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A NEUROFINANCE VIEWPOINT OF THE ROLE OF S&P 500 SIGNAL'S SPECTRAL PROPERTIES ON VISUALLY OPTIMISTIC AND PESSIMISTIC REPRESENTATIONAL MOMENTUMS

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Abstract

In this paper, we explore the role of financial signal's spectrum on visual representational momentums and its effectiveness as visual attention allocation strategy during a financial visual extrapolation task. This paper aims to understand whether visual attention is allocated more on looking into the "bright" or "dark" future, and whether such a visual attention allocation choice is indeed strategically effective. Preliminary results indicate that spectral properties of the S&P 500' signal do have a statistically significant role on generating visually optimistic and pessimistic representational momentums, which is statistical evidence for behavioral markers responsible for visual extrapolation capabilities which human observers have developed throughout evolution. Further results of the analysis indicate that the effectiveness of such strategic visual extrapolation capability is indeed influenced by spectral properties of the S&P 500' signal which biases twice as much the extrapolation effectiveness by lowering it for cases when visual attention is allocated on the "bright" financial future compared to when the visual attention is allocated on the "dark" financial future of the financial graph that is being visually extrapolated. We conclude that financial extrapolation as a predictive tool is much more than a statistical and computational endeavor and investors do have the capability to mentalize the visual representational momentum and to make use of this as a tool for an effective visual extrapolation of the financial graphs.

Keywords: visual attention, finance, extrapolation, spectral, analysis

1. Introduction

Financial analysts are exposed daily to various graphically represented data containing important financial information on behalf of the dynamics during a past period. Their tendency to extrapolate visually the future values based on the past period in the graph, remains the key part of predictive financial analysis (Zhang 2020; Beattie and Jones 2001). Their visual attention resources are limited both in the scope of time and space, therefore when visually extrapolating a graph, they must allocate visual attention strategically (in time and space) as to maximize their predictive capability (Warren et al. 2012). On the other hand, decision-making under uncertainty has been subject of research of signal detection theory in terms of three major applications: sensitivity of the observer with regards to how hard is to detect the target stimulus (Smith and Ratcliff 2009; Banerjee and Green 2015), the observers' bias on behalf of likelihood of responding more liberally or conservatively to stimulus detection and compressed sensing where the observer is capable of recovering high levels of information from a detection process build upon a few linear measurements. In this paper, we make use of the signal detection theory to contextualize the dynamic visual extrapolation bias in terms of the latter three concepts, as to explore its link with the frequency properties of a financial signal measured in frequency domain.

Let us consider a financial analyst who based on the graphical information (financial signal) presented to her, must decide whether a financial signal will go UP, DOWN or being CONSTANT, in the next period. Such situations are ambiguous, uncertain and in many cases the evidence is not obvious which usually requires a technical analysis of the signal's momentums caused by the market sentiment (Picasso et al. 2019). As such, the financial analyst performs a dynamic extrapolative visual search throughout the graphical information and this process of visual search can be expressed in terms of proportion of time that the observer focuses her visual attention resources on an area of interest of upper-right corner (representing the "bright" future) versus lower-right corner (representing the "dark" future), which corresponds with the notion of visual motion extrapolation in cognitive sciences (Battaglini and Ghiani 2021; Warren et al. 2012). The strategic nature of this visual attention allocation relies on the fact that financial observers do have a time constraint when formulating an optimal decision due to the dynamic (and stochastic) nature of the financial signals.

Visual motion extrapolation research has been investigating how the observer is making use of the object's past trajectory to predict its location in the near future (Hogendoorn 2020). Such research acknowledges that the visual system faces with a computational challenge as to compute the extrapolation of the position of a moving object while the time delay in neural transmission is an inherent struggle to deal with as not to miss localize the future position of the moving object while the brain processes its current position. The notion of representational momentum has emerged as one (among many) of the explanations of the perceived displacement of the moving object (Kimura 2021). Representational momentum considers the additional imaginative motion that observers report to "see" when the target moving object suddenly disappears from its trajectory. It is a sort of perceptual forward displacement of the motion trajectory which corresponds with a neurobiological extrapolation mechanism (Merz et al. 2020).

