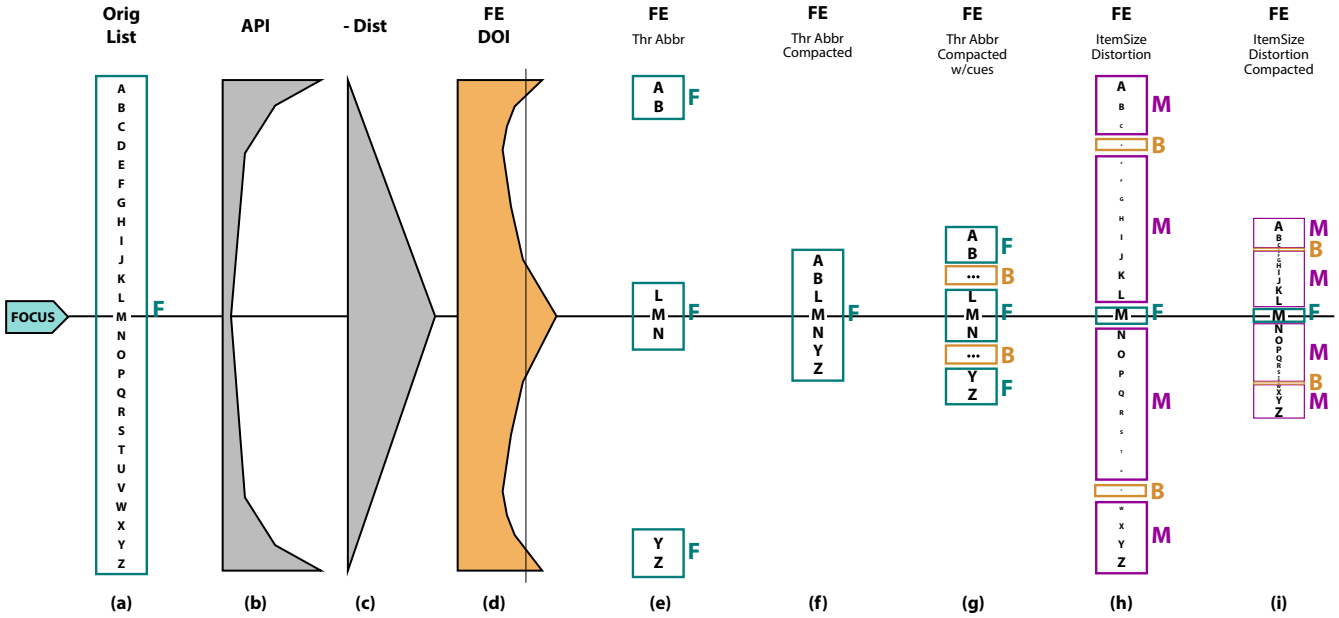

Figure 7: *This image is a facsimile that we have created to emulate Furnas' selection vs. distortion discussion for a fisheye view of a list [Fur06], annotated with F, M, and B. (a) is the original ordered list. (b) is an A Priori Importance (API) function over the list. (c) is a distance (Dist) function from the focus. (d) shows API + Dist, i.e. the sum of the A Priori Importance function and the Distance to focus function. (e,f,g,h,i) are possible Fisheye-DOI subsets representations that can be built based on the additive fisheye-DOI function in (d).*

3.1. Time Invariant Emphasis Effects

An emphasis effect can be the result of using one or more visual variables to alter the visual prominence of data points. A time invariant emphasis effect does not change with time. That is to say, it does not make use of such features as fade-in, fly-in, wipe and other forms of temporally based transitions. Examples of time invariant emphasis effects include: highlighting, blur, overview+detail and lens-based techniques, though one could incorporate temporal variation into these effects.

Highlighting: Highlighting, or coloring, a data point in a visualization emphasizes that data point. Coloring usually makes use of the visual variable hue and is often used in brushing and linking scenarios [BMMS91]. For example, in a scatterplot matrix visualization, brushing several points in a scatterplot will change their hue in that scatterplot and the linked scatterplots to emphasize the connection between brushed points [BC87].

Figure 8(a) illustrates highlighting one data point in a scatterplot. The red dot becomes the most visually prominent data point in the visualization. In Figure 8(a), color is the strongest indicator of the visual prominence of the data points. Therefore, F is the set of colored dots, and B is the set of black dots. M is an empty set, $M = \emptyset$, since the highlighting in Figure 8(a) is binary.

Blurring: Photographers have created depth of field effects based on blur for a long time. In photos involving depth of field effects, only part of the image is in focus while the rest of the image is out of focus and blurred. In the geographic visualization community, researchers have exploited blur to communicate uncertainty [Mac92]. Kosara et al. [KMH02] proposed a semantic version of depth of field as a means of emphasizing a subset of a dataset. Figure 8(b) illustrates this approach where one dot in a scatterplot is shown crisply while the others are blurred. Here, the crispness/blur is the major contributor to the differences in the visual prominence of data points in agreement with the result of depth of field effects in photography. F is the data point that is not blurred and B is the data points contained in the blurred portion of the visualization. If there are varying degrees of blurriness, then B will be the most blurred data in the visualization, M will be the series of subsets of data that are increasingly less blurry, and F will be the least blurry subset of data. Given that the blurring in Figure 8(b) is binary, Figure 8(b) only involves F and B. Figure 8(c–f) show examples of emphasis effects that can be created in a similar fashion by manipulating other visual variables.

Overview+Detail: Overview+Detail is an emphasis effect where the visual variables size and position are manipulated in order to create several views of a dataset such that different views have different magnification values. Figure 1 shows the overview+detail technique for a map. The differences in the magnification values of the views causes data points in different views to have differing visual prominence. In Figure 1, F is the set of data points in the view with the highest magnification. B corresponds to the data points in the view with the lowest magnification. M constitutes the data points in the view with intermediate magnification. In Figure 1, the subsets F, M, and B overlap, i.e., they are not mutually exclusive. If there was no overlap between the three subsets, there would be no information in common between the three views.

Lens-based views: Similar to overview+detail, lens-based views, e.g., focus in context, make use of size and position to vary the magnification of data points, which in turn causes the data points to have varying visual prominence. Figure 3 is one exam-

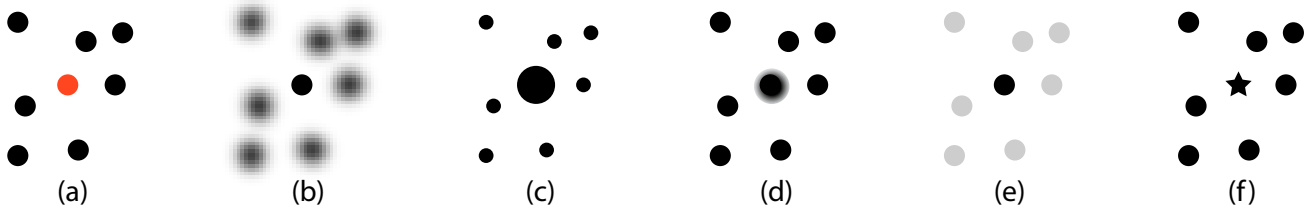

Figure 8: *An emphasis effect created in a scatterplot by using (a) highlighting in red, (b) blurring, (c) size/area, (d) depth, (e) transparency / value, and (f) shape. In all cases, only one data point is emphasized, e.g., in (a) F is the only data point coloured red, B is the set of black data points, and $M = \emptyset$.*

ple of such focus-in-context lens-based views as applied to a map. As with overview+detail, F corresponds to the region of highest and uniform magnification, i.e., the focus. B is the least magnified portion of the image. Finally, M is the regions of the image with magnifications between that of F and B. The regions comprising F, M, and B need not be continuous (e.g., see Figure 3). For the visualization in Figure 3, M can be further subdivided according to the differences in the magnification values, i.e., visual prominence, of data points within the drop-off region.

