BRANDS, VERTICALS AND CONTEXTS: COHERENCE PATTERNS IN CONSUMER ATTENTION

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ABSTRACT

Consumers are expected to partially reveal their preferences and interests through the media they consume. The development of visual attention measurement with eye tracking technologies allows us to investigate the consistency of these preferences across the creative executions of a given brand and over all brands within a given vertical.

In this study we use a large-scale attention measurement dataset to analyse a collection of digital display advertising impressions across a variety of industry verti- cals. We evaluate the extent to which the high attention contexts for a given brand's ads remain consistent for that brand, and the extent to which those contexts remain consistent across many brands within an industry vertical.

The results illustrate that consumer attention on advertising can vary significantly across creatives for a specific brand, and across a vertical. Nevertheless, there are coherence effects across campaigns that are stronger than random, and that contain actionable information at the level of industry vertical categorisation.

1. INTRODUCTION

Contextual targeting is a mainstay of marketing that allows advertisers to target consumers with implicit interests, inferred by the topics they read about. Context is also used as an indirect method of reaching people that belong to certain de- mographic audiences through the observation that demographics and interests are typically aligned [1, 2]. Context is increasingly used in creating and defining brand engagement[3].

Previous research has looked at the impact of different dimensions of media con- text on a variety brand metrics, for example the impact on recall[4]. However, some of these studies have made counter-intuitive, or less-than-ideal, discoveries, for exam- ple, that brand recall can be associated with ads appearing within irrelevant contexts, potentially due to an ability to stand out from a suite of relevant ads [5].

Implementing an effective contextual targeting strategy relies on the coordination of two factors. The media available to purchase must be categorised in an appro-poriate and universal scheme that permits transactional fluidity across media. This categorisation schema needs to be both appropriate for relevant distinctions between brands, and sufficiently granular as to allow targeting to be effective [6]. Secondly, each advertiser must have a method of determining the most appropriate categories to target for a given brand or campaign. This amounts to having an appropriate contextual targeting strategy, methodology or algorithm.

In spite of the emergence of digital first strategies, like contextually competitive targeting [7], contextual targeting for brand advertising continues to be predomi- nantly driven by the principle

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that priming effects are activated or emphasised by the perceived relevance of an ad (by the consumer) thus leading to the desired, and favourable, brand associations[8, 9]. This, in turn has resulted in significant work on developing algorithms that seek to predict or optimise the relevance of ads to pages on the basis of matching pre-specified phrases or semantic categories[10, 11]. Extensions of this approach have typically focused on expanding the potential target- ing combinations[12], rather than questioning whether the strategy of pre-specified phrases or categories is the right model of relevance.

It is worth noting that the effectiveness of perceived relevance may be mitigated by perceptions of privacy violations, potentially surfaced through the complexity[13] or the obtrusiveness of the advertising execution[14]. This suggests that effective perceived relevance extends far beyond a simple match between a brand category and media context and may involve additional psychological mechanisms[15].

In this work use large scale measurements of attention on digital advertising for multiple brands to investigate the coherence of contextual relevance across industries and over time. The attention measurement serves as a universal metric of advertising appeal that reveals whether the same brand resonates in the same contexts over time, or whether brands within a similar industry category have similar contextual coherence. These investigations are then used to evaluate strategies for developing and refining contextual targeting.

1.1. Attention Measurement

Eye tracking studies are widely used as a method of measuring overt attention to visual stimuli and have been applied to study the extent to which people look at, and remember, advertisments [16]. The technology has also allowed the study of many factors that contribute to effective advertising, including the impact of images of faces [17], the use of animation [18] and the relationship with social media posts [19].

Contextual relevance is a method of aligning the message in advertising with the editorial content in which it appears [20]. Such a strategy relies on an implicit expectation that the context reveals something about the consumer's intentions. The importance of this expectation is underlined by the revelation that task relevance is more important than contextual relevance[21]. Consumer attention on advertising provides a feedback signal that illustrates whether a given context is aligned with the advertising message and the interests of the consumers, as is demonstrated by its correlation with many important downstream impacts like brand recall or sales conversions[22, 23].

The goal of the current research is to understand the extent to which brands can learn the right collection of media contexts for their advertising. We seek to understand the extent to which these contexts depend on the industry vertical, the brand itself or the specifics of the creative execution.