The notion of momentum in kinematics is described as the product of object's mass and velocity, where the notion of representation considers the observers' mental representation of the motion of the object. In context of visual graph extrapolation where the stimulus presentation are graphs whose future values are absent, the visual representational momentum can be thought of as the observers' mental representation of the continuation of a signal's line formed from past points toward the future, reflected in eye movements toward that direction (Kimura 2021). There are studies that consider the representational momentum as an embodied mechanism of anticipating implied motion (Fischer et al. 2021; Khatin-Zadeh, Marmolejo-Ramos, and Trenholm 2022). This anticipation mechanism has been researched for both top-down and bottom-up aspects which suggest a strategic nature of perceptual anticipation (Mann et al. 2019). In the context of financial signal extrapolation, the level of implied motion would be the time-series trajectory up to the present moment and the observers' visual attention allocation as part of the perceptual anticipation process, represents a perceptual strategy of whether (and how much) to focus visual attention on the visually optimistic compared to pessimistic representational momentums.

Considering the previous directional contextualization of the future values of a graph as UP, DOWN or CONSTANT pattern, operationally, we define these three categories of dynamic extrapolative visual attention allocation strategies as visually optimistic, pessimistic and neutral representational momentums. Assuming only a binary bias, as to whether the underlying strategy of the financial analyst will be to allocate visual attention more towards optimistic or pessimistic representational momentum formations, we decided that the neutral representational momentum is irrelevant on operational level of analysis and as such we focus only on visually optimistic and pessimistic representational momentums. We suggest that it is this binary bias the one that determines the structure of graph's observers' strategy to address ambiguity in terms of previously built visually extrapolation experiences on behalf of trial and error principle. This strategic addressing during dynamic visual extrapolation does not imply conscious or intentionally pre-defined strategic plan. Instead, it implies a spontaneous, momentary visual search which reflects the visual search toward the "bright" and "dark" future where the latter two represent two different areas of interest (AOIs) on the stimulus presentation (the graph). As such, we formulated our first alternative hypothesis:

> *H1. The mean frequency of S&P 500 signal will influence the spatial allocation of visual attention towards these two areas of interests of the extrapolated graph: "right corner up" (visually optimistic representational momentum) and "bottom right corner" (visually pessimistic representational momentum).*

The effectiveness of such strategy can be evaluated by comparing the real future outcomes of the financial signal to those suggested by visual optimistic and pessimistic representational momentums of the graph observers. To address formally the above-mentioned ambiguity that observers face with when extrapolating a graph, we decided to integrate the framework of signal detection theory. According to signal detection theory, observers are faced with the task of differentiating the information-bearing patterns from the noise (random) distractions in a perceived signal (Wixted 2020). In the financial signal extrapolation context, visually optimistic and pessimistic representational momentums do contain a purpose, but that purpose not necessarily is information search, since future values are absent in the graph. So, in the right part of the graph does not exists any relevant object to look at, despite that spatial area of interest having a contextual relevance as "bright" or "dark" future. However, if we consider that each visual attention allocation toward one of these AOIs on the graph (indicated as "bright"/" dark" future) does count as a behavioral intention corresponding to visual optimistic and pessimistic representational momentums, we gain access to financial graph's observers' attitudes toward the financial future. Furthermore, behavior intentionality is recognized as a distinct category compared to the categories of investors' behavior, cognition, and beliefs in the models of attitude formation (Bossaerts, Suzuki, and O'Doherty 2019).

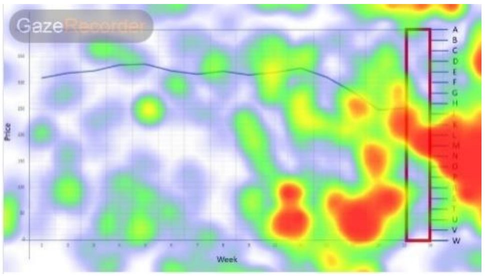
In context of signal detection theory, each of those representational momentums would represent either a Hit, Miss, Correct Rejection or False Alarm category, depending on whether the observers' representational momentum is visually optimistic (rise) or pessimistic (decrease) and in coherence with the real future value of the graph (as in Figure 3). Basically, in terms of signal detection framework, we have a signal whose **spectral properties** influence the ability of the observer to extrapolate the signal (that is to become more strategically oriented by differentiating the information-bearing patterns from the noise present in the signal). This leads us to formulate the second and third alternative hypotheses:

H2. Decrease of normalized mean frequencies of the S&P 500's signal chunks will increase the visual extrapolation effectiveness of visually pessimistic representational momentum.