3.2. Time Variant Emphasis Effects

In contrast to time invariant emphasis effect, time variant emphasis effects involve time variations. For example, animations that emphasize the appearance or disappearance of items are time variant emphasis effects. For some emphasis effects, the data points that exhibit time varying behavior, e.g., flickering, are most visually prominent, i.e., F. For others effects, time is used to segregate views in which data points have differing visual prominence, e.g., zooming. Here we describe some classes of time variant emphasis effects.

Zooming: Zooming is an emphasis effect where views are separated temporally instead of spatially [CKB09]. Because of the temporal separation, human memory plays a role in the creation of emphasis effects based on zooming. For example, Figure 9 illustrates zooming in on the city of Calgary using Google Maps. In this example, an emphasis effect is created by varying magnification over time and perhaps by adjusting the labeling of the map. If one considers only the magnification component of the emphasis effect, B is the data subset in the most zoomed out view; F the data subset in the most zoomed in view; M is comprised of the intervening zoom states between F and B. Similar to overview+detail, F, M, and B overlap, i.e., they are not mutually exclusive.

Assuming spatial zooming, the emphasis effect involves viewing subsets of the dataset with increasing magnification, i.e., varying the visual variables size and position with time. One could imagine an abrupt change from B to F without the use of any intervening views, i.e., $M = \emptyset$. Such a sudden change does not produce the smooth, gradually changing image that a viewer may expect while zooming. The degree to which a zoom appears to be discrete or continuous depends on the number of intervening views between F and B, i.e., the number of prominence subgroups comprising M.

Motion: Motion is a powerful emphasis effect where moving objects are emphasized relative to stationary ones. Bartram et al. found that using motion to emphasize icons resulted in fewer undetected icons compared to using color [BWC03]. Similarly, Ware and Bobrow [WB04] found that using motion to emphasize subgraphs within a graph was more effective than a static highlighting method. Motion is an emphasis effect that varies the visual prominence of data points by varying the positions of data points with respect to time.

For example, consider an interactive node-link representation of a graph where selecting one node causes nearby nodes to oscillate while the other nodes remain stationary. The set of nodes that oscillate are the most visually prominent nodes, i.e., they form F. The set of nodes that remain stationary are the least visually prominent nodes during the effect, i.e., they constitute B. Because of the binary nature of motion in this example, there is no set of data points with intermediate visual prominence between that of the oscillating and stationary nodes, i.e., M is an empty set.

Flickering and Pulsing: Flickering is the cyclic variation of an object's transparency over time. Pulsing is the cyclic variation of an object's size over time. Consider flickering or pulsing data points in a scatterplot. The most visually prominent data points, i.e., F, are those that are flickering or pulsing. The data points that are not changing their appearance with time are less visually prominent, and consequently form B. Once again, M is empty for both flickering and pulsing. Note that motion, flickering, and pulsing can simply be described in an unifying way: in all cases, the emphasis effect is created by changing the value of a visual variable (position, transparency, size) over time.

3.3. Emphasis Effect Descriptors

In the previous subsections, we described important classes of emphasis effects in the common language of visual prominence, and broke down examples from these classes into F, M and B. Through this process, three additional descriptors of emphasis effects became apparent: 1) time variant vs. time invariant, 2) degree of continuity, and 3) multiple representations of data points. In this subsection, we summarize these descriptors, and relate them to F, M and B.

Time Variant vs. Time Invariant: Emphasis effects may or may not leverage time to vary the visual prominence of data points to create F, M, and B (as described in Sec. 3.1 and 3.2. above).

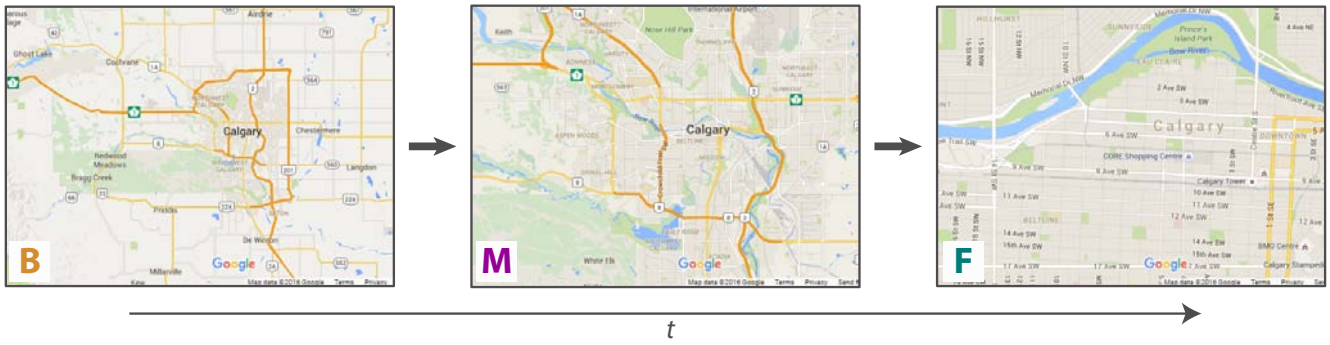

Figure 9: *Zooming in on Calgary, Canada using Google Maps. Map data: Google. The time arrow indicates that the viewer is zooming in as time progresses. The views show how the viewer is transitioning from B to M and then from M to F. Even though the views are temporally dispersed, they all contribute to the emphasis effect that the viewer experiences.*

Degree of Continuity: In terms of visual prominence, the continuity of the transition between F and B, as captured by M, can vary. For example, M can be empty for binary style emphasis effects, e.g., traditional highlighting. M may correspond to a subset of data points that have a common visual prominence, from the perspective of the emphasis effect, as in the overview+detail example shown in Figure 1. Alternatively, M can contain multiple subsets of data points that differ in terms of their visual prominence (e.g., the lens drop-off region in Figure 3), but are nevertheless bounded by the visual prominence of data points in F and B. More continuous transitions between F and B involve increasing numbers of visual prominence subsets comprising M.

Multiple Representations of Data Points: F, M and B are not necessarily mutually exclusive, though they are mutually exclusive for most emphasis effects. Zooming and overview+detail are examples of emphasis effects where data points are represented multiple times in different views, and consequently have multiple visual prominences.

These emphasis effect descriptors and the sets F, M, and B provide a basis for comparing emphasis effects. As an example of this, consider a three-level discrete zooming interface (e.g., Figure 9), and a three-level static overview+detail view (e.g., Figure 1), both using the same representation of a map. By considering three-level versions of each visualization, we are ensuring that the degree of continuity is the same for both, i.e., the number of visual prominence subsets between F and B is the same for both. Both techniques also involve multiple representations of data points. However, they differ in that zooming is time variant while overview+detail is time invariant. For zooming, the multiple representations of a particular data point are spread out over time while they are spatially separated in overview+detail.

Zooming and overview+detail could use identical or different levels of magnification for F, M, and B. If the two techniques have differing magnification levels for any of F, M, or B, then the relative changes in visual prominence can differ for the two techniques. If the techniques have the same magnification levels for F, M, and B, then one can consider whether or not the two techniques involve the same or different F, M, and B subsets. Normally, zoom interfaces have F, M, and B occupy the entire screen. In contrast, overview+detail interfaces generally divide the screen into different regions that are allocated to F, M, and B. Because magnification is inherently tied to screen space, the views for each technique cannot have the same magnification and show the same data while simultaneously occupying different amounts of screen space. Thus, the data points that comprise F, M, and B must differ for the two techniques. Therefore, zooming and overview+detail are closely related, but zooming is not just a time separated version of overview+detail. This example shows how F, M, and B as well as temporal variation can be used to both describe and conceptually compare emphasis effects.

