Market Segmentation for Fashion Retailers: Validating Trend Adoption Strategies

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Abstract

Trendalytics is a SaaS company that specializes in providing extensive insights to fashion retailers regarding their e-commerce behaviors. Still, Trendalytics desire to verify whether their current retailer Market Index assignments are certifiably true. As such, this paper introduces a novel approach to validating retailer trend adoption strategies across various fashion markets. Using internet search data and retailer inventory data, we define a feature space where retailer behaviors are compared against each other for a specified selection of women's fashion trends. Our results include a new retailer labeling methodology for early, medium, or late trend adopters and a Market Score Card to easily compare adoption behaviors across retailers. Overall, we find that retailers exhibit very different behaviors than what their current Market Index labels suggest.

1 Introduction

Trendalytics is a SaaS company that primarily services apparel retailers across high-end and discount markets. Trendalytics' objective is to confidently offer predictive analysis for all different aspects that make up the retailer world. The company helps users optimize their inventory investment decisions by providing them with the required analytics they need to buy into the right products, at the right price, and at the right time. From planners (those who are in charge of deciding the timing for which trends and designs should be available) to buyers (those who are tasked with determining how aggressively a retailer should stock up inventory for specific trends), Trendalytics aims to solve three major problems facing retailers:

1. What do I buy?
2. How much do I buy?
3. When do I buy?

Each of the questions can be broken down into more specific actions. For question 1, this focuses on tracking competitors actions, listening to fashion influencers, unlocking consumer demands, and being on top of new fashion trends. For question 2, this breaks down into determining if a trend is *top door* (more exclusive) or *all door* (wider clientele) and which action is most relevant to push profits depending on the retailer. Lastly, question 3 focuses on a retailers ability to capitalize on trends when the time is right. Trendalytics would like to help their users achieve target sales and margins by maximizing their inventory performance and investments. This will allow for a better understanding of the optimal actionable insights per specific retailer in a given point in time.

1.1 Problem Definition

The main scope of this capstone project is to efficiently gain an understanding of retailer behaviors and establish a methodology to allow for market segmentation. Market segmentation can be defined as a way to classify retailers. There are a few ways in which a retailer can be classified, such as whether they are *trend-setters* or *trend-takers*, as well as how aggressively their inventory is adjusted given different trends. The goal of this methodology would be to help answer the following questions regarding retailers: what drives their specific decisions? what is their target audience? and where are they on the adoption curve?

Currently, Trendalytics has a classification scheme of its clients based off the team's industry and professional experience, so the company would like to incorporate a data-driven market segmentation methodology into their large-scale decision-making pipeline in order to enhance their custumers use of the platform.

2 Related Work

While Trendalytics has built extensive insights on trends and trend-related products for its customers, analyzing and segmenting retailers have been largely unexplored until this point. Trendalytics currently tracks its customers e-commerce inventory and price actions, and believes there are significant insights that can be extracted by marrying inventory data with trend search data. At a high level, Trendalytics believes their data can be used to create a feature space to systematically analyze retailers' behavior on past trends and how their behaviors compare to each other. They are open to the types of features that can be created from their data and the methodology used to map retailers to the feature space. They are also open to the idea of segmentation and identifying ways to measure distance across retailers to describe how similar one retailer is to another. Finally, they desire to view that resulting information through a breakdown of apparel categories and trends.

3 Data

The data provided is comprised of three different sets: search data, market data, and social data. The search data is comprised of Google Trends corresponding to popularity metrics on 30,000 tracked terms. This includes terms such as *neon*, *high-waisted*, *cold-shoulder* and their relative search counts over as a time series, starting from 2014 to the present. The market data is a combination of both Trendalytics' platform and specifically programmed web crawlers that aggregate data regarding product inventory and price from major apparel e-commerce websites. The social data refers to items or actions, such as photos, tweets, comments, tags, etc. derived from various social media platforms. While all data sets were considered in our implementation methodology for market segmentation, the social data is too noisy and convoluted that developing a reasonable use for it was ill-advised. Nevertheless, the search data and market data has updated instances for every, meaning the aggregation of the two sets allows for the discovery of joint insights.

4 Methodology

Generating a concise methodology for market segmentation required a substantial amount of data engineering and feature engineering. Since we pool the data sets from both the search data and the market data, a precise time range has to be set to allow for consistency. The search data dates back all the way to 2013, yet the market data only contains data dating back a few years. As such, we limit the time frame to two years prior (October 1, 2017-present).

