First attention then intention
Insights from computational neuroscience of vision

Milica Milosavljevic and Moran Cerf
California Institute of Technology

Attention is a critical construct for anyone involved in marketing. However, research on attention is currently lacking in the marketing discipline. This is perhaps due to inherent difficulties in measuring attention. The current paper accentuates the importance of better understanding attention, and suggests studying attention as a two-component construct consisting of equally important bottom-up and top-down processes. While research on top-down attention has recently been undertaken by Pieters and Wedel (2004; 2007), the current paper introduces the field of computational neuroscience and its research on visual attention as a useful framework for studying bottom-up attention.

> Attention is a prerequisite for all marketing efforts.
>
> (Sacharin 2000)

Introduction

Research that integrates findings from cognitive psychology, cognitive neuroscience and marketing is in its infancy. Nevertheless, a few marketing researchers have ventured into this brave new world, which is expected to hold much potential for advertising research (Vakratsas & Ambler 1999). Merging cognitive neuroscience with research on consumer behaviour offers tremendous potential for growth in knowledge. This is especially so because 'a great mismatch exists between the way consumers experience and think about their world and the methods marketers use to collect this information' (Zaltman 2003).

Conveniently, neuroscience uses new technologies that make it possible to measure neurophysiological activity in order to study complex human behaviors (for a good overview of neuroimaging methods in terms

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of relevance to consumer behavior research see Egidi *et al.* 2008; Plassmann *et al.* 2007). These tools have the potential to override the methodological problems of the former approaches (Plassmann *et al.* 2007), although whether this will actually occur remains to be seen. The hope is that these physiological measures will be used to augment, not replace, traditional research methods in order for marketing researchers to begin to more adequately validate and refute some of the long-debated theories of consumer behavior, and, by default, human behavior in general.

Within this broad research framework, of interest in terms of the present paper is one currently ignored, but perhaps crucial, aspect of consumer behaviour: selective attention. A recent review of how neuroscience can inform advertising (Plassmann *et al.* 2007) omits the construct of attention entirely. This is surprising given that marketing researchers have declared attention to be a prerequisite for all marketing efforts (see the introductory quote above, from Sacharin 2000). Thus, selective attention should be included within the neuroscience–marketing research framework.

Another omission in the emerging field that combines neuroscience and marketing is that insights from theoretical and computational neuroscience have yet to be introduced. Computational neuroscience combines what is known about the brain from neuroscience with the computing power available to simulate neuronal and psychological processes on a computer (Sejnowski *et al.* 1988). The goal of computational neuroscience is to develop algorithms that can simulate on a computer how the brain functions when we perform tasks (Smith & Kosslyn 2007). Although many computational models of memory, attention, learning and decision making have been introduced, the present paper focuses on perhaps the most developed: computational models of visual attention.

Thus, the current paper has two objectives. The first is to bring into the spotlight the construct of attention. The second is to introduce computational neuroscience of visual attention to the marketing field, and discuss its utility for understanding deployment of attention in the advertising context.

The construct of attention in an advertising context

Due to the plethora of communication channels, consumers are faced with an overabundance of information, where a typical consumer is exposed to several hundred (even several thousand) marketing messages daily. Not all of this information can be processed because of the limited capacity of the brain – known as the attentional bottleneck. In recognition of this cluttered environment, some researchers have declared that we are living in the attention economy, with attention being a scarce resource (Davenport & Beck 2002).

Not surprisingly, everyone involved with marketing knows the importance of getting consumers' attention. In advertising, the importance of attention is evidenced by its prominent position in many advertising models. Originating in 1898, the first formal advertising model, AIDA (Attention → Interest → Desire → Action), positioned attention as the first step that people go through when exposed to advertising and before making a purchase (Vakratsas & Ambler 1999). Furthermore, most hierarchy of effects models suggest that attention is a necessary step before higher-level processes.

Since the importance of attention to marketers is factual, it is surprising that marketing studies of attention are rare (Rosbergen *et al.* 1997). The little space that attention does receive is devoted to describing how it is measured, while little emphasis is placed on any conceptual discussion, as is described next.