H3. Increase of normalized mean frequencies of the S&P 500's signal chunks will decrease the visual extrapolation effectiveness of visually optimistic representational momentum.

2. Methods

We use secondary data generated by a pilot experimental research of ours on dynamic financial visual extrapolation. Preliminary data consist of 10 subjects who have been exposed to 12 graphs representing chunks of S&P 500's signal on weekly time resolution (each graph containing data of consecutive 15 weeks chosen randomly from a time series S&P 500 signal of period 1986-2021, where the subjects had to extrapolate the price of 16th week). Subjects were asked to extrapolate the price of the graph they were observing for the 16th week solely on the graphical information that was provided to them for the previous price levels of 15 weeks. Each graph representation lasted for 10 seconds, and it was required from the subjects to perform a visual extrapolation while a video-based eye-tracking protocol was applied to measure their gazes. From 10 observers visually extrapolating 12 financial graphs (each observation lasting 10 seconds), in total 15671 saccades were recorded cross-sectionally. To isolate the visually optimistic and pessimistic representational momentums, we performed a classification by area of interest (AOIs) by applying a selection procedure of the coordinates (x, y) of the visual plane normalized as Left Top Corner (0,0) and Bottom Right Corner (1,1) of the graph displays as in Figure 1.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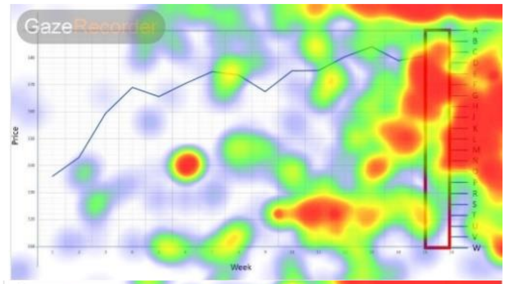
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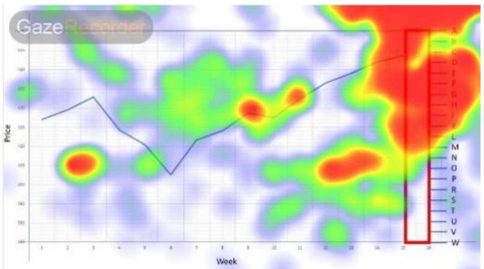
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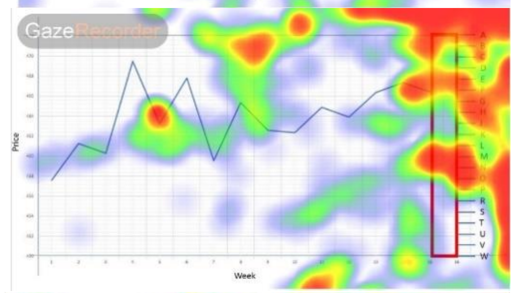
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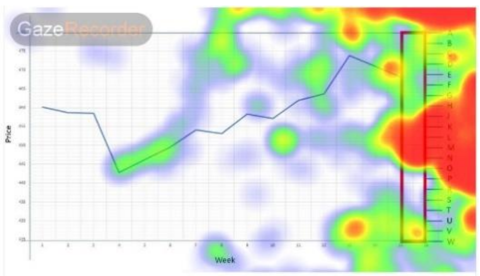
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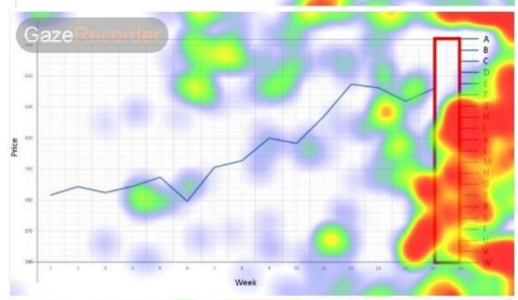
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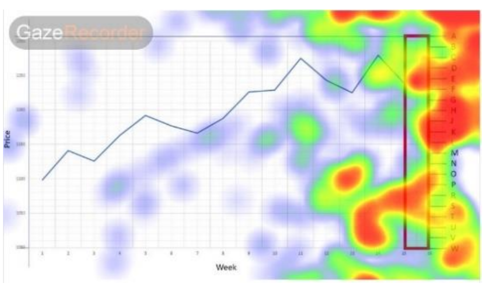
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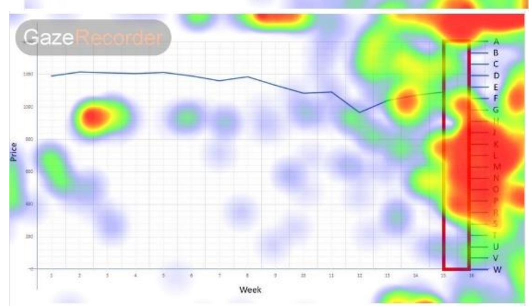
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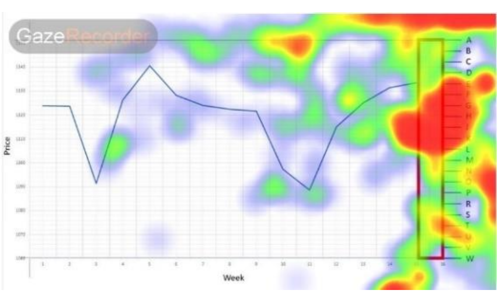
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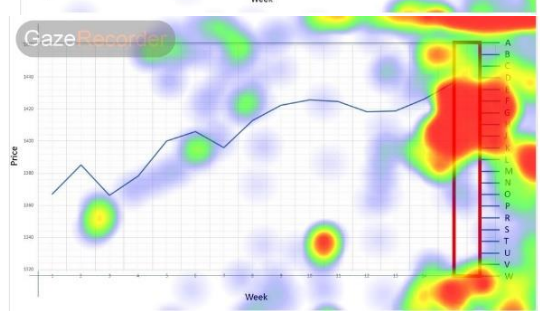
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Figure 1. Heatmaps from the pilot experiment data with 10 subject extrapolating 12 randomly selected chunks of the S&P 500's signal, generating in total 15761 eye saccades (as cross-sectional data points).