Table 1. Dataset of Attention Measured Impressions

Period	May_01_14	May_15_28
Impressions	39865580	40037153
URLs	48550	46081
Brands	183	183
Creatives	743	743
Domains	1239	1077

2. METHODOLOGY

In this research we investigate the consistency of visual attention on advertising across brands and industry verticals. We look at this consistency in terms of both the mean attention time and the consistency of percentage lift in mean attention in a given contenxt over the campaign mean attention time. The later approach helps to normalise results to accommodate the variation in attention that occurs due to changes in ad format. We investigate these factors over the set of creatives that belong to specific brands, industry verticals as well as across the subsets of media inventory that falls into specific iAB categorised contexts.

2.1. Data

The data used in this study was collected from a wide range of advertisers running broadly targeted campaigns during the month of May 2022. The data is broken into two time periods, each of which covers exactly 14 days. The raw data was filtered such that we had impressions for every creative in both periods of time, with at least 20 impression per URL in each period. We use these requirements to ensure we are controlling for effects of changing creatives, and that the mean attention time estimates are robust.

Summary statistics for the complete dataset are shown in Table 1. Note, that each experiment outlined in this research requires filtering this dataset for a subset that meets the specific requirements of the experiment. As such, not every data point in this summary will be in all experiments. For all experiments that require information about the industry vertical of a campaign we rely on the subset that have been manually categorised. Summary statistics for this specific subset of data is shown in Table 2.

2.2. Industry Verticals

To categorise brands into industry verticals we investigate three different ap- proaches. We extracted the schema used in the iAB Online Advertsing Expenditure Report for March Quarter 2022[24] (iAB). We adopted the MSCI Global Industry Categorisation Standard[25] (GICS). Finally we developed a bespoke classification scheme to focus on the specific types of goods and services that are common in dis- play advertising that align with the common contextual categories (PXYZ). Each of these three classification schemes was applied to an identical subset of our data in a manual data annotation process. The results of which is summarised in Tables 3, 4 and 5.

Table 2. Dataset of Attention Measured Impressions with Verticals

Period	May_01_14	May_15_28
Impressions	1262365	1273379
URLs	8418	9126
Brands	55	53
Creatives	397	383
Domains	781	737

Table 3. PXYZ Verticals

Vertical	Brands	Creatives	Impressions
Automotive	7	53	17515
Business & Services	3	44	439692
Education & Careers	1	5	2139
Finance	6	25	50039
Food & Drink	2	22	23209
Gov, Charity & NGO	5	38	205513
Health & Fitness	4	13	21332
Home & Garden	8	80	106366
Media & Entertainment	2	11	31602
Real Estate	3	10	217738
Shopping & Retail	3	26	84845
Sports	1	1	42129
Style & Fashion	2	15	8342
Technology & Hardware	1	1	175
Travel	6	51	10148
Utilities & Infrastructure	1	2	1581

It is worth noting that the primary difference between these categorisation schemes is the granularity of categories. The GICS schema is the least specific of the three, and the majority of the additional categories in the iAB and PXYZ schemas are involved in providing fine grained classifications within the Consumer Discretionary category. This is clearly illustrated by the dominance of the Consumer Discretionary category in Table 5.

2.3. Contextual Categories

In order to derive contextual categories for each record in our dataset, we applied the Verity API[26] to the URLs. We convert the results of the API response into the Tier 1 contextual category from the iAB V2.0 hierarchy[27]. We do this by identi- fying the iAB category for which Verity had returned the highest score, regardless of position in the hierarchy, and trace that category back to the Tier 1 level in the hierarchy.

Table 4. iAB Verticals

Vertical	Brands	Creatives	Impressions
Automotive	7	53	17515
Charities	1	6	7363
Education	1	5	2139
Entertainment	2	6	43472
FMCG	2	22	23209
Finance	4	21	49732
Government	4	32	198150
Health & Beauty	4	13	21332
Home Products/Services/Utilities	8	80	106366
Insurance	2	4	307
Media	1	6	30259
Other	1	26	421698
Real Estate	3	10	217738
Retail	5	41	93187
Technology	1	1	175
Telecommunications	1	15	17702
Travel	7	53	11729

Table 5. GICS Verticals

Vertical	Brands	Creatives	Impressions
Communication Services	2	21	47961
Consumer Discretionary	24	189	257990
Consumer Staples	4	32	35102
Financials	6	25	50039
Healthcare	5	19	28695
Industrials	4	32	4165
Information Technology	1	1	175
Real Estate	3	10	217738
Utilities	1	10	652

2.4. Attention Measurement

For the purposes of obtaining large scale measurements of attention time on dis- play advertising we utilise a machine learning system trained on data collected from eye-tracking studies. The attention model provides an impression level estimate of attention time, that aggregates up into low error measurements of mean attention time over inventory groups.