4. Intrinsic vs Extrinsic Emphasis Effects

Previous frameworks have typically not considered the emphasis that is implicit in the original visual mapping chosen for a visualization. However, as we discuss in this section, differences in prominence due to the original visual mapping are not always negligible, and can even interfere with emphasis effects. To take this into consideration, we introduce the concepts of: 1) *intrinsic emphasis effects* – the baseline prominence differences between data points resulting from the initial visual mapping process when creating a visualization, and 2) *extrinsic emphasis effects* – changes in the prominence of data points resulting from applying visual effects on top of existing visualizations. Figure 10 (a) illustrates the concepts of intrinsic and extrinsic emphasis effects as a data point in a scatter plot undergoes highlighting. The original visualization at the top left of Figure 10 has a position-based intrinsic emphasis effect while the visualization on the right now has a highlighting, i.e., an extrinsic emphasis effect. In this case, the initial intrinsic emphasis effect is both weak and distinct from the extrinsic emphasis effect.

4.1. Intrinsic Emphasis Effects

Mapping data dimensions to visual variables [Ber83, CM84, Mac86] results in data points having varying visual properties (e.g., color, size and position). This means that the visual mapping process alone will create initial differences in the visual prominence of data points. Therefore, a visual representation of a dataset involves an intrinsic emphasis effect before any subsequent alterations to visual variables are applied (e.g., magnification or highlighting during brushing and linking).

For example, consider the intrinsic prominence differences between visual features on a map. Cartographers generally represent longitude and latitude, or some projection thereof, using position. Water is represented as blue regions while land masses are colored to indicate countries or terrain. The cartographer (or a designer creating a visualization) will rely on their considerable skills, their experience and the intent of the map when make these choices. The cartographer's choices determine the intrinsic emphasis effect in the map.

4.2. Extrinsic Emphasis Effects

Extrinsic emphasis effects are additional visual variations applied on top of an existing visualization (which has its own intrinsic emphasis effect) to create further variations in prominence.

Consider altering one or more visual variables of a given visual representation in order to create an extrinsic emphasis effect on top of the intrinsic emphasis effect. Assuming that the changes in visual prominence stemming from an extrinsic emphasis effect are sufficiently strong (e.g., color highlighting), one can consider that the intrinsic emphasis effect is negligible in comparison. In this case, one can focus solely on how the visual prominence of the data points is affected by the changes in the visual variables used to create the extrinsic emphasis effect.

For example, consider the map shown in Figure 3. A lens-based distortion has been applied to an image, i.e., the distortion is an extrinsic emphasis effect applied on top of the existing intrinsic emphasis effect present in the map. If one focuses on magnification and not the details of the map, then the most visually prominent region in the image is the central flat region of the lens, and so this region is F. B is the least magnified region. M consists of the regions of intermediate magnification.

In this example, the intrinsic and extrinsic emphasis effects are easily distinguished, i.e., we can easily see F, B and M for the lens while also still interpreting the map. Previous frameworks have assumed that the intrinsic emphasis effect is negligible compared to the extrinsic emphasis effect; however, this may not always be the case, as we discuss in the next subsection.

4.3. Conflicting Intrinsic and Extrinsic Emphasis Effects

We describe two examples where intrinsic and extrinsic emphasis effects are in conflict and we discuss the implications of such conflicts. The first example uses a simple scatterplot visualization and shows how the intrinsic emphasis effect constrains the available choices for creating efficient extrinsic emphasis effects. The second example uses a more complex study [CDF14] and shows how considering intrinsic and extrinsic emphasis effects can explain study results.

We start with a simple example illustrated in Figure 10: highlighting a point in a scatterplot. In Figure 10(a), data points are mapped to x and y to create the initial visualization. In Figure 10(b), data points are mapped to x, y and *color* to create the initial visualization.

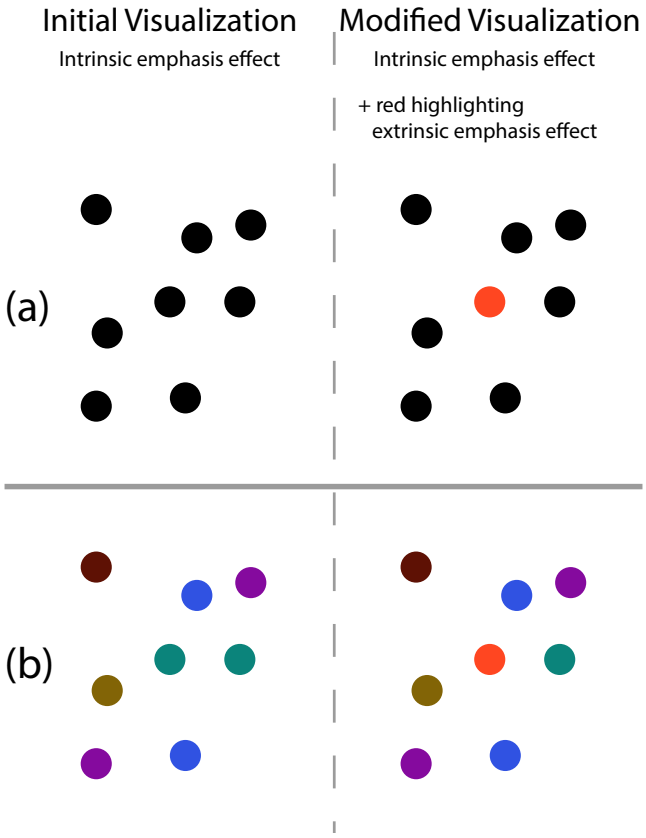

Figure 10: *Potential conflicts between extrinsic and intrinsic emphasis effects. (a) shows a scatterplot where only the visual variable position is used to encode data point properties. In (b) hue is used in addition to position to encode additional information. The extrinsic emphasis effect that consists of highlighting the point in the center in red makes this point much more prominent in (a) while it fails at making this point much more prominent in (b). This is because the intrinsic emphasis effect in (b), using the visual variable hue, conflicts with the extrinsic emphasis effect, which also makes use of hue.*

The success of an extrinsic emphasis effect is dependent on the already existing intrinsic emphasis effect in a visualization. For the two initial visualizations in Figure 10, consider highlighting a single point. In Figure 10, the extrinsic emphasis effect consists of highlighting a data point by changing the data point's color to red, using the visual variable hue. In Figure 10(a), this extrinsic emphasis effect is successful as it makes the emphasized data point much more prominent than other data points. In this case, F, M and B are easily identifiable: the red dot is the most prominent data point, the black dots are the least prominent data points, and $M = \emptyset$. In contrast, in Figure 10(b), this extrinsic emphasis effect is not as successful. The intrinsic and extrinsic emphasis effects are in conflict because both make use of the same visual variable (hue). As a result, F, M, B are not straightforward; in particular, we cannot assume that F is the data point to which the extrinsic emphasis effect has been applied.

As a more advanced example of competition between extrinsic and intrinsic emphasis effects, we explain the results of Chevalier et al.'s study [CDF14]. This study compares the effects of staggered and non-staggered animations on a tracking task during the re-arrangement of dots on a 2D plane. In the non-staggered condition, dots move synchronously. In the staggered condition, an incremental delay in start times across the moving elements is introduced. Figure 11 illustrates this experiment.

Trials for both conditions consist of three phases. In Phase 1, dots appear on a 2D plane, and some dots are highlighted, e.g., the red dot. In Phase 2, this highlighting disappears. In Phase 3, an animation (either staggered or non-staggered) takes place where the dots rearrange to a new configuration. Both types of animation use slow-in/slow-out effects for the motion of the dots, and all dots move the same distance. At the end of Phase 3, participants have to identify the originally highlighted dots.

The intrinsic emphasis effect in each trial arises from the initial positions of the points on the 2D plane (i.e., from the visual variable position). Phase 1 consists of applying an extrinsic emphasis effect using the visual variable hue on top of the intrinsic emphasis effect. For this extrinsic emphasis effect, F and B are the sets of colored and black dots, respectively. In Phase 2, this extrinsic emphasis effect is removed, and participants must try to mentally maintain the original hue-based F and B, which may conflict with the position-based intrinsic emphasis effect for the set of data points. The dots then begin to move to their new locations, with either a staggered or a non-staggered animation. Finally, at the end of the animation, the dots have new positions on the 2D plane, which result in a new intrinsic emphasis effect.