Additionally, the data from each source is stored in a different way, each requiring specific efforts to transform and load into a usable format. The search data is provided as a pickle file object, while the market data is stored in Trendalytics' platform, requiring us to utilize the company's API to extract the necessary data. The product histogram API call is used to aggregate product counts and prices over a time series. The API can handle different categories and specific terms as they are displayed on Trendalytics' platform, including specifying the retailer and even the geographical region. Our team focuses specifically on the *Women's Clothing* category and the *US* geographical region to provide a narrowed yet still general scope for analysis. Likewise, we observe retailer behaviors with respect to seven selected trends: *neon*, *paper bag waist*, *high waisted jeans*, animal print, *open shoulder*, *puff sleeve*, and *black cargo pants*.

With these parameters, we are able to aggregate information from the Trendalytics platform for any trend of interest from any retailer of interest. Moreover, the retailers themselves are grouped into the following categories: *Mass Index*, *Contemporary Index*, Fast Fashion Index, *Luxury Index*, and *Specialty/DTC Index*.

4.1 Feature Engineering: Creating t0

To interpret retailers' behaviors across trends, we first develop a way of detecting when a trend is actually "trending." In other words, at which point does a fashion trend start to pick up in search activity on Google Trends in a significant way? This point in time, which we denote `t0`, becomes an anchor for our feature development. Defining `t0` informs us of "where to look" across the time series data available in Trendalytics and allows us to create features with which to compare retailers' inventory actions.

Engineering `t0` essentially involves scanning the search volume time series, trying to locate a period where the slopes of search volume are positive most of the time and to a meaningful degree. After some time of exploring various solutions, we proceeded with a momentum signal methodology, an approach commonly used in finance that is highly transferable to this problem. Similar to stock prices, search trends can also be viewed as exhibiting strong momentum when an item is "trending."

Momentum signals are calculated using short-term and long-term moving averages. The points where the short-term moving average cross the long-term moving averages are considered points of interest. The intuition is that when the short-term moving average breaks out above the long-term moving average, it indicates the beginning of positive momentum. When the short-term moving average dips below the long-term moving average, it often signals momentum to be declining.

As seen in Figure 1, we took the difference between 3 weeks (short-term) and 12 weeks (long-term) moving averages and added them as green bars below the time series line in order to visualize periods of positive and negative momentum. We then picked the week with the highest positive difference as the peak, assigning it as `t_peak`. Once we find the peak within the period of October 1st, 2017-present, we scan back in time to find `t0`. Naturally, search volume data is very noisy and the difference between short-term and long-term moving averages can oscillate between positive and negative territory even within a broader period of positive momentum. Therefore, we define t0 to be the time when the negative momentum period occurring just prior lasts longer than 8 weeks.

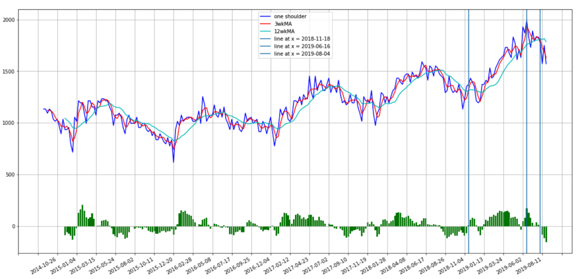


Figure 1: Momentum signaling method for *one shoulder* search trend and `t0`. See Figure 8 for enlarged plot.

4.2 Visualizing Retailer Behavior

Our objective is to visualize each retailer within a feature space in order to provide Trendalytics and their customers with a consolidated snapshot of retailer behaviors. As such, we define two features to quantify a retailer's response to a trend:

1. **Retailer Stocking Delay**: the number of weeks between trend `t0` date and retailer's `t0` date for that trend. This value corresponds to how long a retailer took in weeks to "pick up" and increase their stock of this trend

2. **Retailer Stocking Aggression**: the (log) difference in slope between the maximum slope of the trend for a retailer and the maximum slope of the trend search data. This value is a proxy for how aggressively a retailer increased their stock of a particular trend in response to a surge in the trend's popularity

The log of the slope differences feature is used to better visualize the points on the scatter plot. Likewise, given the large difference in range between a trend's search data slope and a retailer's inventory trend slope, the trend search data slope is normalized by the ratio of $\frac{\text{range of the search data}}{\text{range retailer data}}$. This scaling allows a fair comparison between the trend's search data slope and the retailers' inventory slope.