To test for the role of spectral properties of S&P 500's signal chunks on visually optimistic and pessimistic representational momentums, we performed a binary logistic regression. Whereas to evaluate the effectiveness of visual attention allocation strategy we performed a multinomial logistic regression analysis as to be able to estimate the proportion of times that visually optimistic and pessimistic representational momentums correspond to the true16th week price result of the chunks of S&P 500's signal, based on S&P 500 signal's spectral properties. There are four categories where we evaluate the effectiveness of the strategy. The optimistic representational momentum contains the category False Alarm (looking at the "bright" future incorrectly) and the category Hit (looking at the "bright" future correctly). Whereas the pessimistic representational momentum contains the category Correct Rejection (looking at the "dark" future correctly) and the category Miss (looking at the "dark" future incorrectly). These categories are represented in Figure 3b.

a)

Trial type	**Response** NO	YES
NOISE	Correct rejection	False alarm
SIGNAL	Miss	Hit

Real future momentum	**Visual attention allocation strategy** Pessimistic representational momentum	Optimistic representational momentum
Down	Correct rejection	False alarm
Up	Miss	Hit

Figure 2. a) The general matrix representation of signal detection framework
b) Adapted matrix representation of visual attention allocation through the signal detection framework

3. Results

3.1 Binary logistic regression results: The majority of the total 15671 saccades allocated towards the "future", are allocated on the top-right corner of the graph (65.5 %), which means that observers during a visual financial extrapolation task do have approximately two times more of a tendency for visually optimistic representational momentum compared to the tendency for pessimistic representational momentum (Table 4).

The Omnibus Tests of Model Coefficients reveals that a model's general fit exists. The significant result ($p<0.05$) suggests that the model of visually optimistic and pessimistic representational momentums, estimated with the normalized mean frequencies of the S&P 500 signal's chunks, is better than the null model, with a Chi-square of 294.5 and p-value of 0.000 (Table 5). By this, we can conclude that the normalized mean frequencies of the S&P 500 signal's chunks do influence the of visually optimistic and pessimistic representational momentums' variation, thus we reject the first null hypothesis. This can be seen also with the analysis of the logistic regression model coefficients. The normalized mean frequency of S&P 500's signal has a positive effect (196.84) on probability of visually optimistic representational momentum. When the normalized mean frequency of S&P 500's signal increases for one unit, the probability that the observer of the financial graph will allocate her visual attention more towards the "bright" financial future is increased for 3 times (Table 5). The next step of our analysis was to evaluate the quality of the model's fit. The – 2 log likelihood of the estimated model by maximum likelihood, converged after 4 iterations and it is reduced from 20186.48 (in the null model) to 19895.87 in the model which considers the normalized mean frequency of the S&P 500's signal. This is an additional reassurance that our binary logistic model has a better fit than the null model.

