A Data Driven Approach to Zingerman's Mail Order Seasonal Peak in Sales

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Abstract

Zingerman's is a mid-sized Jewish Deli, based in Ann Arbor, Michigan, that has garnered the praise of celebrities, chefs, and everyday people over the years. Its national recognition and critical acclaim has made their e-commerce platform, Zingerman's Mail Order, a go-to for holiday gifting across the country; however, the heavy influx in orders around November and December is not sustainable and places a lot of strain on company resources. Through this paper, we aim to leverage data science methodologies such as time series analysis, seasonal decomposition, natural language processing, and machine learning clustering to better equip Zingerman's Mail Order with the tools necessary to help guide data-driven decisions around flattening this seasonal spike. In doing so, Zingerman's can continue to strive towards their ongoing mission of valuing their customers by offering more consistent, reliable service and supporting their employees by mitigating burnout and reducing the need for overtime or temporary hires.

1 Introduction

Zingerman's Mail Order is an online shop that procures Zingerman's brand products, luxury food items, curated gift collections, and more across the United States. Due to the nature of the services Zingerman's provides, this e-commerce business model experiences a severe increase in demand around indulgent gifting periods in the American culture. In fact, nearly one half of Zingerman's annual sales are conducted in the final six weeks of the year. Although these sales are necessary for Zingerman's bottom line, this inherent, extreme seasonality places undue stress on company resources. In order to continually grow and evolve as a business, Zingerman's is searching for new approaches to leveling out the annual peak in sales and mitigating the negative effects of this persistent problem.

1.1 Question

Data science can be leveraged to help flatten seasonal sale spikes through a variety of approaches. In this report, we aim to conduct sales forecasting, characterize the seasonal peak (temporally and via product trends), and examine the behaviors of 'regular' customers. These three diverse objectives complement one another and culminate in a more holistic understanding of the problem space. Sales forecasting provides a data-driven foundation to help guide our analysis and decision making for both product demand and customer behavior. It helps predict the timing and scale of spikes, when product trends will be most impacted, and where to look for off-season behaviors of regular customers. Characterizing seasonal spikes allows us to understand how seasonality may impact certain product categories and purchasing trends, which can ultimately be applied to targeting strategies aimed at increasing off-season sales or anticipating the seasonal peak. Examining 'regular' customers' behavior enables us to segment and analyze how they interact with the company throughout the year and suggest strategies to encourage more regular customer purchases during quieter times to help level demand.

1.2 Broader Implications

Many companies struggle to manage the high demand that often accompanies the holiday season and the ease of online shopping has led e-commerce companies such as Zingerman's Mail Order to experience this phenomenon at an even greater magnitude. Extreme seasonal spikes in online sales can result in operational challenges, supply chain issues, higher labor costs, worsened customer service, and employee burnout. Without consulting previous data trends, seasonal products may be overproduced and have excess inventory at the end of the season, causing a costly clear out, while other seasonal products may be in high-demand and sell out unpredictably quickly, leaving customers frustrated and lost opportunities for the company to profit.

Companies that are able to flatten seasonal sale spikes and achieve a more consistent demand profile are often better positioned to respond to market changes; enabling them to focus on product quality, customer service, and operational excellence year-round, rather than just during peak seasons. Overall, data-driven insights can offer a competitive advantage by allowing businesses to better understand consumer behavior, predict demand trends, adjust strategies to stay ahead of competitors, build a loyal customer base, foster a healthy work environment, and optimize operations.

1.3 Related Works

Recency-Frequency-Monetary (RFM) analysis is a commonly used customer segmentation approach that helps companies better understand and segment their customers according to three essential behavioral metrics: Recency, Frequency, and Monetary. Recency measures how recently a customer made a purchase or interacted with the company; frequency quantifies how often a customer makes a purchase or engages with the company over a given time period; monetary gauges how much money a customer spends with the company over a specific time frame. The goal of this technique is to identify different consumer groups to tailor marketing strategies, improve engagement, and increase customer loyalty. Although this strategy can be effective, RFM is a purely behavioral segmentation model based on previous transaction data, thus it does not explicitly account for customer lifestyle or consider motivations, values, and interests. By focusing on what customers do instead of why they do it, RFM risks neglecting valuable insights.

Previous work has been done to provide alternative techniques to the standard Recency-Frequency-Monetary customers segmentation approach. In a 2012 study from the *Expert System with Applications* journal, researchers were consulted to perform a more advanced analysis over the existing RFM technique a grocery chain previously used (Miguéis et al., 2012). Instead of solely focusing on consumer behaviors, the authors sought to see if they could identify different types of customer lifestyles that the grocery store catered to via data mining techniques. The authors of this report tracked how much of each product customers purchased over a period of time (a proxy for lifestyle), and clustered them based on this information. The resulting clusters revealed how much certain lifestyle groups spent in different categories of products.

The methods used in this paper influenced our project where we tried to identify 'lifestyles' that correspond with customers who shop on a regular basis. We then directly analyze what product categories they spend the most money on during the off-season and on-season months. This is a particularly useful perspective for our main goal of 'flattening the curve' by guiding the business on what types of products to market and introduce to customers during off-season months to boost sales.