Thus, for each trend, we plot all the retailers for the selected trends, where they fall in the feature space, and colored their corresponding market index labels as provided by Trendalytics. Figure 2 shows the plot for the neon trend.

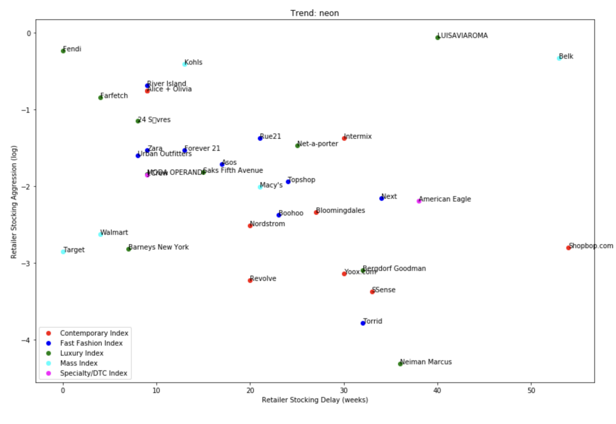


Figure 2: Scatter plot for the neon trend. See Figure 9 for enlarged plot.

The goal of this landscape is to visualize if the retailers labeled under the same Market Index exhibit similar behaviors (indicated by close positions). A retailer located farther right in the feature space indicates a slower response time to the trend. A retailer located higher up indicates that it stocks its inventory more aggressively in response to a trend's demand.

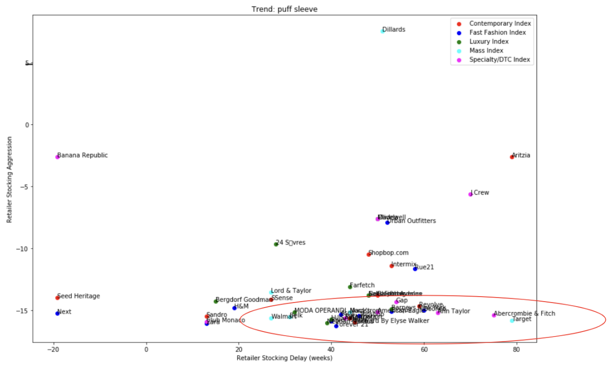


Figure 3: The puff sleeve trend without sub-trend terms added. See Figure 10 for enlarged plot.

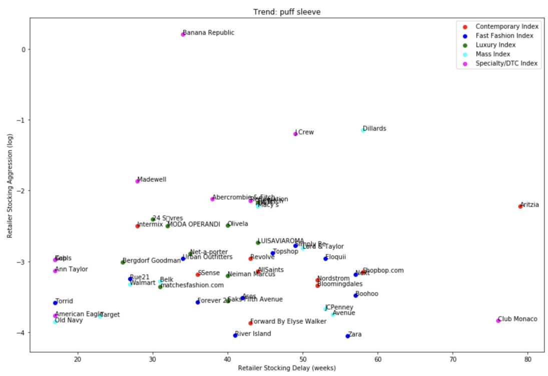


Figure 4: The puff sleeve trend after aggregating sub-trend terms. See Figure 11 for enlarged plot.

The plots for some trends in particular (e.g. *one shoulder*, *animal print*) did not produce meaningful results. As seen in Figure 3 for the *puff sleeve* trend, the points are almost all clustered near the bottom right-hand corner of the plot, indicating that all the retailers did not necessarily "follow the trend" or adequately stock their inventory accordingly. We determine that these trends have corresponding sub-trends with their own data that we were presently not including in the current trend calculations (e.g. *animal print* has sub-trends *leopard*, *cheetah*, *tiger*, *snakeskin*, *zebra*). As such, we aggregated the data from these sub-trends together and, as seen in Figure 4, this

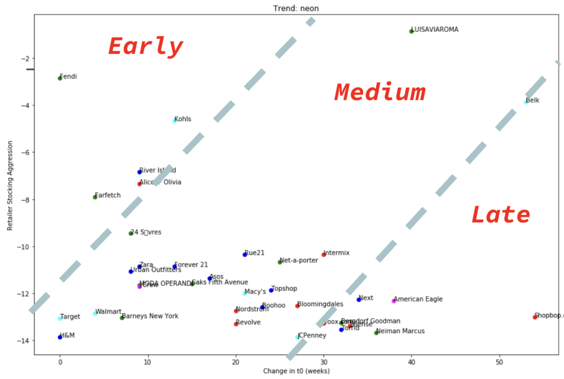


Figure 5: Scatterplot for the neon trend with approximate trend adoption behavior labels

adjustment resulted in more representative trend plots.