We developed an attention measurement system that predicts attention time from user behavioural signals. The training data is collected from eye tracking panels in which users read media in a self-directed sessions while eye tracking data is collected using the a model trained on facial images[28].

As the eye tracking data is collected, we track a large number of other signals about the user experience including environmental signals like the page structure, geographical region and time of day. The core features of the model are a set of be- havioural signals derived from the scrolling behaviour and position of the advertising in the viewport.

Table 6. Attention Measurement Model - Aggregate Error

Metric	Banner	MREC
Aggregate MAE	35 ms	48 ms
95% Upper Bound	102 ms	83 ms
95% Lower Bound	-94 ms	-158 ms

The signals collected along with the eye tracking data allow us to build and deploy an attention measurement model that can predict the attention time paid to specific ad units within a page. The attention model can be applied to all digital inventory that accepts the javascript tag.

Our model evaluation process focuses on the accuracy of measuring mean attention time for a specific ad format. To generate the performance statistics we run bootstrap sampling of the test data to look at the expected error when predicting the mean attention time over impressions for a specific ad format. Each metric is calculated by taking 500 impression samples 10,000 times, and using the resulting distribution of mean error. The mean attention time measurement performance is summarised in Table 6. We see that the aggregate mean absolute error (MAE) for both formats is very low at 35ms and 48ms for banners and MRECs respectively. Furthermore, the 95% confidence intervals for these values is tightly constrained to be on the order of approximately 100ms either side of the true value.

We apply this attention measurement model across large scale digital inventory to collect a data set of attention time paid to a range of advertisements over time. We use these attention measured impressions to investigate the impact of contextual categories of media on the attention paid to advertising.

2.5. Experiments

The purpose of our experiments is to understand the extent to which the attention received by a creative execution is predictable on the basis of either the brand or the industry vertical. In particular, we are looking for dependable patterns in the media contexts in which a creative achieves maximum attention.

3. RESULTS

We present result across two key sets of experiments. The first experiments look at the phenomenon of contextual category dominance for both brands and verticals. The second experiment looks at the coherence of vertical to context alignment across time.

3.1. Contextual Category Dominance

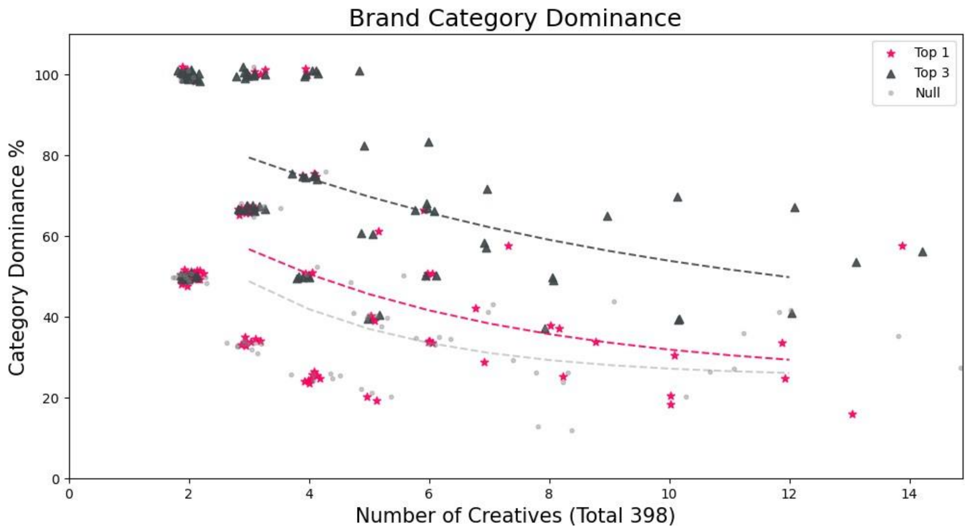

Figure 1:

We investigate the idea of category dominance, which is the extent to which a given category will be a consistent top performing context across creatives for the same brand or across brands within a vertical. The results for individual brands are shown in Figure 1. We show both performance of the most common category in the number one position (Top 1) and the most common category in any of the top three positions (Top 3).