Given that the points in Chevalier et al.'s study are in a 2D Cartesian environment, we can express the speed of the points, v, as $v = \sqrt{\left(\frac{dx}{dt}\right)^2 + \left(\frac{dy}{dt}\right)^2}$. In the non-staggered condition, the dots have the same speed at each point in time, i.e., v is constant across the points, and v varies with time according to the chosen slow-in/slow-out effect. However, the dots are moving in different directions, so $\frac{dx}{dt}$ and $\frac{dy}{dt}$ vary across the points. These differences in the x and y speeds create a new time-variant extrinsic emphasis effect based on motion. There is no guarantee that this extrinsic emphasis effect will align with the original position-based intrinsic emphasis effect or the previous hue-based extrinsic emphasis effect. Therefore, there are possibly several different F subsets that the viewer sees during the experiment, and the viewer is supposed to be able to pick out the points that comprised F for the color-based extrinsic emphasis effect. From the perspective of competing emphasis effects, the dot tracking task is nontrivial.

In the staggered condition, dots start moving at different points in time, so v is not the same for all of the dots at each point in time. This means that there is an even greater diversity in the movement of the dots during the staggered animations compared to the non-staggered animations. This greater diversity could lead to stronger motion-based emphasis effects, which would only be helpful in tracking and differentiating the original hue-based F when these staggered animations make the original F subset visually prominent relative to other data points in the visualization. The stronger emphasis effects of staggered animations would be detrimental if they increased the visual prominence of other dots relative to those in the original hue-based F as they would just increase the difficulty of the dot tracking task. This can explain Chevalier et al.'s observations that staggering was only marginally beneficial in some cases and detrimental at times compared to their non-staggered animation technique. The complexity of emphasis effects at play during the staggered animations is greater than during non-staggered animation, so there are more opportunities for viewers to encounter problems with tracking the dots.

A staggered animation for a set of dots moving between two configurations would result in particular F, M and B subsets, i.e., a particular emphasis effect. This animation would only be beneficial for tracking the subset of the dots on a 2D plane that the animation makes visually prominent. Given that Chevalier et al. optimized some of their staggered animations for the dots that were highlighted in Phase 1, we can expect that those particular staggered animations are only beneficial for tracking the dots for which the animations were optimized. This aligns with Chevalier et al.'s finding that their staggered animations only reduced task complexity for their arbitrarily chosen targets, i.e., dots highlighted in Phase 1 of a trial.

Visual prominence subsets (F, M and B) provide a new perspective on Chevalier et al.'s experiment - that of competing intrinsic and extrinsic emphasis effects. Based on this, we have provided an explanation of the previously-unexplained results of Chevalier et al.'s study – that is, why staggered animation was not found particularly useful for their tracking task. Given that position and speed are intimately related (the latter is the time derivative of the former), Chevalier et al.'s animation-based emphasis effects are intertwined with the position-based intrinsic emphasis effects amongst the dots. However, hue does not necessarily couple to either position or motion. Therefore, it should come as no surprise that it is difficult to recall and follow the F of one extrinsic emphasis effect when there are other powerful emphasis effects at play that are coupled to each other. While the community has previously implicitly assumed that extrinsic and intrinsic emphasis effects are separable, this analysis shows how interactions between extrinsic and intrinsic emphasis effects are important. Our analysis of Chevalier et al.'s work also highlights that the concepts of F, M, B, intrinsic emphasis effects, and extrinsic emphasis effects are tools that researchers can use to analyzing existing visualization literature.

5. Generating a Visualization with Emphasis

We have shown how the data points in a visualization can be divided according to visual prominence to create subsets (F, M and B) and that these subsets serve as a basis for describing and comparing emphasis effects. We have also introduced a set of related concepts: time variant vs. time invariant emphasis effects, degree of continuity, multiple representations of data points, and intrinsic vs. extrinsic emphasis effects. In this section, we leverage these concepts to provide a three-step process for generating visualizations with extrinsic emphasis effects:

1. Determine an initial representation of the data.
2. Determine the contents of the sets F, M and B
3. Select a means by which to vary the prominence of data points and differentiate F, M and B in the representation of the data.

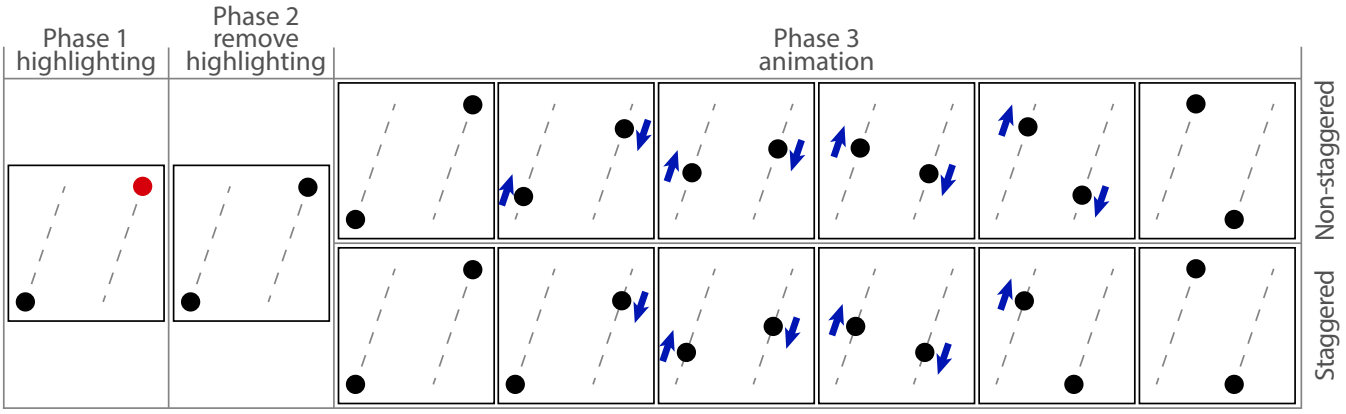

Figure 11: *An illustration with two dots of Chevalier et al.'s staggered vs. non-staggered animation experiment [CDF14]. The dashed lines indicating the trajectories of the dots and the arrows indicating if a dot is moving in a particular frame were not visible in the experiment. Note that Phase 1 and 2 are the same for both animation types.*

Step 1 yields a visualization with an intrinsic emphasis effect. Taken together, steps 2 and 3 create an extrinsic emphasis effect. For each step, we illustrate the advantages of using the concepts that we have introduced in the previous sections.

5.1. Determine an Initial Representation of the Data

By differentiating between intrinsic and extrinsic emphasis effects, it is clear that the initial representation of a dataset contains an emphasis effect before any subsequent explicit emphasis effect, e.g., a lens-based effect, is applied. Determining an initial representation for any dataset is a standard task in information visualization where a visualization designer maps data dimensions to visual variables. An appropriate initial representation depends on the nature of the data, the tasks that are to be performed, and the characteristics of the people using the data. As an example of the complexity that an initial visualization can involve, consider visualizations of streaming data. Visualizations of streaming data can involve a variety of visual changes depending on: 1) how data points are mapped to visual variables, and 2) whether or not data points can appear/disappear in the visualization (see Cottam et al.'s taxonomy [CLW12]). However, the choices made here, e.g., the visual variables used for the visual mapping process, will constrain subsequent extrinsic emphasis effects and subsequent manipulations of the visualization.

5.2. Determine the Content of F, M and B

As a visualization designer populates F, M and B, the designer is choosing *what* the extrinsic emphasis effect will emphasize. Using these sets as a basis for constructing extrinsic emphasis effects has the advantage that either set operations, functions (which are defined in terms of sets), or some combination thereof can be used to specify what should be emphasized in a visualization.