4.3 Data-driven Retailer Segmentation

As seen in Figure 5, we desire to assign the different retailers with a label corresponding to their trend adoption behavior (early, medium, or late) based on their locations within a created feature space. We cluster the retailers using the average stocking aggression and average retailer stocking delay over the selected trends for all retailers. The average is taken to create a single metric to represent the retailer during clustering. The clustering algorithm we use is KMeans because, being a distance-based algorithm, it assigns the retailers early, medium, or late trend adoption labels according to the natural groupings of the data.

One preliminary approach we considered included taking a weighted average of the stocking aggression and delay for the selected trends for each retailer. The weight was calculated as the amount of inventory per trend across all relevant weeks divided by the total inventory across all trends for that retailer. This approach, however, did not yield particularly insightful results as the points treated with the weighted average were too clustered together in the feature space. As such, the former approach of applying a naive average was chosen to prepare the data for clustering.

Figure 6 shows all retailers' positions according to their averaged features across all seven selected trends. Retailers that adopt the trends faster adopters cluster to the left, while those who act slower cluster to the right.

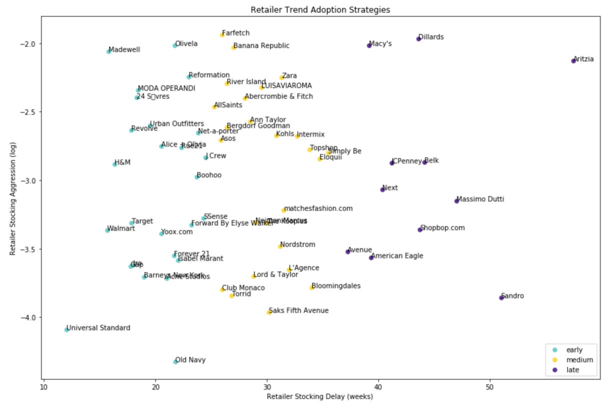


Figure 6: Averaged retailers with trend adoption behavior labels. See Figure 12 for enlarged plot.

4.4 Market Score Card

To summarize the outcome of our feature engineering and clustering, we provide a Score Card that succinctly captures all trend behavior labels and provides a comparison across retailers. The Score Card is intended to help retailers understand:

1. How many of the selected trends are they active in, relative to their peers?
2. If they participate in those trends, what is the speed at which they "catch on" to the trends?

In Figure 7, we showcase the Score Card for just one Market Index: Fast Fashion, which includes 13 retailers. For the seven selected trends that were very popular in 2018 and 2019, we show which trend adoption segment each retailer maps to. We also provide an aggregated segmentation label for each retailer across the trends.

Interpreting the example in Figure 7, Asos is a retailer that participated in all seven trends. It is an early adopter for four trends (*neon*, *high waisted jeans*, *animal print*, *open shoulder*) and is a medium adopter for three trends (*paper bag waist*, *puff sleeve*, *black cargo pants*). However, at an aggregated level as seen in Figure 6, Asos is actually a medium adopter, despite being widely known as an early trend adopter.

These labels become more meaningful when a user compares Asos to H&M, another retailer that has a similar customer base and brand profile. Using our methodology, H&M is categorized as an early adopter across the seven trends, as seen in Figure 7. While H&M did not participate in *neon* due to low inventory counts, it was an early adopter for 5 of the remaining 6 trends.

Fast Fashion Index	neon	paper bag waist	high waisted jeans	animal print	open shoulder	puff sleeve	black cargo pants	aggregate
Asos	early	medium	early	early	early	medium	medium	medium
Boohoo	medium	early	medium	early	early	late	early	early
Eloquii	X	X	X	early	medium	late	late	medium
Forever 21	early	X	early	early	medium	medium	medium	early
H&M	X	early	early	early	early	medium	early	early
Next	medium	X	medium	medium	medium	late	late	late
River Island	early	medium	medium	early	early	medium	medium	medium
Rue21	medium	X	early	early	medium	early	late	early
Simply Be	X	X	X	medium	early	medium	late	medium
Topshop	medium	medium	late	early	early	medium	medium	medium
Torrid	medium	X	X	medium	medium	early	medium	medium
Urban Outfitters	early	X	early	early	early	medium	late	early
Zara	early	X	late	early	medium	late	late	medium

X No Participation

Figure 7: Score Card for Fast Fashion Cohort. See Figure 13 for enlarged plot.