In these plots we show the expected proportion (y axis) of creatives that share a top performing category as the number of creatives increases (x axis). Visual inspec- tion suggests that the expected proportion of creatives that share a top performing category decreases non-linearly with the number of creatives. To capture this fun- damental trend we fitted a line to these data points using the exponential function shown in 1.

$$f(x) = ae^{-bx} + c \qquad (1)$$

In addition, we include the result of a NULL model experiment for the Top 1 category by permutation of the underlying dataset. For the brand data this involves randomising the allocation of creatives to brands.

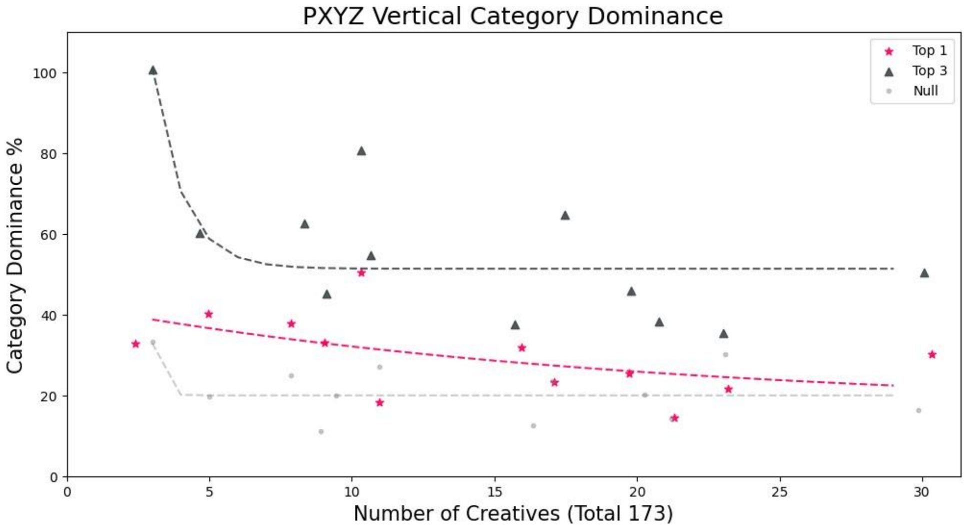

Figure 2:

Similarly to the brand study, we look at the extent to which a given industry vertical that a brand belongs to exhibits some form of contextual coherence. We show these results for the three different schemes of vertical classification. The Playground XYZ verticals in Figure 2, iAB verticals in Figure 3 and GICS in Figure 4.

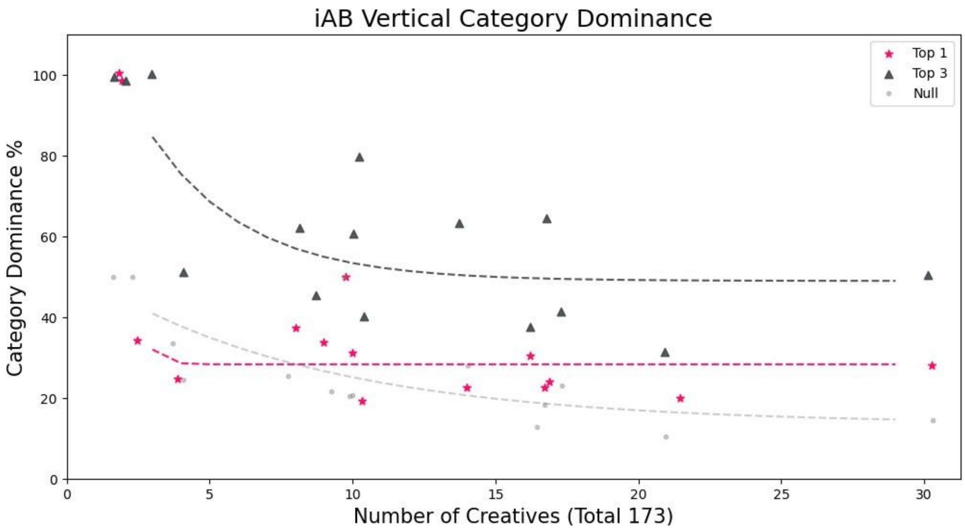

Figure 3:

As in the brand study we fit the same exponential curve to understand the ex- pected decay in category dominance for each vertical schema. We also include the results of a permutation based NULL model by randomising the allocation of brands to verticals.