DOI functions are typically the basis of focus-and-context emphasis effects. A designer could use *DOI* functions in conjunction with thresholds to populate F, M and B in our framework. There is a long history of using functions to create magnification effects [CM01, Kea98, LA94] (see Figure 3). Furnas' work with *DOI* functions provides classic examples of using functions in conjunction with thresholds to create subsets, specifically the fisheye-DOI subset [Fur86, Fur06] (see Figure 7).

Alternatively, F, M, and B could be populated by applying set operations to pre-existing sets. These pre-existing sets could be intrinsic to the dataset as with set-typed data. Alsallakh et al. discuss set-type data in a recent survey of visualizations for sets [AMA*14].

When defining F, M and B, a key consideration is the degree of continuity between F and B. If a designer wants F to be very prominent relative to the other data points in the visualization, then they may opt to have M empty, i.e., there is no intermediate prominence between F and B. This is the case for the emphasis effects in Figure 8. Alternatively, a designer may want a more gradual transition between F and B, in which case the cardinality of M will have to increase and the designer will have to define an increasing number of subsets of data points to comprise M. A designer does not have to explicitly define the subsets of M. For example, consider how the lens-based visualizations of the EPF [CM01] use functions to magnify data points (as illustrated in Figure 3) and how Keahey's work [Kea98] uses fields to magnify data points. These techniques specify the magnification of each data point, and implicitly F, M, and B form based on magnification even though the techniques themselves do not explicitly create the F, M, and B subsets. Implicit definitions of F, M, and B may not provide the same level of control as explicit definitions.

A second important point is how F, M and B overlap. If the designer wants to provide a person with multiple views on a dataset, then overlap in these views can be useful to, for example, show connections between the views. As such, the designer will have to represent some data points multiple times in the visualization, and so F, M and B will overlap. The designer needs to decide which data points will be common between F, M and B either explicitly (e.g., using a data point as reference point and making it common to F, M and B), or implicitly (e.g., as with zooming and overview+detail).

5.3. Varying Prominence to differentiate F, M and B

As a designer chooses how to representationally vary F, M, and B, the designer is deciding *how* the viewer will experience the data points in F as being more visually prominent than those in M and B. We highlight some of the new options for extrinsic emphasis effects, i.e., some alternative ways to make the data points in F more prominent than those M and B. A designer will have to consider many context-dependent factors when creating an extrinsic emphasis effect for a visualization (e.g., what visual variables the visualization already uses and the nature of the intrinsic emphasis effect). Consequently, we do not attempt to cover all cases but instead provide some recommendations about varying prominence to differentiate F, M and B.

The increased visual prominence of F relative to B is related to the extent to which the representations of F and B differ in terms of the visual variable the designer chooses for creating the extrinsic emphasis effect. For example, when using size, the difference in the visual prominence of the data points in F and B depends on the magnitude of the size difference between the respective data points in F and B. Just-noticeable differences [SJ10] could be used to provide indications about what are the minimum changes needed in a visual variable in order for a change in that visual variable to be noticeable to a viewer. Note that the visual encoding process in step 1 (creating an intrinsic emphasis effect) limits which visual variables remain available for differentiating F, M, and B (when creating an extrinsic emphasis effect), as we discussed in Section 4.3.

Some visual variables and combinations of visual variables remain underexplored for creating emphasis effects (e.g., texture and orientation as shown in Figure 2) even though even though these visual variables strongly affect perception. Exploring the full set of visual variables and their time variation (e.g., varying either orientation or texture with time) may open up new and exciting emphasis effects. If some visual variables are less overtly noticeable but still interpretable upon inspection, further work could develop "attention-based emphasis". That is to say, emphasis effects that are unobtrusive unless someone is specifically considering a particular visual variable; this would leverage the principle that sensitivity to perceptual features is heightened with attention [Nei76, War12]. Also, when a visualization does not already use all visual variables, a designer can leverage the non-utilized visual variables to reinforce an extrinsic emphasis effect.

Lastly, different visual variables may be more or less effective at creating extrinsic emphasis effects depending on what other visual variables are in use. For example, motion is a powerful means of creating emphasis effects; however, in visualizations where position has meaning, large-scale motion effects could lead to erroneous interpretations of the dataset. A designer needs to be aware of potential interactions between visual variables when creating extrinsic emphasis effects, and assessing such interactions should be part of the community's research agenda.

6. FIVE: Framework for Information Visualization Emphasis

In the previous sections, we analyzed previous emphasis frameworks and a wide variety of emphasis effects. We showed how the visual prominence subsets F, M, and B are a basis for describing, comparing and generating emphasis effects. In this section, we provide a mathematical framework that captures F, M, and B. Previous frameworks have provided mathematical formalisms (e.g., [CM01, Fur86, Hau06, LA94]). Mathematical formalism are powerful because they aid researchers and designers as they analyze, describe, compare, generate and implement emphasis effects. Our analysis of emphasis effects has revealed five general features of emphasis effects, which we now summarize.

General Features of Emphasis Effects:

GF1 A wide variety of visualizations can be described in terms of subsets of data points of differing visual prominence (i.e., F, M, and B).
GF2 There are time variant and time invariant emphasis effects.
GF3 Some emphasis effects represent data points multiple times, i.e., there can be overlap between F, M and B.
GF4 Emphasis effects have varying degrees of continuity between F and B, i.e., varying numbers of intermediate levels of visual prominences comprising M.
GF5 There are both intrinsic and extrinsic emphasis effects, which can interact with one another.

We now introduce an emphasis framework that captures these general features and the prominence subsets F, M and B.

6.1. The FIVE Mathematics

Let p be the prominence of the visual representation of a data point such that a high value of p coincides with a more prominent data point and a low value indicates a less prominent data point. Let p be null for a data point that is not represented. An emphasis effect is the result of either representing a dataset such that data points have varying p (e.g., highlighting dots in a scatterplot), or representing only a subset of a dataset (e.g., zooming in on a particular city in a map).

In order to formally demonstrate this, we first define the absence of emphasis. Let D be the set of data points in a dataset. Let P_d be the set of p values associated with $d \in D$ for a given representation of D. $d \in D$ can have multiple p values because some techniques involve representing data points multiple times, e.g., overview+detail or zooming. By allowing data points to have multiple p values and representations, we are laying a foundation for supporting **GF3**.

A representation does not involve an emphasis effect when there are no differences in the P_d sets associated with the data points in D, i.e., $\forall a \in D \wedge \forall b \in D : P_a = P_b$. As soon as data properties are mapped to visual variables, then $\forall a \in D \wedge \forall b \in D : P_a = P_b$ is not satisfied. A representation that satisfies $\forall a \in D \wedge \forall b \in D : P_a = P_b$ may not be useful, and may be difficult to construct. However, at the very least, this condition can be satisfied for a dataset containing a single data point because $|D| = 1 \Rightarrow a = b$.

As DiBiase et al. [DMKR92] have pointed out, a viewer takes time to survey a data representation even if the representation is static, and animation can emphasize different aspects of a dataset. Therefore, we define an emphasis effect with respect to an interval of time. A representation involves an emphasis effect when a representation of a dataset has the property that $\exists a \in D \wedge \exists b \in D | P_a \neq P_b$ for some time interval $[t_E, t_E + \Delta t_E]$, with t_E being the time at which the emphasis effect is created and Δt_E the duration of the emphasis effect. By defining emphasis effects over intervals of time, we are supporting the consideration of both time variant and time invariant emphasis effects, i.e., supporting **GF2**.