5 Results

Our results culminated in Table 1, a consolidated view of trend adoption segment counts and percentages for all retailers within a given Market Index. Moreover, since our project employs unsupervised learning to profile and segment retailers, our evaluation is largely done by cross checking our segmentation results with our partners at Trendalytics.

Market Index	Segment	Retailer Count	Percentage
Contemporary	early	8	44%
Contemporary	medium	6	33%
Contemporary	late	4	22%
Fast Fashion	early	5	38%
Fast Fashion	medium	7	54%
Fast Fashion	late	1	8%
Luxury	early	5	45%
Luxury	medium	6	55%
Luxury	late	0	0%
Mass	early	3	30%
Mass	medium	2	20%
Mass	late	5	50%
Specialty/DTC	early	5	50%
Specialty/DTC	medium	4	40%
Specialty/DTC	late	1	10%

Table 1: Segmentation Results by Market Index

6 Analysis

As Trendalytics has assigned retailers a Market Index label based on their industry knowledge, one of the main objectives of the project was to validate whether these labels are accurate. As seen above in Table 1, our results show that retailers exhibit very different behaviors across different trends. In the Fast Fashion Index alone, only 38% of retailers are early adopters, 54% are medium strength, and 8% are late. Similarly, 30% of Mass Index are early adopters, while 50% are late adopters. This is very important information for Trendalytics because it allows them to uncover details about retailers' buying and inventory actions that was too difficult to track and analyze before.

Likewise, the Market Score Card is a tool that facilitates Trendalytics' discussions with its clients on business strategy and trend investments. For example, the Market Score Card in Figure 7 reveals that a widely known early trend adopter like Asos is actually not an early adopter for select trends. Trendalytics can use these results to dig deeper into more nuanced topics such as whether a retailer's inventory action aligns with its intended business strategy, whether it participates in the trends it wants to target, and the strength at which its participation compares to its competitors.

7 Future Work

The methods developed here provide a solid foundation for future work in fine-tuning existing features, developing new features, and conducting more granular segmentation of retailers and trends. This includes incorporating the unused product price data on Trendalytics' platform. Supplementing the search data and inventory counts with price history data will allow for us to determine how retailers adjust their pricing by either inflating prices or offering discounts in reaction to trend demand.

Similarly, our methodology does not focus on trends that occur seasonally (i.e. *plaid*, *holiday sweaters*). Experimenting further with this can allow for a better understanding of when cyclical trends begin their ”upward increase” and can give retailers more insight and intuition when it comes evaluating their e-commerce behavior.

8 Conclusions

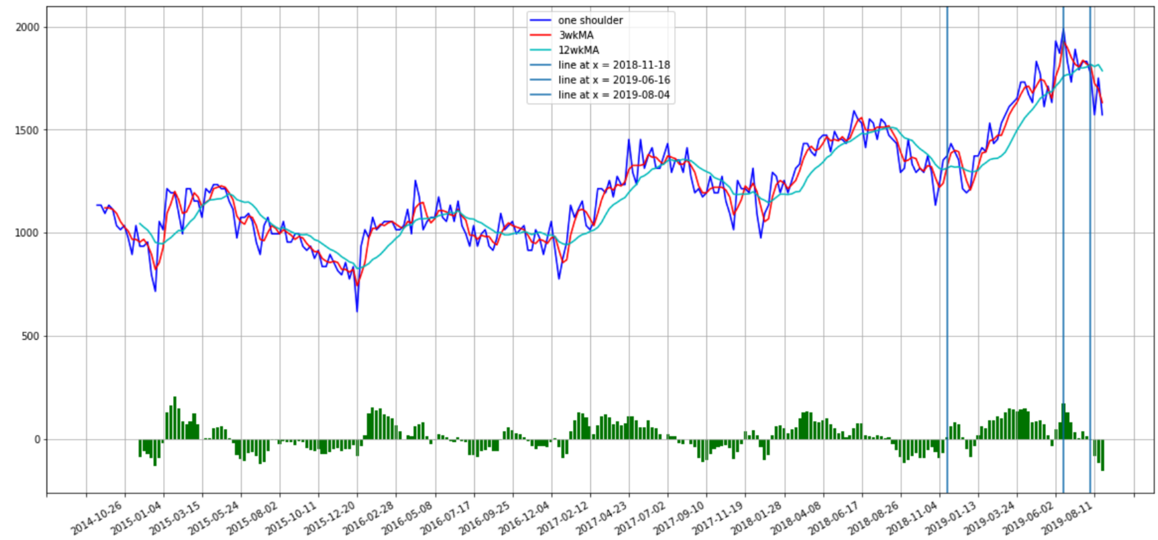
At its core, identifying trend adoption behavior is a very nuanced task that requires sourcing data from multiple sources. Given the resources and platform of our sponsor company, Trendalytics, we were able to aggregate search data on over 30,000 terms of interest for the relevant period of the past two years. With their API, we coupled the search data with inventory quantity data corresponding to these trends, allowing us to feature engineering for analysis.