The concept of attention

Even today, most marketing researchers' understanding of attention is similar to William James' view dating back to 1890: 'Every one knows what attention is. It is the taking possession by the mind, in clear and vivid form, of one out of what seem several simultaneously possible objects or trains of thought.' A single exception is the recent work of Pieters and Wedel (2004) and Rosbergen *et al.* (1997), who suggest that attention is a much more complex phenomenon than is currently studied in marketing.

Pieters and Wedel (2004) introduced two determinants (found in psychology and neuroscience) of attention to advertising. The two determinants are: (1) bottom-up and (2) top-down attention.

Bottom-up attention is a rapid, automatic form of selective attention that depends on the intrinsic properties of the input, such as its colour or intensity (Koch 2004). It is also known as saliency-based attention, indicating that the more salient an object, the higher the probability of it being noticed. Top-down attention is a volitional, focal, task-dependent mechanism, often compared to a spotlight, that enhances processing of the selected item (Koch 2004).

In the present work, bottom-up processes are referred to as pre-attention, while top-down processes are referred to as focal attention. Thus, attention is viewed here as a two-step process, consisting of pre-attention and focal attention, although this is not necessarily a sequential process as top-down attention can sometimes moderate the bottom-up processes (Cerf *et al.* 2008).

Pieters and Wedel (2007) made important first steps towards improving our understanding of how top-down factors (i.e. consumers' goals – 'memorise the ads', 'collect brand information', 'evaluate product', etc.) may influence attentional deployment within magazine ads. However, it is also important to spark research on the effects of bottom-up, automatic attention. This type of research is virtually non-existent in the marketing literature. As the work of Pieters and Wedel is focused on print advertising, the same context will be used in the remainder of the current paper to demonstrate the importance of research on bottom-up attention.

The research on bottom-up attention may be especially important since, as with the other types of media, clutter is an imposing problem for magazine advertising. For example, a 318-page issue of *Glamour* magazine contains 195 pages of advertisements and 123 pages of editorial content (Clow & Baack 2004). Faced with such a large amount of clutter, consumers often have a singular goal: to avoid advertising. Even Pieters and Wedel (2007, p. 224) highlight that 'processing goals may have a lower likelihood of surfacing during the few seconds that consumers typically spend on ads during self-paced exposure', and that 'competitive clutter may favour reflexive control and hinder systematic goal control'. Also, they state that attention to ad objects is very low during free viewing of magazines because object salience, or the bottom-up driven attention, primarily determines attention during free viewing (Janiszewski 1998; Pieters & Wedel 2007). Thus, on many – although not all – occasions, bottom-up attention may be as close as advertisers can get to consumers before the top-down goal of 'ignore advertising' kicks in.

An earlier study by Pieters and Wedel (2004) serves well to further emphasise this point. They instructed more than 3,600 consumers to freely browse through magazines, and used eye tracking to measure where they directed their gaze. The experimental magazines included 1,363 print ads. They found that, on average, 95.7% of participants fixated at least once on ads, but that the lowest-scoring ad was skipped by 39% of the participants. Further, people spent on average 1.73 seconds with each ad, ranging from 0.037 seconds to 5.30 seconds.

This study shows that, even when people are seated in a laboratory and asked to look at a magazine, the time spent with ads is very low. It can be assumed that time spent with ads and the number of ads that people look at are even lower during natural magazine browsing when people's attention is also consumed by other factors in their environment.

Thus, the construct of attention in advertising should be studied based on the two-component framework, consisting of bottom-up and top-down attention. The biggest challenge in such undertaking is that while marketers recently began using improved measures of focal attention, measuring pre-attention is still challenging.

Measurement of attention

Perhaps the most common method of measuring attention to advertising is by using self-reported memory measures (e.g. 'To what extent did you pay attention to this ad?'). However, memory measures are poor indicators of what consumers pay attention to (Rosbergen *et al.* 1997), for at least two reasons. First, attention is known to precede awareness. Thus, it is possible that a stimulus was attended to, but has not reached the awareness stage, thus making it impossible for individuals to have it in their memory or to report it. Second, even if a stimulus was attended to, people are known to forget most of the stimuli they process.