2 Dataset

This analysis builds upon Zingerman's e-commerce data that has been gathered over the past 20+ years by Zingerman's proprietary software. The data is stored in a database that normalizes every product purchased as part of an order into 49 features. Relevant fields include unique order and customer IDs, item stock names, unit price and order date; however, shipping details, order status, discount amounts, and recipient information are also tracked and available.

Although there are over two decades of Zingerman's customer transaction data available, this analysis focuses on a fixed amount of data collected from the beginning 2013 to the end of 2023. While historical data is useful and necessary in identifying trends, the older the data, the less relevant the information is to sales forecasting and understanding the current customer base. Apart from consumer behaviors changing overtime, Zingerman's has also evolved and grown as a business throughout the years; thus, it seems unreasonable to include data from years when Zingerman's mail order was in its infancy and buying items online was not the cultural norm that it is today.

In addition to consumer and company shifts, it is also important to consider national and international events and how they may have impacted purchasing trends. The effects of the COVID-19 pandemic must be addressed and accounted for when analyzing more recent data and making future predictions. Data from 2013 to 2023 seems appropriate in order to establish patterns from before the pandemic and observe how COVID has potentially impacted consumer trends in a 'long-

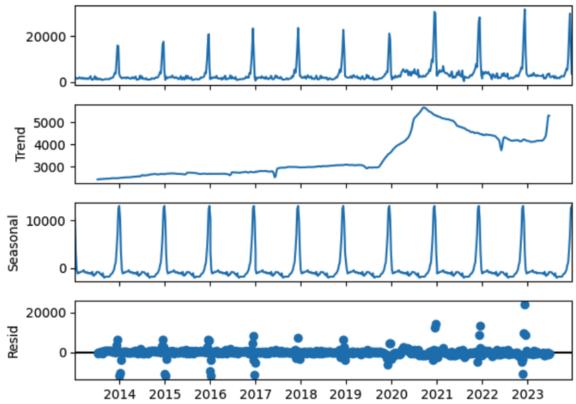


Figure 1: Seasonal Decomposition

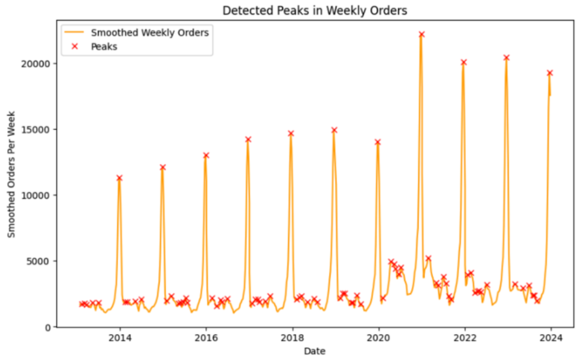


Figure 2: Peak Analysis

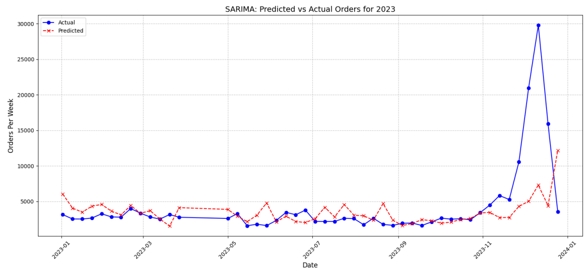


Figure 3: 2023 Prediction

term' sense.

3 Analysis - Methods

3.1 Proving the Peak

The time series analysis of sales data over the past decade reveals compelling insights into market dynamics and consumer behavior. Decomposition of the data, as shown in Figure 1, displays a consistent upward trend in sales, with a notable inflection point occurring around 2020. Interestingly, while sales volumes have moderated post-2020, they remain elevated, suggesting a persistent alteration in consumer behavior. The seasonal component of the decomposition highlights a pronounced cyclical pattern characterized by significant spikes in December of each year, indicative of robust seasonality likely attributable to increased consumer activity during the holiday shopping period.

The peak analysis in Figure 2 reveals a distinct seasonal pattern characterized by notable spikes at consistent intervals. These significant increases in orders typically manifest towards the conclusion of each calendar year. The timing of these peaks strongly suggests a correlation with major shopping periods, particularly those associated with the traditional holiday season in America. This pattern likely reflects a surge in consumer demand for Zingerman's products during festive times, when people are more inclined to purchase specialty food items for gifting or celebratory consumption.