To measure the model's predictive capacity, we analyzed the classification table or as it is named also as "confusion matrix". The classification table used the conventional standard of 50% when allocating cases as visually optimistic or pessimistic representational momentums, that is, if probability for visually optimistic representational momentum on a particular level of S&P 500's signal's mean frequency was $p>0.5$, the classification appoints the observers' saccade as a looking towards the "bright" financial future, and vice versa, if $p<0.5$ it appoints the observers' saccade as looking toward the "dark" financial future. The accuracy of our model is measured as the proportion of true positive and negative cases, which results to be 68.1%. The predictive power of our model is considerably higher for visually optimistic representational momentum with 95.6% correct predictions, compared to the predictive power for visually pessimistic representational momentum with 15.8% correct predictions (Table 8).

In summary, our binary logistic regression model suggests that the more visually "smashed" (or dense) the graph is (due to higher normalized mean frequency of the signal or due to higher sampling rate of the signal), the greater is the tendency of the observer to allocate visual attention towards the upper right corner of the graph being visually extrapolated. Interpreted in an additional perspective, the higher is the sampling frequency of a financial signal which is being visually extrapolated, the higher becomes the observers' bias of looking towards the "bright" financial future. To understand whether the latter bias is counterproductive or not in terms of the success rate of matching the visually representational momentums with the real future outcome, we further discuss the results of our second model, namely the multinomial logistic regression model of visual attention allocation strategy builds upon the spectral properties of the S&P 500's signal.

Table 4. Frequency distribution for the dependent variable Y (visually representational momentum)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Optimistic	10270	65.5	65.5	65.5
	Pessimistic	5401	34.5	34.5	100.0
	Total	15671	100.0	100.0	

Table 5. Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	294.500	1	.000
	Block	294.500	1	.000
	Model	294.500	1	.000

Table 6. Logistic regression model coefficients

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1	Normalized mean frequency of the S&P 500's signal	196.844	11.468	294.631	1	.000	3.070	5.329	1.776
	The intercept	-.869	.022	1603.189	1	.000	.419		

Table 7. Model goodness of fit measures

Iteration		-2 Log likelihood	Coefficients	
			Constant	Normalized mean frequency of S&P 500 signal
Step 1	1	19895.874	-.827	186.451
	2	19891.983	-.868	196.774
	3	19891.983	-.869	196.844
	4	19891.983	-.869	196.844

Table 8. Classification table of the binary logistic regression model

Observed			Predicted		
			Visual representation momentum		Percentage Correct
			Optimistic	Pessimistic	
Step 1	Visual representation momentum	Optimistic	9823	447	95.6
		Pessimistic	4547	854	15.8
	Overall Percentage (cut value is .500)				**68.1**

3.2. Multinomial logistic regression results: From the total of 15671 saccades build up from 10 observers trying to visually extrapolate 12 different financial graphs (different in spectral properties), 45.7% are Hit responses and 12.8% are Correct Rejection responses which in total is 58.5% (45.7% + 12.8%) of successful visual extrapolation cases derived only from the visually optimistic and pessimistic representational momentums (observed through saccades patterns as behavioral intention not as a reported extrapolation). This indicates the dominance of visually optimistic over the pessimistic representational momentum, but whose shift from optimistic towards pessimistic representational momentum represents an interesting successful visual extrapolation mechanism.

The multinomial logistic regression model for estimating the effectiveness of visual attention allocation strategy, regressed against the normalized mean frequency of the S&P 500's signal was statistically significant (Chi-square 20308.107; p<0001 (Table 10 and Table11)). The Miss category was used as a reference category in the multinomial logistic regression model. Due to the inability of the statistical program to compute the exponential value of the model coefficients, we were unable to interpret the scale of effect in addition to its polarity. Results show a negative effect of the normalized mean frequency of the S&P 500's signal on effectiveness categories Correct Rejection and False Alarm while a positive effect on the effectiveness category of Hit. This means that increase of normalized mean frequency of the S&P 500's signal decreases both, the probability of Correct Rejection which corresponds to the increase of the extrapolation effectiveness of visually pessimistic representational momentum, and it increases the probability of False Alarm which corresponds to the decrease of the extrapolation effectiveness of visually optimistic representational momentum.