A somewhat improved, although less frequently used, method of measuring attention in marketing is eye-tracking, where eye movements are recorded to indicate individuals' attentional patterns. The main weakness of eye-tracking, as currently used in advertising, is that findings are 'rather superficial' (Rayner *et al.* 2001, p. 220). For example, the size of the advertisement has been found to influence participants' looking times, which was pointed out by psychophysicists over a century ago (Tatler *et al.* 2005).

Thus, although some progress has been made in studying and measuring top-down attention, these methods do not account for bottom-up attention. What may prove to give life to research on bottom-up attention is a branch of neuroscience known as computational neuroscience. To initiate this stream of research within marketing, computational neuroscience of visual attention is introduced next.

Computational neuroscience of visual attention

The goal of computational neuroscience is to relate the data of the nervous system to algorithms used by the brain to conduct higher-level human behaviours such as attention, learning, memory, emotions and decision making. The idea is to create a computer simulation of real human behaviour inspired by biological systems in the brain.

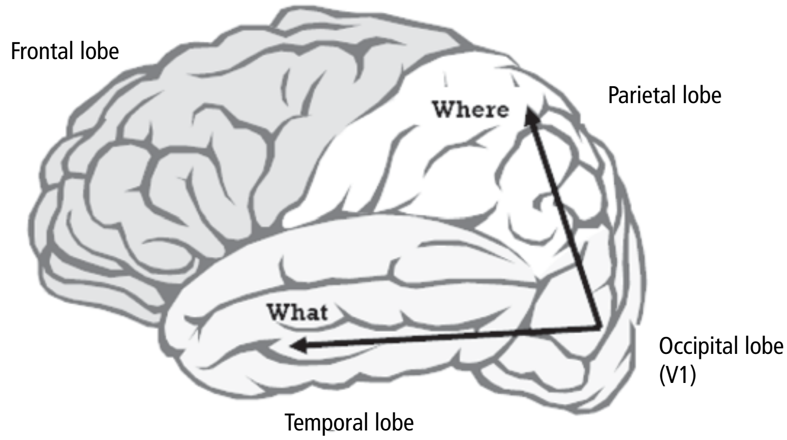
Computational brain modelling attempts to produce either (1) realistic brain models or (2) simplified compact brain models. A realistic brain model is a large-scale simulation that goes to the level of a single cell (Sejnowski *et al.* 1988). Since the model becomes much more realistic at the cellular level, it becomes less helpful in understanding its function at the nervous system level. Further, realistic simulation is computation-intensive, meaning that it requires a substantial computer power.

On the other hand, simplifying brain models are networks of brain cells or 'neural networks', which capture important principles of the functionality of a system (Sejnowski *et al.* 1988). Most importantly, neural networks are being used as models for psychological phenomena such as attention, emotions and decision making. Of those, perhaps the most realistic and advanced computational models are those that simulate visual attention.

Vision means 'finding out what is where' (Smith & Kosslyn 2007), and computational modelling attempts to provide algorithms that successfully locate and identify informative objects in a visual scene. Thanks to advances in neuroscience, it is known that certain brain areas give rise to visual attention, as shown in Figure 1.

Specifically, two separate cortical routes are involved in vision, giving rise to two streams of visual information (for a detailed review, see Koch 2004). Spatial deployment of attention ('where') is known as dorsal pathway. It proceeds from the primary visual cortex (V1) in the occipital lobe, through the posterior parietal cortex, and to the dorsolateral prefrontal cortex. Object recognition ('what') happens via the ventral pathway, which involves V1, the inferotemporal cortex, and the ventrolateral prefrontal cortex.