Identifying `t0` allowed us develop two new features *Retailer Stocking Delay* and *Retailer Stocking Aggression* which quantify the time in which a retailer ”picks up” on a trend and the degree to which they increase their stock of this trend, respectively.

In addition to creating a Market Score Card for the selected trends for each retailer within a Market Index, we conclude that most retailer Market Index labels inaccurately describe their actual demonstrated adoption behaviors. Moreover, we experienced a few challenges throughout the process including being provided with extremely noisy trend search and e-commerce data, as well as not having a established ”ground truth retailer” that reacts in a known and consistent way to trends. This required us to use market knowledge to define our own ground truth for typical trend adoption behaviors.

Regardless, we hope this approach to validating trend adoption behaviors offers Trendalytics a solution to see how various retailers in their customer base actually compare to their competition.

9 Appendix



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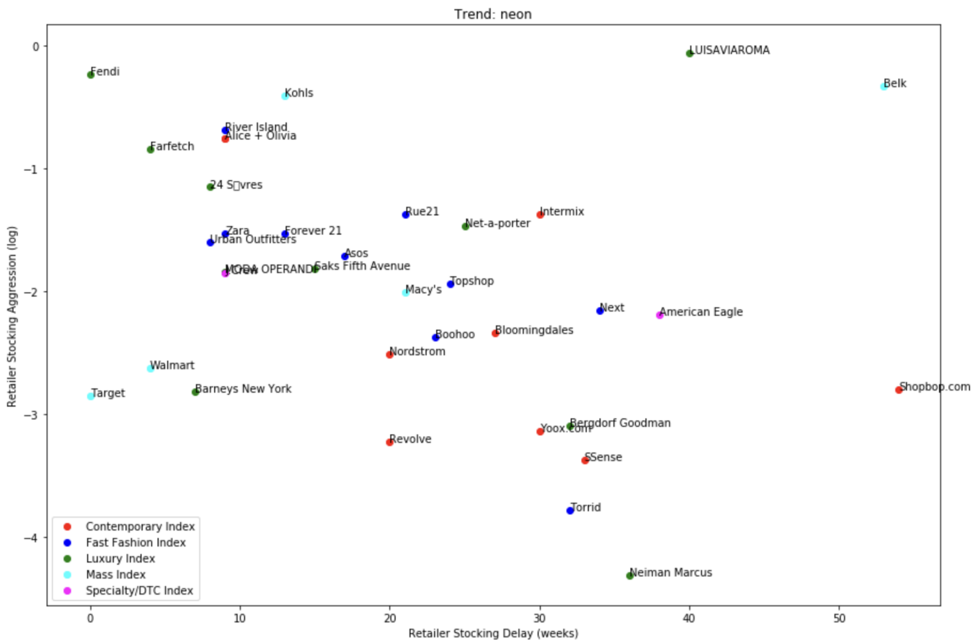