There are two ways of satisfying $\exists a \in D \wedge \exists b \in D | P_a \neq P_b$. Let R and N be the sets of data points that are represented and not represented, respectively, during the time interval $[t_E, t_E + \Delta t_E]$. The two ways of creating emphasis are:

1. Only a subset of the dataset is represented.
$R \subset D \Rightarrow N \neq \emptyset$. Indeed, in this case, $\exists a \in D | P_a = \emptyset$ and $\exists b \in D | P_b \neq \emptyset$, thus $P_a \neq P_b$.

2. The represented data points have varying p.
There exist subsets of R where data points have differing p values, i.e., $\exists a \in R \wedge \exists b \in R | P_a \neq P_b$.

These two conditions express the necessary conditions for emphasis, but they are not meant to indicate a strict dichotomy between suppression-based emphasis effects (i.e., Condition 1) and emphasis arising from varying prominence (i.e., Condition 2). Many emphasis techniques in visualizations use a combination of suppression and variable data point representation. To further explain the second means of creating emphasis effects, we define the terms foreground, background, and midground to specify subsets of R based on p. These subsets are closely related to the inner zone, active rim, and outer zone of lenses [TGK*14]. However, we have not used this terminology in our paper in favor of using the terminology from previous emphasis frameworks, e.g., drop-off regions. We are now formally defining F (the foreground), M (the midground) and B (the background), i.e., supporting **GF1**.

The foreground F is the subset of R corresponding to the data points with the highest p values for the time interval $[t_E, t_E + \Delta t_E]$. The background B is the subset of R corresponding to the data points with the lowest p values for this time interval. The transition between the foreground and the background may be sharp or gradual, and occurs via midground subsets where data points have intermediate p values. There is no *a priori* reason that the foreground, midground, and background must be constrained to occur at the same moment in time so long as they occur within the time interval $[t_E, t_E + \Delta t_E]$. The foreground, midground and background can be temporally separated e.g., with zooming.

Foreground

Let p_F represent the highest p value for all of the data points in R i.e., $p_F = max(\bigcup_{d \in R} P_d)$. In turn, F is the set of data points that have this p value, i.e., $F = \{d \in R | p_F \in P_d\}$.

Background

Let p_B represent the lowest p value for all of the data points in R excluding p_F i.e., $p_B = min(\bigcup_{d \in R} P_d \backslash \{p_F\})$. Then, B is the set of data points that have this p value, i.e., $B = \{d \in R | p_B \in P_d\}$.

Midground

The midground M is comprised of data points that have p between p_F and p_B. These prominences are $P_M = \bigcup_{d \in R} P_d \backslash \{p_F, p_B\}$. M can be subdivided into the subsets of data points associated with each p value in P_M. That is to say, for $p_i \in P_M$, $M_i = \{d \in R | p_i \in P_d\}$. M is then given by $M = \bigcup M_i$. Given $p_{M_i} > p_{M_{i+1}}$, then $p_{M_1} > p_{M_2} > \ldots > p_{M_{n-1}} > p_{M_n}$ for the time interval $[t_E, t_E + \Delta t_E]$. By not constraining the number of different subsets comprising M, we are allowing for a variable degree of continuity between F and B (such as using a *DOI* function to populate the sets), and are supporting **GF4**.

Overall, all subsets of R can be ordered with respect to their p values. Namely, $p_F > p_{M_1} > p_{M_2} > \ldots > p_{M_{n-1}} > p_{M_n} > p_B$. The number of subsets comprising M determines the degree to which the transition between F and B has the appearance of being discrete or continuous for the viewer. Intrinsic and extrinsic emphasis effects both stem from differences in data point prominence. By focusing on data point prominence and not the designer intentions, this mathematical description of F, M and B applies to intrinsic and extrinsic emphasis effects, i.e., supporting **GF5**. When one wants to focus on extrinsic emphasis effects, one simply ignores the contributions of the intrinsic emphasis effect to data point prominence.

6.2. Properties of FIVE

We now elaborate on the characteristics of FIVE arising from its formal construction.

Nonempty subsets. By definition, $R \neq \emptyset \Rightarrow F \neq \emptyset$, as F constitutes the subset of the data with the highest p values, which cannot be the null set if a representation of the data exists. All other subsets can be null. However, $B \neq \emptyset$ as soon there are two or more subsets of R such that data points within these subsets have differing p values for the time interval $[t_E, t_E + \Delta t_E]$.

Overlapping subsets. $F, M_1, M_2, \ldots, M_n, B$ need not be mutually exclusive and can be overlapping. This occurs in the case of multiple views (e.g., overview+detail and zooming), or when some data points are represented multiple times in a visualization (e.g., when data points are duplicated according to their multiple set memberships [RD10]). In this situation, a data point may have multiple p values associated with it.

Changes in visual variables over time. Perceptual properties of data points (e.g., their visual variables) can change with time to produce emphasis effects such as flickering [WLMB*14]. Let V be a visual variable, such as position, and $V(t)$ be the temporal progression of this visual variable for a given data point. Static emphasis effects such as static highlighting, have the property that $V(t)$ satisfies Equation 2. Emphasis effects where visual variables change with time, such as flickering, have at least one visual variable V such that $V(t)$ does not satisfy Equation 2 for one of the subsets F, M, and B. Depending on the nature of $\frac{dV}{dt}$, it may be possible to create an emphasis effect that results solely from the variation of V over time. For example, motion can act as an emphasis effect when $\forall d \in F : \frac{dV}{dt} \neq 0$ while $\forall d \in M \bigcup B : \frac{dV}{dt} = 0$. Previous work has shown that motion produces a powerful pop-out effect in visual representations, e.g., [WB04, BWC03, HR07].

$$\frac{dV}{dt} = 0 \; for \; t \in (t_E, t_E + \Delta t_E) \tag{2}$$

Temporal separation. Given that an emphasis effect occurs during a time interval $[t_E, t_E + \Delta t_E]$, we can consider emphasis based on animations. A particularly common type of animation-based emphasis effect is zooming. Zooming is based on temporally separating different views of a dataset [CKB09] where, according to Furnas [Fur06], the aggregate of the views is a fisheye degree of interest subset. We now have the mathematical foundations to provide a new mathematical description of zooming.

6.3. An Example of Using the Mathematics of FIVE: Zooming

To illustrate using the mathematics of FIVE, we consider the example of zooming. For this explanation, we assume that we are moving from B to F through M. If we assume that the intrinsic emphasis effect is weak in comparison to the extrinsic emphasis effect arising from zooming, then the prominence of data points is proportional to their magnification.

Let m_d, m_B and m_F represent the magnification factors used to represent a data point d, data points in B, and data points in F, respectively. In order to define zooming, we first define a magnification boxcar function to describe the time evolution of the magnification factor for a given zoom state. In Equation 3, $H(t)$ is the Heaviside step function. Now let $t_{A\to B}$ be the moment in time when transitioning between subsets A and B involved in zooming, e.g., B and M_n. Zooming can then be mathematically described according to Equation 4.

$$boxcar(m, t_{start}, t_{end}, t) = m * [H(t - t_{start}) - H(t - t_{end})] \tag{3}$$

$$\begin{aligned}
&\forall d \in B, m_d = boxcar(m_B, t_E, t_{B\to M_n}, t) \\
&|t_{B\to M_n} \in (t_E, t_E + \Delta t_E) \\
&\\
&\forall d \in M_n, m_d = box(m_{M_n}, t_{B\to M_n}, t_{M_n\to M_{n-1}}, t) \\
&|t_{M_n\to M_{n-1}} \in (t_{B\to M_n}, t_E + \Delta t_E) \wedge m_B < m_{M_n} < m_{M_{n-1}} \\
&\vdots \\
&\forall d \in M_1, m_d = box(m_{M_1}, t_{M_2\to M_1}, t_{M_1\to F}, t) \\
&|t_{M_1\to F} \in (t_{M_2\to M_1}, t_E + \Delta t_E) \wedge m_{M_2} < m_{M_1} < m_F \\
&\\
&\forall d \in F, m_d = box(m_F, t_{M_1\to F}, t_E + \Delta t_E, t)
\end{aligned} \tag{4}$$

Figure 12 illustrates the set of equations in Equation 4 for a three level zoom-in, i.e., a zoom transitioning from B to F through M_1. First B is represented with a magnification factor of m_B. As B is replaced by M_1, the magnification factor of the elements in B drops from m_B to 0, and the magnification factor of the elements in M_1 increases from 0 to m_{M_1}. A similar process occurs when transitioning from M_1 to F. Note that if $d \in B \cap M_1 \cap F$, we could alternatively describe the magnification of d using a step function that begins at m_B, transitions to m_{M_1}, and finally transitions to m_F.