Table 9. Frequency distribution for the dependent variables indicating the extrapolation effectiveness of visual representational momentums

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	**Correct Rejection**	2002	12.8	**12.8**	12.8
	False Alarm	3114	19.9	**19.9**	32.6
	Hit	7156	45.7	**45.7**	78.3
	Miss	3399	21.7	**21.7**	100.0
	Total	15671	100.0	100.0	

Table 10. Results of the multinomial logistic regression analysis

Effectiveness of visual attention allocation strategy during extrapolation task[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp (B)	
								Lower Bound	Upper Bound
Correct Rejection	Intercept	-282.253	7.543	1400.220	1	.000			
	Normalized mean frequency of S&P 500;s signal	234526.515	18.923	153599761.9	1	.000	.[b]	.[b]	.[b]
False Alarm	Intercept	-280.813	7.543	1386.018	1	.000			
	Normalized mean frequency of S&P 500;s signal	234159.709	.000	.	1	.	.[b]	.	.
Hit	Intercept	.475	.033	213.528	1	.000			
	Normalized mean frequency of S&P 500;s signal	808.940	78.388	106.497	1	.000	.[b]	3.931E+284	.[b]

a. The reference category is: Miss.

b. Floating point overflow occurred while computing this statistic. Its value is therefore set to system missing.

Table 11. a) Multinomial model fitting information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	21078.206			
Final	770.100	20308.107	3	.000

b) Likelihood ratio test

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	21853.479	21083.379	3	.000
Normalized mean frequency of S&P 500's signal	21078.206	20308.107	3	.000

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Table 12. a) Classification table for multinomial logistic regression model

Observed	Predicted				
	Correct Rejection	False Alarm	Hit	Miss	Percent Correct
Correct Rejection	854	1148	0	0	42.7%
False Alarm	447	2667	0	0	85.6%
Hit	0	0	7156	0	100.0%
Miss	0	0	3399	0	0.0%
Overall Percentage	8.3%	24.3%	67.4%	0.0%	**68.1%**

b) The role of normalized mean frequencies of S&P 500's signal chunks on the effectiveness of visual attention allocation strategy

Visual attention allocation strategy

Real future value of the S&P 500 signal (16th	Pessimistic representational momentum	Optimistic representational momentum
Down	42.7 %	85.6 %
Up	0 %	100 %

From Table 12a) we constructed the Table 12b) in the framework of signal detection theory. We can see that visual attention allocation strategy as a behavioral marker for the success rate of visual representational momentums during an extrapolation task is considerably more biased (thus less effective) for the pessimistic representational momentum than for the optimistic representational momentum, both for the increase and decrease of the S&P 500's signal.

4. Discussion and conclusions

Since its discovery (Freyd and Finke 1984), the representational momentum has achieved an important place in perceptual motion studies. Its model formation capabilities through an internalized dynamic perceptual system, are known even to follow the basic principles of Newtonian physics (Freyd 1987). As such, the role of the representational momentum as an implied prediction mechanism of a non-apparent motion, is offering to the observer the capability to extrapolate additional mentalized frames of the directionality of such non-apparent motion. As our results indicate, in terms of financial graphs, mentalizing the non-apparent motion of a signal through a visual representational momentum offers the investors the capability to mentalize the future directionality of the financial signal. Yet, the effectiveness of such an evolutionary mechanism of visual attention and visual representational momentum remains subject of change and upgrade through a prediction error logic when trying to isolate and to learn the decomposed parts of a random signal such as the trend, seasonality, and noise.

We conclude that during visual extrapolation task, the frequency resolution of the financial signal creates a behavioral intention and a tendency for the observer to look towards the "bright" financial future (this being defined as AOI of the right upper corner of graph) through a visually optimistic representational momentum, that is, without having any visual cue to motivate this tendency. This means that during financial graph extrapolation, the observers' internal mentalization of the financial future, reflects itself behaviorally as an intention through visual attention allocation. Moreover, this emphasizes the strategic nature of visual perceptual anticipation financial analysts have. With the estimation of the effectiveness of such evolutionary derived mechanism through the framework of signal detection theory, we conclude that such mechanism is relatively effective in extrapolating visually the financial signal in terms of pessimistic visual representation momentums but not as effective in optimistic visual representation momentums. Furthermore, this is statistical evidence that visual financial graph extrapolation is not a random visual search, instead it has a behavior intentionality component in it, because it builds up upon the past spectral properties of the financial signal.