Figure 1: Visual processing pathways

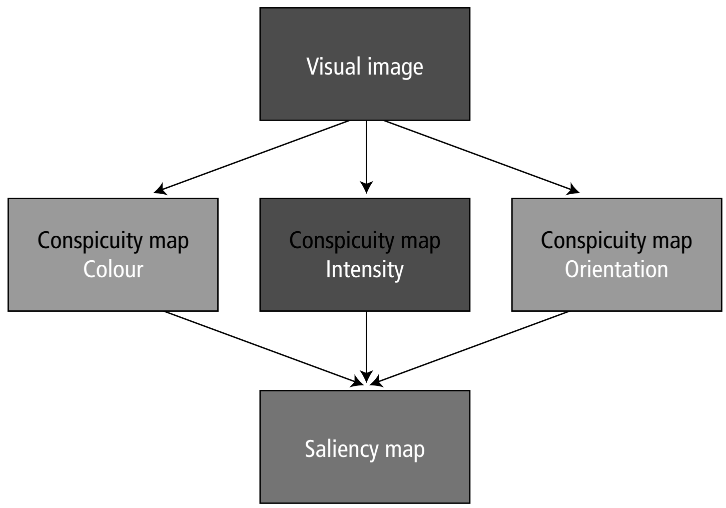


As mentioned earlier, attention is not given to all visual input. Since our visual environment is cluttered, attention serves as a processing bottleneck, allowing only a selected part of sensory input to reach visual awareness. This process depends on the two previously mentioned mechanisms: bottom-up and top-down attention. This two-component framework of visual attention was introduced by Treisman and Gelade (1980), and formed the basis for the development of computational models of visual attention. Guided by the idea that a visual scene is initially analysed automatically, based on the physical properties of objects in the scene, the first neurally plausible computational algorithm of bottom-up attention was developed by Koch and Ullman (1985), and later extended and implemented by Itti *et al.* (1998). The model is briefly introduced next.

Itti, Koch and Niebur's model of bottom-up attention and saliency

The model's flow (a rough outline of the model's architecture is depicted in Figure 2) begins by analysing the physical characteristics of objects in a given visual image. It analyses colour, intensity and orientation of objects, and sorts these into three conspicuity maps, which are grey-scale maps where brighter areas represent more salient locations while darker ones are less salient. One conspicuity map is created for each of the three characteristics: colour, intensity and orientation. For example, an object may be identified as highly salient because of its colour (the object's location

Figure 2: Computational model architecture



would be represented as a brighter area on the colour conspicuity map), while another object may be deemed salient due to its intensity (the objects' location would be brighter on the intensity conspicuity map).

The values from the three conspicuity maps are summed up into a saliency map, which is a two-dimensional topographic map that represents the saliency at every location in the visual image (Itti *et al*. 1998). The most salient locations are potential targets for visual attention (Schall & Thompson 1999). The most salient location is identified first. Then, this location is inhibited in a biologically motivated fashion and the next most salient location is determined, and so on. In this manner, attentional scan-paths are created for a given visual image (Itti 2004).

The model of bottom-up attention and saliency discussed here is a neurally based model – that is, it mimics human performance in a manner that is inspired by biological circuitry. Currently, it is probably the most widely used model of bottom-up visual attention (Cerf *et al*. 2007). It has been validated for the past decade on a number of classical visual search experiments, and was found to be 'consistent with observations in humans' (Duchowski 2002, p. 161). Recently, the model has been tested and improved in a number of contexts, including the presence of (1) motion, (2) faces and (3) text. These are discussed briefly next.

First, while the saliency model was initially implemented on static images, it could easily be scaled to motion – taking frame-by-frame video data and analysing them as a single image. For example, recent additions to the model include flicker channels that allow for attention allocation to rapidly changing content that was shown to attract human fixations, and various semantic channels (Cerf *et al.* 2008).

Second, it was recently shown (Cerf *et al.* 2007) that adding a face channel – taken from existing face detector algorithms – can significantly enhance the predictions of the model when it comes to telling what human observers are looking at in an image. Also, and relevant to marketing research, when observers are looking at faces in an image this can also increase the amount of time spent viewing the image.

Finally, since we are exposed to text very often in our lives, it was shown in recent work by Cerf *et al.* (2008) that inclusion of a text channel in the saliency model further increases the ability of the model to predict what people are looking at. The performance of the model has been compared to the eye-tracking data collected from people exposed to a number of different images, and was found to be comparable.

It is important to note that the model is consistently found to perform comparable to results obtained from eye-tracking. The cost-benefit properties of such findings are the following: no expensive eye-tracking equipment is necessary, participants are not needed since the model simulates universal human bottom-up attention allocation, and significant time efficiency can be achieved as the algorithm can provide real-time analysis.

As this brief review of the current research on bottom-up attention shows, there has been much progress in modelling this process. It is important to remember that this sensory input is sometimes modulated by top-down, person and task-dependent input (Cerf *et al.* 2008). Computational models that include top-down cues are currently being developed by several research groups but are not as well developed as the models of bottom-up attention (Torralba & Oliva 2007; Cerf *et al.* 2008).