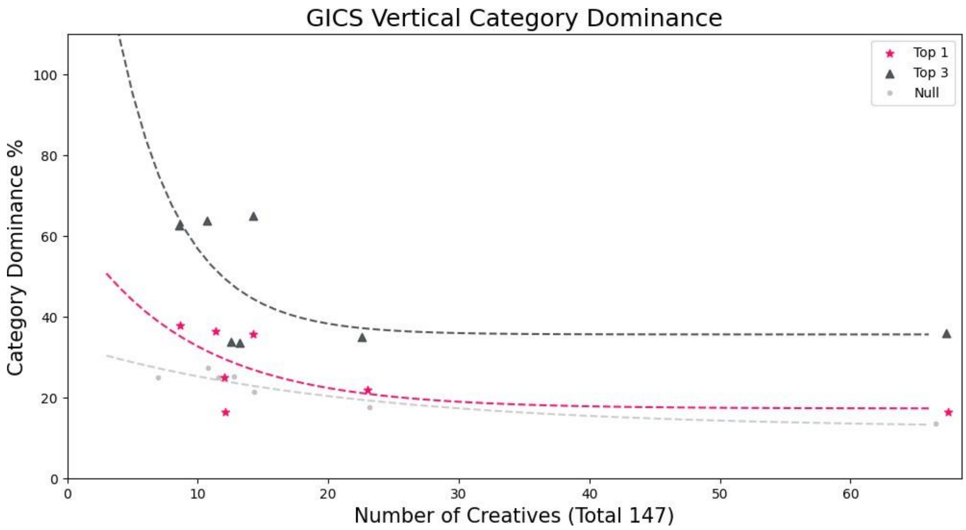

Figure 4:

3.2. Vertical and Context Coherence over time

The second experiment involves evaluating the coherence between brand verticals and the media contexts over time. This experiment is predicated on the idea that if coherence between verticals and contexts is consistent then it would allow us to anticipate the attention that a campaign will receive in the future, based entirely upon the correspondences observed with previous campaigns.

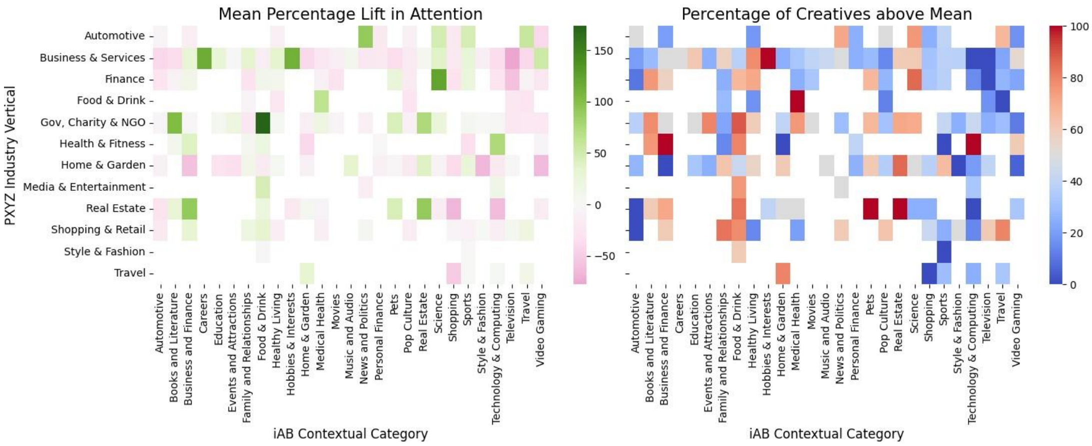

Figure 5: PXYZ Verticals Vs iAB Contexts - Period 1

In this experiment we create heatmaps of the relationship between industry ver- ticals and media contexts. These heatmaps are generated for the two time periods outlined in Section 3.1. We group the data by vertical and context and calculate the multiple metrics for all creatives that belong to the advertisers in the specific industry vertical that have appeared in that context. We add additional logic to ensure thatthere is a minimum of 4 unique creatives in each point.