References

[1]. Banerjee, Snehal, and Brett Green. 2015. "Signal or Noise? Uncertainty and Learning about Whether Other Traders Are Informed." Journal of Financial Economics 117 (2): 398–423.

[2]. Battaglini, Luca, and Andrea Ghiani. 2021. "Motion behind Occluder: Amodal Perception and Visual Motion Extrapolation." Visual Cognition 29 (8): 475–99.

[3]. Beattie, Vivien, and Michael John Jones. 2001. "A Six-Country Comparison of the Use of Graphs in Annual Reports." The International Journal of Accounting 36 (2): 195–222.

[4]. Bossaerts, Peter, Shinsuke Suzuki, and John P O'Doherty. 2019. "Perception of Intentionality in Investor Attitudes towards Financial Risks." Journal of Behavioral and Experimental Finance 23: 189–97.

[5]. Fischer, Martin H, Arianna Felisatti, Elena Kulkova, Melinda A Mende, and Alex Miklashevsky. 2021. "Measuring the Mathematical Mind: Embodied Evidence from Motor Resonance, Negative Numbers, Calculation Biases, and Emotional Priming." In Handbook of Embodied Psychology, 149–70. Springer.

[6]. Freyd, Jennifer J. 1987. "Dynamic Mental Representations." Psychological Review 94 (4): 427.

[7]. Freyd, Jennifer J, and Ronald A Finke. 1984. "Representational Momentum." Journal of Experimental Psychology: Learning, Memory, and Cognition 10 (1): 126.

[8]. Hogendoorn, Hinze. 2020. "Motion Extrapolation in Visual Processing: Lessons from 25 Years of Flash-Lag Debate."

Journal of Neuroscience 40 (30): 5698–5705.
[9]. Khatin-Zadeh, Omid, Fernando Marmolejo-Ramos, and Sven Trenholm. 2022. “The Role of Motion-Based Metaphors in Enhancing Mathematical Thought: A Perspective from Embodiment Theories of Cognition.” Journal of Cognitive Enhancement 6 (4): 455–62.
[10]. Kimura, Motohiro. 2021. “Prediction, Suppression of Visual Response, and Modulation of Visual Perception: Insights from Visual Evoked Potentials and Representational Momentum.” Frontiers in Human Neuroscience 15: 730962.
[11]. Mann, David L, Joe Causer, Hiroki Nakamoto, and Oliver R Runswick. 2019. “Visual Search Behaviours in Expert Perceptual Judgements.” In Anticipation and Decision Making in Sport, 59–78. Routledge.
[12]. Merz, Simon, Hauke S Meyerhoff, Christian Frings, and Charles Spence. 2020. “Representational Momentum in Vision and Touch: Visual Motion Information Biases Tactile Spatial Localization.” Attention, Perception, \& Psychophysics 82 (5): 2618–29.
[13]. Picasso, Andrea, Simone Merello, Yukun Ma, Luca Oneto, and Erik Cambria. 2019. “Technical Analysis and Sentiment Embeddings for Market Trend Prediction.” Expert Systems with Applications 135: 60–70.
[14]. Smith, Philip L, and Roger Ratcliff. 2009. “An Integrated Theory of Attention and Decision Making in Visual Signal Detection.” Psychological Review 116 (2): 283.
[15]. Warren, Paul A, Erich W Graf, Rebecca A Champion, and Laurence T Maloney. 2012. “Visual Extrapolation under Risk: Human Observers Estimate and Compensate for Exogenous Uncertainty.” Proceedings of the Royal Society B: Biological Sciences 279 (1736): 2171–79.
[16]. Wixted, John T. 2020. “The Forgotten History of Signal Detection Theory.” Journal of Experimental Psychology: Learning, Memory, and Cognition 46 (2): 201.
[17]. Zhang, James Yibo. 2020. “The Impact of Vivid Graphical Presentation of Financial Information in Digital Annual Reports on Investors’ Impressions of Management and Firm Performance.” Journal of Information Systems 34 (3): 233–53.