The following section discusses how computational modelling of visual attention may benefit both marketing theory and practice.

Potential contributions of computational neuroscience for marketing research

Using computational modelling of bottom up visual attention in marketing studies has the potential to make significant (1) theoretical, (2) empirical and (3) substantive contributions.

First, the conceptual understanding of attention will be enhanced by investigating factors that determine its key component: preattention. A better understanding of how to manipulate preattention will enable researchers to study its consequences, such as attitudes, intentions and/or choices. The effects of preattentive processing on attitudes towards the ad and brand were mentioned in the context of mere exposure effects when Janiszewski (1993, p. 376) highlighted the importance of investigating whether 'preattentive processes [are] instrumental in the formation of affective responses and, if so, how these preattentive processes operate'. About half a dozen marketing studies investigated the role of preattention within the mere exposure phenomenon, but no clear conclusions have been reached (Janiszewski 1993; Shapiro *et al.* 1997, 1999).

Second, although focal attention is being measured by somewhat improved methods of eye tracking, the measurement of preattention is still challenging. Yoo (2005) highlights this by stating that one of the most important emerging issues in the study of preattention to advertising is 'empirically detecting the existence of preattentive processing'. This can finally be addressed by introducing computational modelling of bottom-up attention, which a priori identifies objects that are likely to be preattentively processed by a viewer.

Finally, potential applications of computational modelling in the domain of advertising pretesting and evaluation are abundant. As an example, the following section demonstrates the utility of computational modelling of visual attention in the context of print advertising.

Application of computational modelling of visual attention to evaluation of print advertisements

As already suggested, many people purposely avoid looking at ads, or look at ads only very briefly. In such an environment, advertisers should be (and perhaps already are) trying to ensure that the key information in the ads is at least automatically, preattentively processed by consumers. This makes sense since it is known in psychology and neuroscience that automatic, preattentive processing is very rapid, occurring within less than one second of exposure to a visual scene (Quian Quiroga *et al.* 2008). The previously described computational model of visual attention (Itti *et al.* 1998) offers a tool that can be used in the design of print ads to ensure that key elements of an ad are salient, and thus more likely to be at least preattentively processed by viewers during these brief exposures.

To illustrate this process, two magazine ads from Procter & Gamble's Tide campaign, which won the 2007 Clio Award (available at www.clioawards.com/winners), are evaluated using a numerical computing software program – MATLAB – and the saliency algorithm of Itti *et al.* (1998), available at http://ilab.usc.edu.

Figure 3 shows the computational modelling output for the first ad (original images are in colour, but are shown here in greyscale). The image of the ad is used as a visual input and is decomposed into three conspicuity maps (one for each of colour, intensity and orientation), which are then summed into a saliency map. The saliency map shows conspicuous ad objects, where the brighter the location the more noticeable the object. Based on the saliency map, and as shown in the 'Attentional Scanpath' image, the most salient locations (light-tinted circles) and the order in which attention shifts (black lines) are identified. Also, the time required for each shift of attention is calculated by the programme. In this example, the analysis simulates what an individual would preattentively process during the first half second of exposure to the ad.

The analysis shows that the most salient location is the left, dark side of the building (high intensity, shown on the intensity conspicuity map), which provides no information about the product or the brand. Perhaps a viewer may spend up to half a second on this shaded area before turning the page, without receiving any useful communication about the brand or the product. Since many people are unlikely to consciously pay attention to the ad, and computational modelling shows that the ad is not likely to be preattentively processed either, there is no reason to expect any positive advertising effects in this example.

The second ad comes from the same campaign and the output of computational modelling of this ad is shown in Figure 4. Once again, colour, intensity and orientation of objects in the ad are presented in the conspicuity maps, which are then summed into the saliency map.