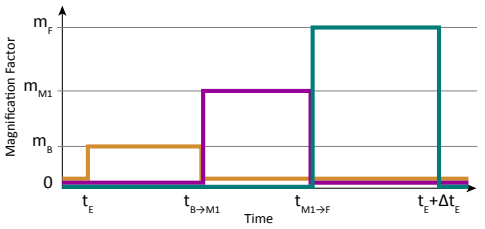

Figure 12: *An illustration of the set of zooming equations in Equation 4 for a three-level zoom-in. The orange line is the magnification factor for B, the purple line the magnification factor for M_1, and the green line the magnification factor for F. Lines are offset with respect to 0 for clarity purposes only.*

This explication of zooming shows that the framework can offer a new mathematical lens for considering well-known existing emphasis effects. Historically, there have been many different approaches to magnification-based effects, each with their pros and cons. For example, a designer can achieve magnification-based emphasis effects for a 2D visualization by:

1. Applying transformation functions such that some regions of the visualization are magnified and other demagnified, but all of the visualization remains visible in the interface [LA94]
2. Distorting the visualization according to nonlinear magnification fields [KR97] and using the resultant magnification to vary data presentation within the visualization [Kea98],
3. Manipulating the visualization as a pliable sheet in 3D and then back-projecting into 2D [CM01], and
4. Using a *DOI* function to determine a data point's size in a visualization [Fur86, Hau06].

A possibility with our new mathematical formulation of zooming is that other visual variables could be varied according to the mathematics already described to help viewers focus on specific data points during the zooming, e.g., highlighting that varies as zooming occurs based on Equations 3 and 4. In general, the different levels of p involved in creating an emphasis effect, e.g., F and B, need not be available for viewing at the same point in time, but can be spread over the range $[t_E, t_E + \Delta t_E]$. In this situation, human memory will be important because the emphasis effect is created through the aggregation of the views over the time period $[t_E, t_E + \Delta t_E]$.

7. Opportunities for Using FIVE & Future Research Directions

Based on our analysis of the literature, we introduced the prominence of data points within visualizations as a way of unifying diverse emphasis effects both algorithmically and visually. Based on prominence, we developed five general features of emphasis effects **GF1** to **GF5** that we explicitly enumerated in Section 6. These general features and the idea of data point prominence provide a basis for describing, comparing and generating emphasis effects. We then formalized these concepts within FIVE, a mathematical framework, similar to how previous frameworks have provided formal mathematical descriptions, e.g., [Fur86]. FIVE is descriptive, comparative and generative. Therefore, FIVE conceptually satisfies Beaudouin-Lafon's criteria for a design framework [BL04, BL00].

We now consider future prospects and opportunities for studying emphasis effects in information visualization - opportunities opened up by the concepts and descriptions in FIVE.

7.1. New Ways to Decide *What* to Emphasize

In Section 5, we discussed how one can use set operations, functions, or a combination of the two to define the subsets of data points that will have varying visually prominence in a visualization (i.e., F, M and B). Because functions are by definition a special case of set relationships, a set-based perspective on emphasis effects is mathematically more general. Sets and subsets are also the language that the community uses to describe emphasis effects [Fur86, Fur06, Hau06]. Although *DOI* functions are powerful on their own, sets provide a new perspective on emphasis. Also, this new set-based perspective can be used in harmony with the *DOI* functions to extend their possibilities.

Synergistic combinations of set operations and functions for defining F, M and B could provide visualization designers with greater freedom for defining *what* an extrinsic emphasis effect should emphasize compared to using functions alone. For example, F, M and B could be the result of someone working with a dataset, e.g., brushing queries or previous selections. In a collaborative context, multiple people working in a visualization can result in multiple focus sets (e.g., [IES*11, IBH*09, IFP*12]). Each collaborator has his or her own notion of F, M, B, thus each collaborator could have his or her own set of sets $\{F, M, B\}$. The different sets-of-sets could be independently represented with different visual variables, or set operations could be used to create new sets. For example, F in a shared visualization could be determined by using the union of all $\{F\}$; or M could consist of the intersection of all $\{F, M\}$. More complex combinations of set operations could be used to compare information that is used between different collaborators.

7.2. New Ways to Decide *How* to Emphasize

In Sections 2 and Section 5, we showed that historically the scope of *how* we create emphasis effects has remained relatively narrow, as is highlighted in Figure 2. The FIVE framework sheds light on unexplored opportunities for novel emphasis effects based on visual variables, e.g., the time variation of texture. Given its focus on the idea of prominence, FIVE captures these new opportunities, while also pointing to even broader opportunities for creating emphasis effects beyond visual variables.

Even though the literature focuses on visual variables and we have structured our discussion as such, prominence is not solely the consequence of mapping data points to visual variables and manipulating these visual variables. Previous work has proposed sound variables (audio equivalents of visual variables) as a basis for audibly encoding data [Kry94]. These sound variables (e.g., timbre, pitch, and volume) could serve as a basis for creating emphasis effects in audio formats. Alternatively, frequency and amplitude of vibration could convey emphasis in haptic systems. Researchers have started to investigate non-visual modalities such as physicality, haptics, and audio in visualization, e.g., [JD13, JDF13, JDI*15, Moe08, RW10, MB06, HH12]. However, as of yet, no research has formally investigated emphasis effects based on these modalities. By looking at emphasis effects from the perspective of prominence, FIVE provides the Infovis community with a way of considering non-visual modalities. That is to say, F, M, B could vary in prominence through non-visual effects.

For example, Huron et al. [HVF13] applied a sound-based extrinsic emphasis effect to a visualization of SVN commits based on visual sedimentation [HVF13]. In visual sedimentation, tokens fall from the top of the screen into containers. Tokens shrink over time until they are small enough to be aggregated into the area of their corresponding container. Designing an extrinsic emphasis effect for a visualization based on visual sedimentation is difficult because the visualization already uses powerful visual variables (motion, size and position). Huron et al. used sound to emphasize new tokens entering their visualization such that the extrinsic emphasis effect (for new tokens) was distinct from the intrinsic emphasis effect of the base visualization. This sound-based emphasis cannot be described using previous emphasis frameworks, but fits within FIVE.

Non-visual emphasis effects will become increasingly important as researchers continue to augment their visualizations with other modalities, and FIVE's focus on prominence will support this research.

7.3. New Methods for Implementing Emphasis Effects

Beyond helping designers explore the *what* and *how* of emphasis effects, F, M and B provide an alternative approach through which designers can consider the technical aspects surrounding the generation of emphasis effects.

One could use F, M and B to allocate computational or storage resources when handling large datasets in order to increase data retrieval efficiency. For example, if a viewer is likely to explore F in greater detail, it may be reasonable to store all of the data attributes corresponding to F locally while storing fewer of the attributes for M and even fewer for B. Therefore, visualization designers can use the prominence subset view of emphasis effects (i.e., F, M and B) and related concepts (e.g., intrinsic vs. extrinsic emphasis effects) to consider how to realize a desired effect.

Alternatively one can define F, M and B using the functions from other frameworks. Moreover, one is not limited to using the same function to define all three of F, M and B. One could, for instance, use a *DOI* to define F, and a drop-off function like those in the Elastic Presentation Framework [CM01] to define M and B. This opens a whole new array of possibilities for implementing emphasis effects.