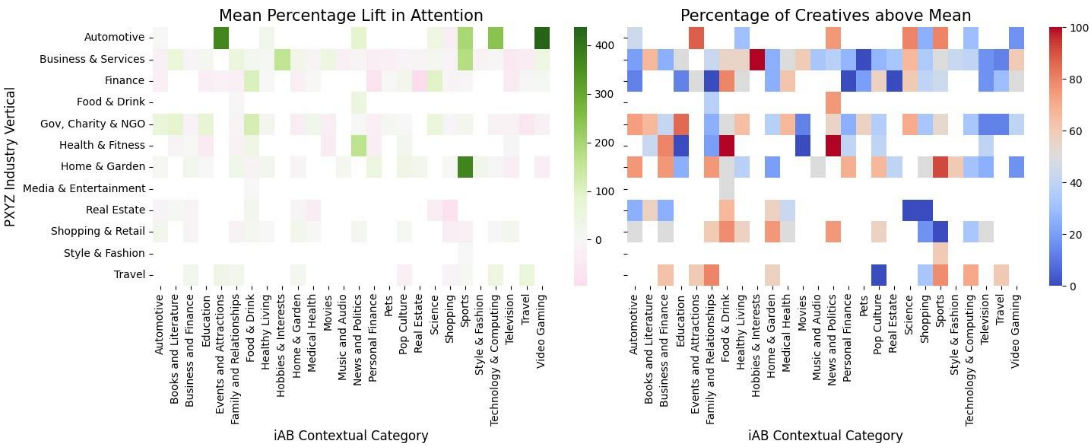

Figure 6: PXYZ Verticals Vs iAB Contexts - Period 2

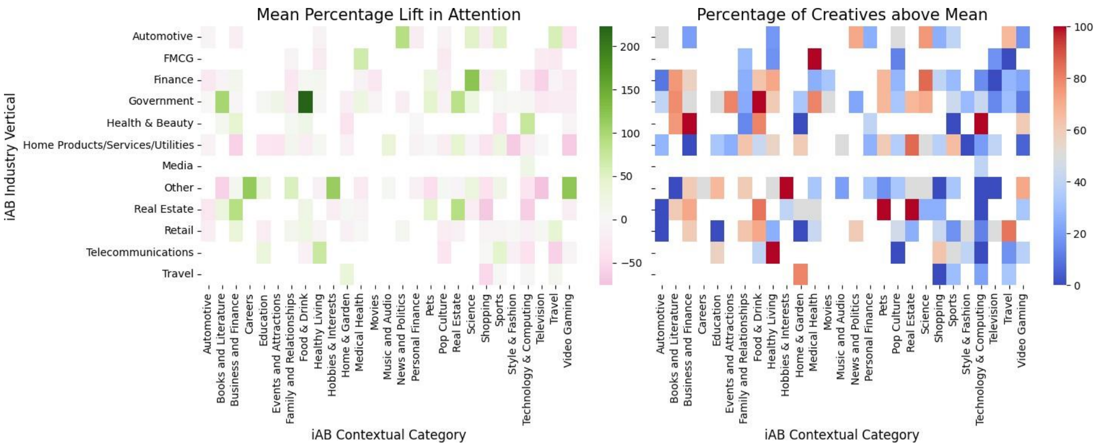

Figure 7: iAB Verticals Vs iAB Contexts - Period 1

The two metrics we look at are the mean lift in attention, which is the percentage difference in attention that each creative receives in that context, relative to its own mean. Secondly, we look at the percentage of creatives whose attention in that context exceeded their own mean, in other words what is the probability that a creative from an advertiser in this vertical will over-index in attention time in the given context.

The heatmaps for the Playground XYZ vertical categorisation are shown in Figure 5 for period 1 and in Figure 6 for period 2. Similarly, we show the heatmaps for the iAB vertical categorisations in Figure 7 for period 1 and in Figure 8 for period 2. Visual examination and comparison of these heatmaps reveals that there are instances in which the association between advertising category and media category is retained across periods. However, these appear to be much sparser than would be expected. In somes instances this is driven by the absence of data for certain combinations in both periods (which can be seen in the significant number of white blocks across all heatmaps).