Figure 3: Bottom-up attention to ad 1

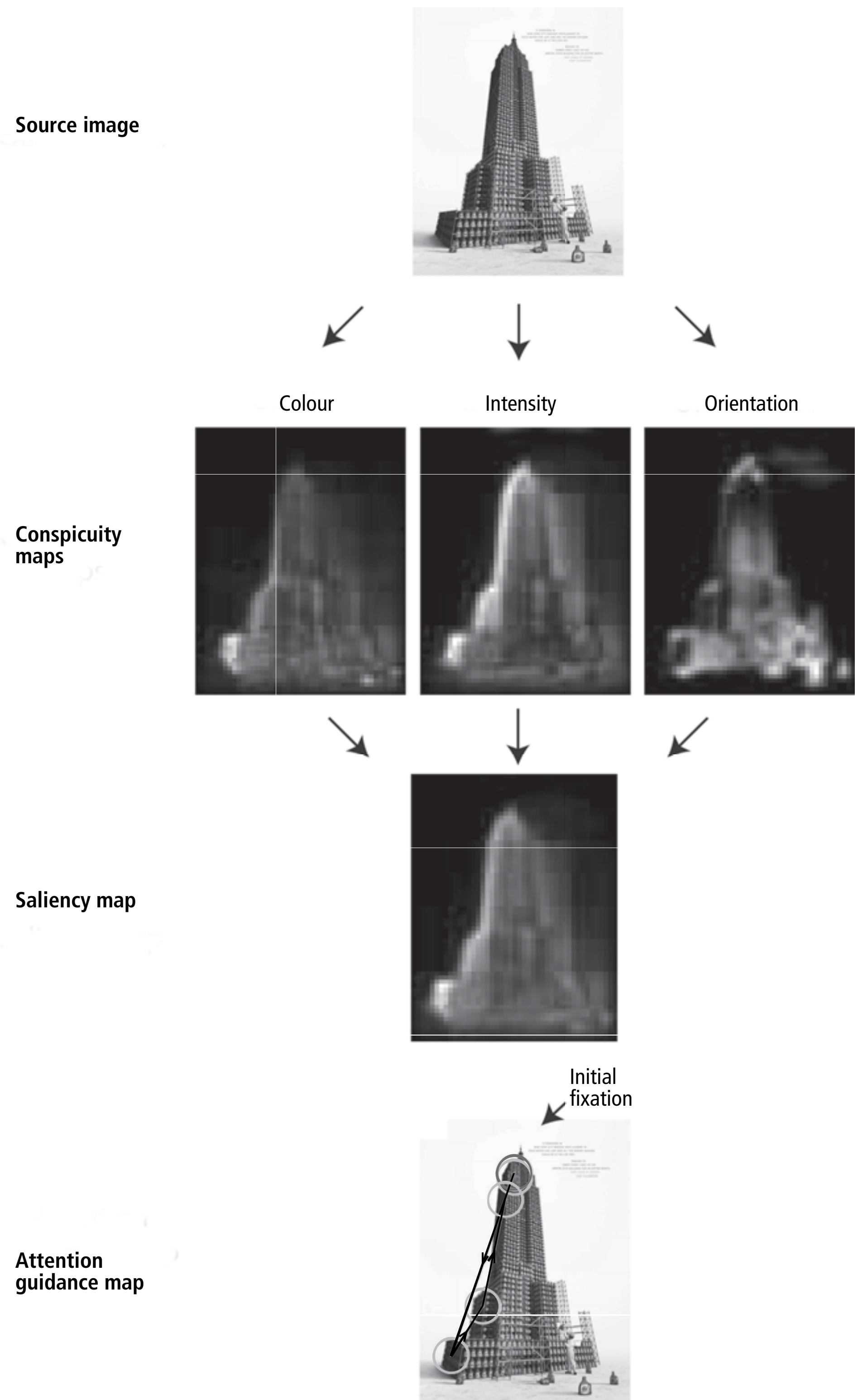