Figure 9: Scatterplot for the neon trend

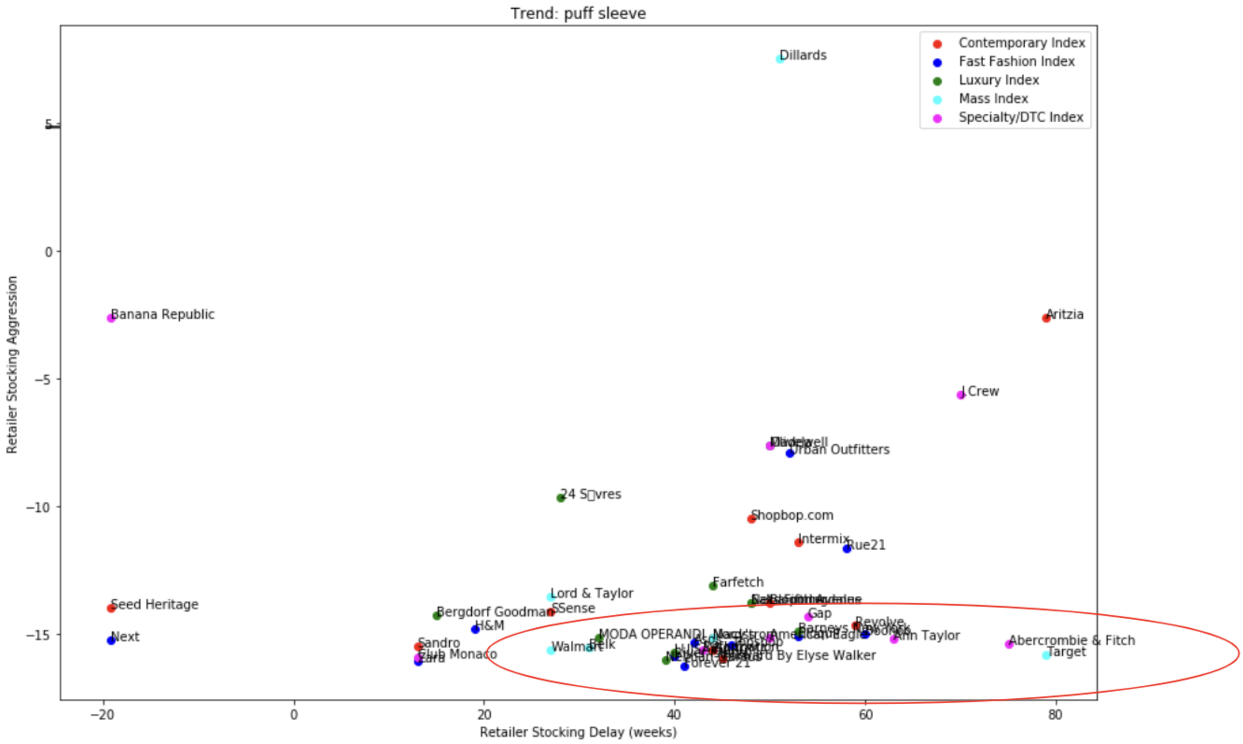
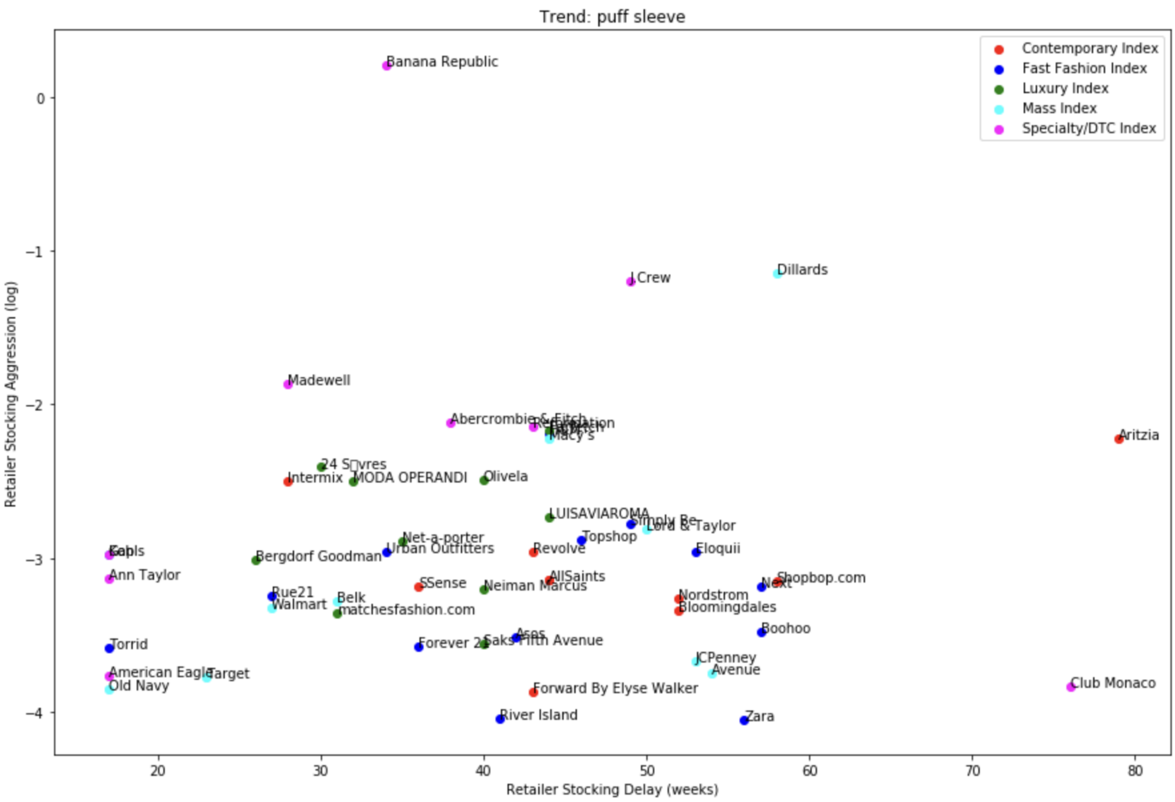