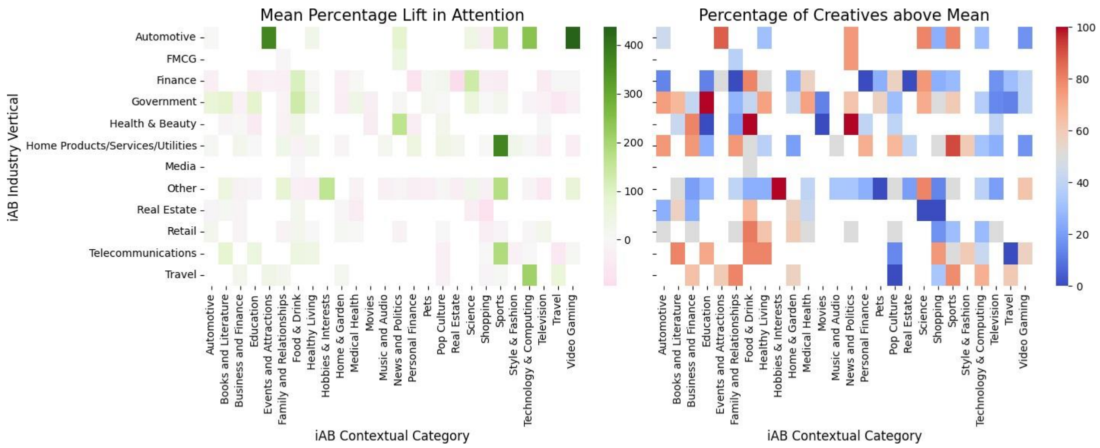

Figure 8: iAB Verticals Vs iAB Contexts - Period 2

Table 7. Results of Vertical Based Contextual Targeting on Attention

	PXYZ				iAB			
Signal	R	S	Rate	Lift	R	S	Rate	Lift
1. Attn Lift > 0%	50	38	76.0%	40.9%	54	41	75.9%	48.5%
2. Attn Lift > 20%	30	24	80.0%	53.8%	29	25	86.2%	63.6%
3. Prob of Lift > 0.5	38	31	81.6%	40.3%	36	27	75.0%	44.9%
4. Prob of Lift > 0.7	19	15	78.9%	38.1%	18	16	88.9%	50.7%

3.3. Contextual Trageting Strategies

Using these heatmaps as a guide we devised a series of tests to evaluate potential contextual targeting strategies that are informed by the performance of media context using data about previous performance of all brands within a specific vertical. These approaches and the results are shown in Table 7.

For both the PXYZ and iAB Vertical schemas we see the number of records (R) for which the vertical/context strategy could be applied. We show the number of times it was successful (S) in the next time period, wherein success means that it delivered a lift in attention (relative to the creative's own baseline mean attention). In addition we look at the success rate of the strategy (S/R) as a percentage and calculate the overall expected lift in attention time when following that strategy.

The results indicate that vertical based targeting strategies can indeed deliver increased attention times. Furthermore, these experiments suggest that the iAB schema performs consistently better than our bespoke PXYZ industry categorisations in terms of average lift, but not in terms of the probability of achieving lift. The trade- off here is between the assurance of getting some lift in attention, against the chance of maximising that lift.

4. CONCLUSION

The investigation into contextual coherence demonstrated that individual brands should expect relatively low consistency in the top performing contexts over time. This coherence appears to assymptote toward a value of approximately 30% of cam- paigns possessing the same top performing category, and 60% with a category con- sistently in the top 3. As the number campaigns increases brands should expert variability in the contexts in which their ads garner more attention. The coherence at the level of industry vertical is weaker than it is for the individual brand, regardless of the categorisation scheme used. In addition, the industry vertical categorisation schemes appear more difficult to differentiate from the null model. We can interpret this to mean that there is information about contextual coherence contained in the brand identity and industry vertical, but the utility of an industry vertical varies by both brand and categoristaion scheme.

The specific nature of the vertical categorisation scheme exerts a discernible in- fluence over the strength of the coherence. We see that the PXYZ and iAB schemas (both more granular than GICS) assymptote toward a higher baseline category dom- inance. The GICS scheme also suffers from limited data due to the lower cardinality of its structure. Nevertheless, all schemes appear to provide value above the null as the number of campaigns increases. It remains to be seen if there is single industry categorisation scheme that will produce optimal insights for all brands.

When we look at the coherence of industry verticals to media contexts over time we see that there appear to be both strong correspondences that are retained, and others that appear fleeting. We experimented with multiple candidate contextual targeting strategies derived from an initial observation period. We observed that all approaches provided lift in measured attention, however the use of the iAB industry categorisation provided consistent lift above other approaches. This suggests that determining ideal targeting can be informed by previous observations within a given vertical, but that advertisers must remain vigilant in observing performance and optimising as the media and consumer marketplace changes.

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