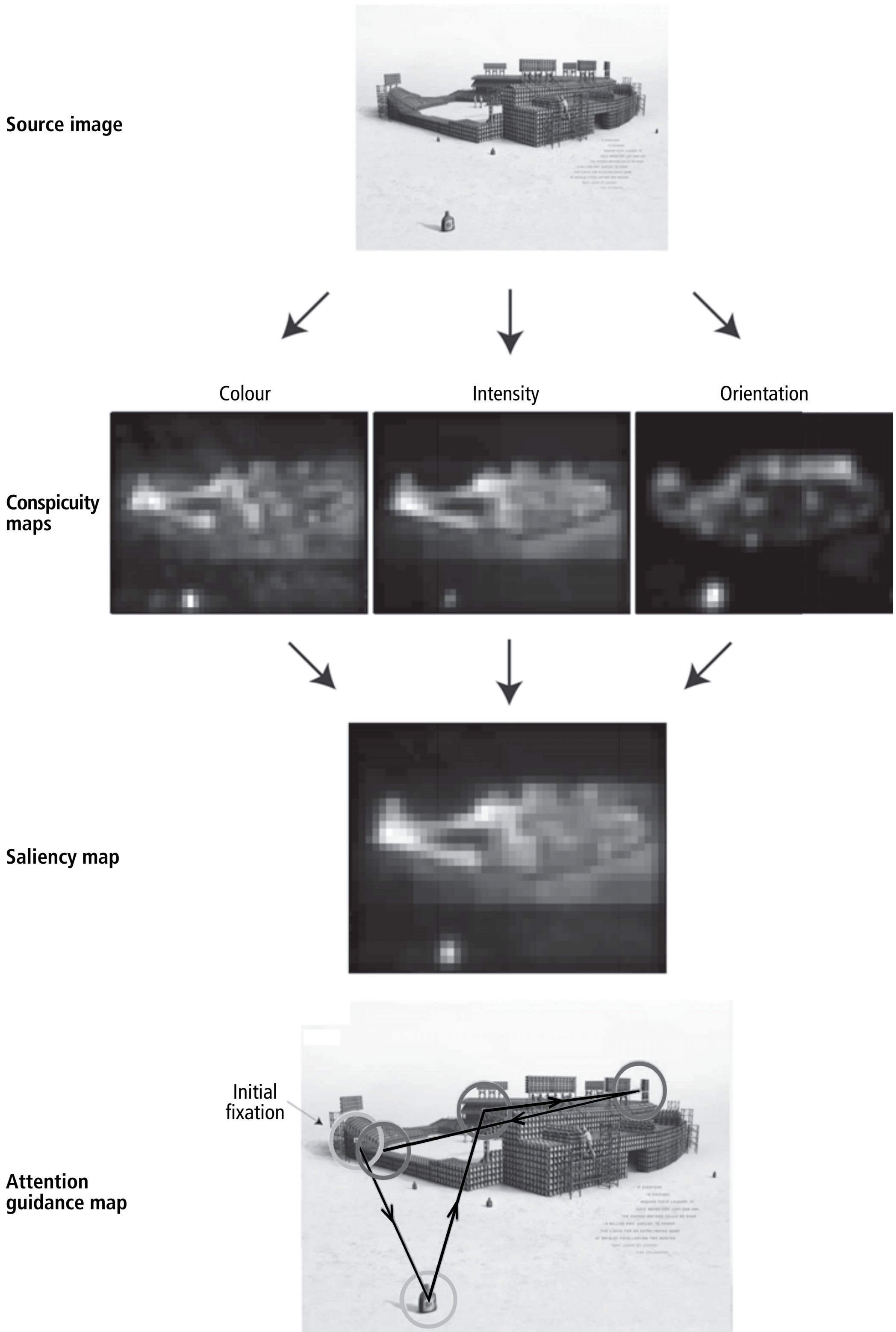