Figure 10: Puff sleeve trend without sub-trend terms added



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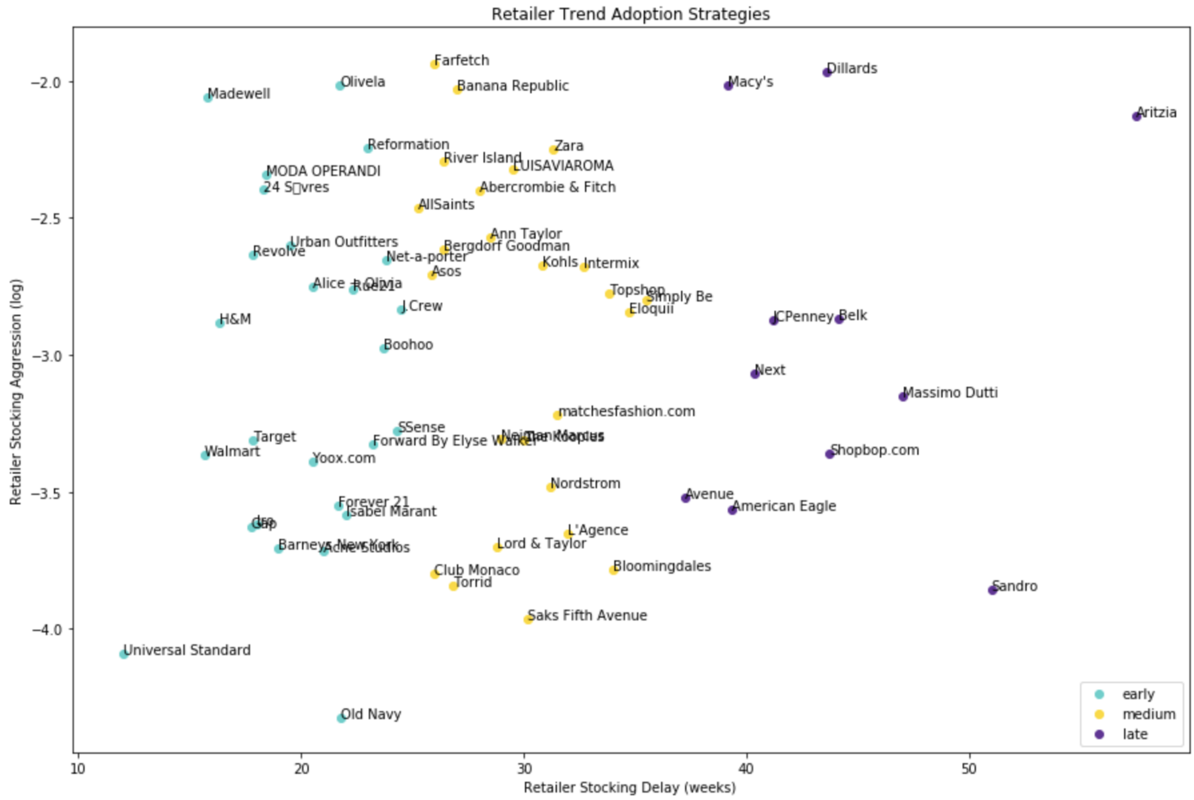

Figure 12: Averaged retailers with trend adoption behavior labels

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H&M	X	early	early	early	early	medium	early	early
Next	medium	X	medium	medium	medium	late	late	late
River Island	early	medium	medium	early	early	medium	medium	medium
Rue21	medium	X	early	early	medium	early	late	early
Simply Be	X	X	X	medium	early	medium	late	medium
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Figure 13: Score Card for Fast Fashion Cohort