7.4. New Empirical Studies of Emphasis

Designers may wish to experimentally evaluate how a specific emphasis effect is experienced by a viewer. The FIVE provides support for such empirical studies.

With FIVE and its connection to data point prominence within a visualization, researchers can use empirical measures to determine the relative prominence of data points. As an example of such empirical measures, consider fixation times, t_{fix}, in eye-tracker experiments. Visual fixation, as measured using eye-trackers, has been

used to understand people's visual attention in a variety of fields, e.g., [AL15, DAE15, MPSG15]. If a researcher is only interested in the bottom-up descriptions of prominence in the context of a particular visualization and task, we can assume that $p \propto t_{fix}$. By using a metric such as fixation time as a proxy to measure the prominence of data points, one can then analyze both intrinsic and extrinsic emphasis effects.

Analyzing Intrinsic Emphasis Effects: As an example of empirically analyzing the intrinsic emphasis effect of an existing visualization using t_{fix}, consider presenting a scatter plot to a viewer. A researcher could measure t_{fix} for each data point in the visualization in an eye-tracker experiment. The researcher could then assign data points to the sets F, M, and B according to their respective t_{fix} values using $p \propto t_{fix}$. For example, the dots with the maximum t_{fix} value would be in F, those with the minimum t_{fix} value would be in B, and the dots with intermediate t_{fix} values would be in M.

Now consider a visualization where hue is used to discriminate certain data points, for example a colored map where rivers, land, and mountains have different hues. Running the same eye-tracker experiment with people who have red-green color vision deficiency (CVD) would determine F, M, and B for CVD individuals. A researcher could then compare the sets for normal vision and CVD individuals, and assess the extent to which the visualization is CVD-compliant.

Analyzing Extrinsic Emphasis Effects: A researcher can also use visual prominence and FIVE to compare extrinsic emphasis effects using empirical measures, e.g., using eye-tracker t_{fix} measurements. Consider designing extrinsic emphasis effects to emphasize some data point, d. Using the same eye-tracker procedure as we described for intrinsic emphasis effects, a researcher can then determine F, M, and B in the presence of different extrinsic emphasis effects. For example, the extrinsic emphasis effect in Figure 8(b) is based on blur with F and B being the crisp and blurred dots, respectively. Since color is not used in Figure 8(b), we can expect that both normal vision and CVD individuals would experience the same extrinsic emphasis effect. In contrast, with the hue-based extrinsic emphasis effect in Figure 8(a), we can expect differences in how normal vision and CVD individuals would experience this emphasis effect.

In some cases, the researcher may find that some of these extrinsic emphasis effects do not significantly alter F, M, and B, i.e., they do not effectively increase the visual prominence of d. However, other extrinsic emphasis effects may be so effective that F contains only d, the data point that the extrinsic emphasis effect is meant to emphasize. For the latter situation, the researcher can then compare such extrinsic emphasis effects by calculating the difference between t_{fix} for d and t_{fix} for the other data points for each extrinsic emphasis effect. Assuming that $p \propto t_{fix}$, the extrinsic emphasis effect with greatest fixation time difference would be the strongest emphasis effect. Therefore, FIVE enables: 1) the empirical analysis of intrinsic emphasis effects, 2) the empirical comparison of intrinsic and extrinsic emphasis effects, and 3) a basis for empirically determining the relative strengths of emphasis effects.

Eye-tracker experiments are becoming increasing popular in information visualization research. There has already been some work using eye-trackers to compare emphasis techniques. Steinberger et al. [SWS*11] have used fixation times and gaze paths to qualitatively compare extrinsic emphasis techniques (color-based highlighting and visual links). Griffin and Robinson [GR15] have used eye-tracker experiments to compare how different extrinsic emphasis effects (color-based highlighting and visual links) enable individuals to find related data across multiple coordinated views. Specifically, they considered the time required for participants in their study to visually find two associated highlighted regions on a map and a coordinated statistical plot (i.e., scatter plot or parallel coordinate plot). They then used these search times to statistically compare highlighting techniques (color-based highlighting and visual links). Depending on the situation, the time taken for a participant to look at a particular data point could serve as an alternative proxy for prominence. The aim of our proposed procedure is to show that researchers can use FIVE to conduct empirical studies, and we fully expect that researchers will use the framework to empirically probe emphasis effects in other ways.

Bridging Emphasis and Perception: Emphasis is more than the use of visual variables on a page or a screen. Emphasis occurs as people consider, use and explore visualizations. By enabling empirical studies on emphasis effects, FIVE can be a key enabler as research moves towards understanding the perceptual and cognitive origins of emphasis techniques in information visualization. The cartography community appreciates that maps and cartographic visualizations are intimately connected with cognitive processes, perception and thinking, e.g., [Woo94, Pet94]. In the visualization community, Healey and Enns [HE12] have discussed the connections between visualization and perceptual theories of visual attention and memory. Automaticity and visual awareness are other important facets of visual perception [EHH*11]. Human perception is complex, with entire books dedicated to exploring of the intersection between visualization and human perception (e.g., [War12]). Nevertheless, emphasis techniques have their origins in, for example, saliency, preattentive processing [Tre85], attention, visual search, Gestalt concepts, and top-down cognitive processes. In fact, some researchers are already starting to consider human perception when designing [WLMB*14] and comparing [Rob11] emphasis techniques. However, we as a community still lack explicit understanding of how emphasis effects relate to perceptual and cognitive mechanisms. By enabling empirical studies, FIVE empowers researchers to tackle these questions. We believe that profound insights into emphasis techniques will come as the community undertakes this challenging line of research.

7.5. Future Work

The idea of visual prominence and FIVE point to new research possibilities and how much research remains to be done in order to improve the general understanding of emphasis effects. We see four important research directions for the community moving forward.

1. Creating emphasis effects using underexplored visual variables and time variation.
2. Exploring alternative ways to vary data point prominence to create emphasis effects, e.g., annotations and non-visual modalities.
3. Providing a richer space of how to define and implement emphasis effects,

4. Conducting empirical studies of visual prominence in visualizations and extrinsic emphasis effects, and relating emphasis techniques to perceptual and cognitive mechanisms.

We are confident that tackling these challenges will both broaden the community's understanding of emphasis and lead to novel techniques.

8. Conclusions

Inspired by the usefulness of previous frameworks and the growing variety of novel emphasis effects that are not described by these frameworks, we reviewed previous frameworks and classes of emphasis effects with the intention of providing a unifying description of emphasis in information visualization. Through this review, we extracted visual prominence as a common theme across all emphasis effects, based on the fact that visualizations have some data points that are more prominent than other data points.

Visual prominence provides an approach for describing, comparing and generating emphasis effects. From the previous frameworks and techniques, we derived five general features of emphasis effects: 1) that they can be described in terms of three subsets F, M and B; 2) that *time* is a principle factor, and that both time variant and invariant methods need to be included; 3) that emphasis effects may, as deemed appropriate, incorporate duplication; 4) that the degree of continuity in emphasis is an important freedom; and 5) that there is an interplay between intrinsic and extrinsic emphasis effects. In FIVE, we have provided a mathematical framework that aligns and formalizes these general features. FIVE provides a mathematical foundation for describing, comparing and generating emphasis effects in ways that encompass and extend previous frameworks. FIVE is operational in several ways:

1. The mathematics in FIVE can be used to algorithmically create emphasis effects, and are compatible with existing approaches to creating emphasis effects while also enabling new ones.
2. FIVE provides a new perspective on both the importance of emphasis and the ways by which emphasis techniques can be created (e.g., underexplored visual variables, and non-visual modalities).
3. FIVE also lays the groundwork for subsequent empirical studies comparing and evaluating emphasis techniques.

There are still many open questions and opportunities for future work. FIVE and the concepts described here will help researchers as they undertake this work. We are confident that some of the most exciting emphasis effects have yet to be discovered.

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