Figure 4: Bottom-up attention to ad 2



In this case, the product packaging at the bottom of the image (light-tinted circle) is the second most salient object (after the corner of the stadium), and even the third most salient location is within the product bottle (the label is salient due to its colour and then the top of the label becomes salient because of its orientation, as shown in Figure 4). Thus, even if a viewer consciously ignores the ad and spends as little as half a second on it before flipping the page, the brand name and product bottle are likely to be at least preattentively processed, opening a possibility for positive advertising effects. One can even argue that, although much research is needed to prove this hypothesis, a more relevant top-down goal – 'I am out of and need to buy laundry detergent' – may at this point override the 'avoid advertising' goal, thus resulting in focal attention to the ad.

Once again, it is important to note that a major advantage of using the computational model of bottom-up attention described here, if additional studies demonstrate its validity for advertising research, is that it does not require recruiting participants or employing time- and cost-intensive eye-tracking methodology.

Conclusions

The purpose of the current paper was twofold: (1) to highlight the importance of studying attention within the emerging research paradigm that combines marketing and neuroscience, and (2) to introduce the field of computational neuroscience to the marketing discipline.

First, the paper points out that attention currently receives virtually no space in the neuroscience–marketing literature, even though attention is a necessary step for all other marketing efforts. More so, it was emphasised that studying attention as a two-component construct consisting of a combination of bottom-up and top-down processes provides a useful framework for increasing understanding of the ways by which attention operates. In such a quest, the context of consumer behaviour proves to be a very relevant and natural way to study and better understand attentional processes.

Second, using computational modelling of visual attention to simulate early attention on a computer offers much potential for improving conceptual understanding and methods of measuring preattention, as well as a host of opportunities for application in the field.

In summary, the current paper identified a gap in the marketing and, more specifically, advertising literature, and thus has opened numerous research possibilities, some of which are discussed briefly next.

Directions for future research

Future research should uncover how preattention operates; for example, which physical characteristics of objects result in preattention, and when are they effective? Once a better understanding of preattention has been achieved, the studies that assess the relationship between preattention and focal attention, as well as between preattention and attitudes, emotions and decision-making processes, should follow. This will enhance our understanding of the concept of attention, its antecedents and its consequences.

The present paper has demonstrated the utility of the computational modelling of visual attention in a specific advertising context – magazine advertising. Some recent preliminary studies that are yet to receive attention of marketing researchers are mentioned next.

First, in the work of Torralba and Oliva (2007), it was shown that people can quickly identify the 'gist' of the image which can bias attention allocation. For example, attention is allocated faster to an image of pedestrians (expected to be walking on the ground) when they are shown at the bottom of the image than to an image of pedestrians located at the top of the image (Torralba & Oliva 2007). In the context of magazine advertising, for example, if we want to emphasise the shoes of the model in an ad, they should probably be placed in the bottom margin of the page, thus increasing the probability that the object will be noticed. Future research in advertising context is needed to test to which extent attention allocation depends on such general properties of a scene.

Second, the role of attention allocation by bottom-up-driven saliency models has been studied in the context of video gaming. Peters and Itti (2007) recently showed that some bottom-up-driven attention mechanisms may not only govern ad viewing, but even computer game playing. Future research in this context is warranted given current escalation of in-game advertising.

Finally, in a preliminary study, the computational model of bottom-up attention and saliency (Itti *et al.* 1998) was used to design banner ads on a website in order to make them more or less salient (Milosavljevic 2007). In an experiment where all other factors were controlled and only the saliency of the banner ad was manipulated, consumers' attitudes towards the banner ad were progressively enhanced as they spent increasingly more time on the website in the condition where the banner ad was designed to be salient, while no such change was observed for non-salient banners (Milosavljevic 2007).

It is important to note that, as argued earlier, recall and recognition rates for the target ad were very low (less than 20%), even in this extreme condition where most people spent two to three minutes exposed to the ad on various web pages. This provides further support for the argument that people often purposely avoid looking at the ads, and once again points to the importance of studying the confluence of bottom-up and top-down attention. The hope is that the current paper will motivate both marketing academicians and practitioners to better understand the construct of attention and to perhaps do so by utilising knowledge and tools from cognitive and computational neuroscience.

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About the authors

Milica Milosavljevic is associate researcher at the California Institute of Technology. Her research interests are at the intersection of psychology of consumer behavior and cognitive/computational neuroscience. Her recent research focuses on the interplay of visual processing/visual attention and decision-making. She received her PhD from Florida Atlantic University and has taught several marketing courses, including consumer behaviour, at both undergraduate and graduate level.

Moran Cerf is a researcher at the California Institute of Technology pursuing a PhD in Neuroscience. His research focuses on the ways by which the brain encodes information of high level sensory and cognitive processes at the neuronal level, and the interplay between those processes and conscious attention allocation. He studies attention using direct recordings from human brain as well as eye-tracking in order to develop models of attention allocation in the visual system.

Address correspondence to: Milica Milosavljevic, Division of the Humanities and Social Sciences, California Institute of Technology, MC 228-77, 1200 E. California Blvd, Pasadena, CA, 91125, US.

Email: mmilosav@hss.caltech.edu