Sales forecasting is essential to future product purchasing analysis and customer segmentation goals as it provides quantitative insights into seasonal demand patterns and targeted marketing strategies. In order to forecast future sales trends, a seasonal autoregressive integrated moving average (SARIMA) model was implemented. We utilized the dataset spanning from 2013 to 2023, with the data from 2013 to 2022 serving as our training set and the 2023 data as our test set. The model was trained using the designated training data, exhibiting satisfactory convergence. Subsequently, we applied the trained model to forecast sales figures for 2023. To visualize our results, we employed pyplot to graphically represent both the predicted (red) and actual sales (blue) data in Figure 3. Our analysis of the visualization revealed that the model demonstrated proficiency in identifying the onset of peak sales periods. However, it showed limitations in accurately predicting precise sales volumes. This observation suggests the need for further investigation and potentially the exploration of alternative modeling approaches to enhance the accuracy of our sales predictions. The more data we put into the model, the better its accuracy, thus we inputted data from 2013 to 2023 into the SARIMA model to predict 2024 sales. The results delineated a recurring peak season commencing in late November, culminating in the first week of December, and gradually subsiding by February. This pattern is consistent with typical holiday-related consumer behavior and can provide valuable insight for strategic planning.

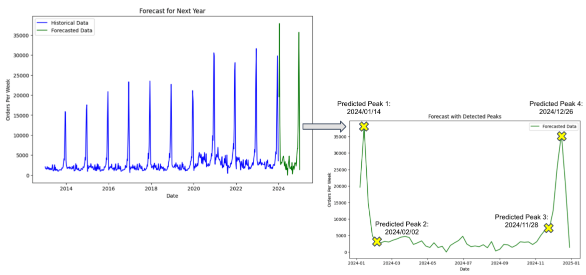


Figure 4: 2024 Prediction

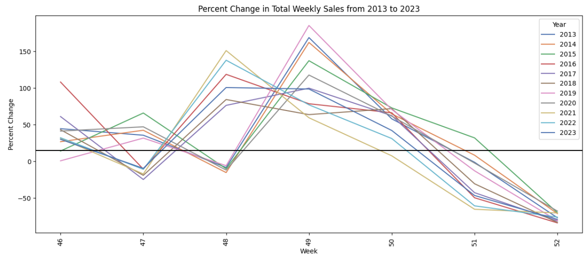


Figure 5: Weekly Sales Aggregated by Week

3.2 Defining the Seasonal Peak

The previous finding provides confirmation that the severe seasonal peak in sales behaves consistently between years. As demonstrated in Figure 4, weekly sales seem to generally align with one of two patterns: a sharp increase in sales after week 47 or a sharp increase in orders after week 48. We can presume that this difference in the first peak week depends on when Thanksgiving falls. Regardless of this notable variance, the proven annual spike appears to consistently begin around weeks 47 and 48, thus we will only consider the last six weeks of the year in the analysis below.

To further investigate if seasonal sales vary by magnitude, average total cost, and product type from year to year, we calculated a numerical heuristic to measure the difference in orders between weeks. A peak week will be defined by the condition that orders in week t are x percent more than the orders in week $t-1$. In order to determine an appropriate percent change in weekly orders, we investigated how different thresholds affect the average length of the season in weeks per year.

In Figure 5, the average peak week count remains constant between a threshold value of 15 and 25, suggesting that a 15 to 25 percent change in sales compared to the previous week may be the optimal definition for a 'peak' week. Upon enforcing a threshold of 20%, it appears most peak seasons last 4 weeks while only a couple of years

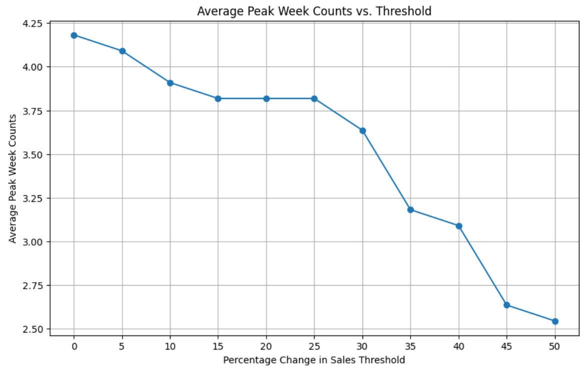


Figure 6: Difference in Sales Thresholds

between 2013 and 2023 experience slightly shorter seasons of 3 weeks. Upon further investigation, these shorter seasons seem to coincide with a later Thanksgiving.

3.3 Seasonal Product Purchasing

To better understand the intuition and nature of purchases during on and off seasons, we determined some simple, product-based metrics. Doing so allowed us to determine which items perform better throughout the year and identify common trends or relationships among products. We began by leveraging the results of the previous finding to count the number of times each product appeared in an order placed during the 'off season' versus 'on season' and normalized these counts by the item's total number of sales across the entire dataset. The resulting pivot table contained each products on and off season order distribution and their total count. We then separated this table by products that perform better during the off season and products that are more successful during annual peaks.

Given the feelings of abundance and altruism commonly associated with the holiday season, we hypothesized that items purchased more frequently during the peak season tend to cost more than products that are more popular during the off season. As displayed in Figure 7, we plotted the distribution of product unit price during the on and off seasons to visually identify a difference in average cost. There appeared to be a significant difference, favoring our original hypothesis; but, in order to formally confirm or deny this assumption, we performed a hypothesis test where the null hypothesis is there is no significant difference in average cost of an individual item across on and off seasons. Our resulting p-value was much smaller than our significance level of $\alpha = 0.05$ thus we rejected

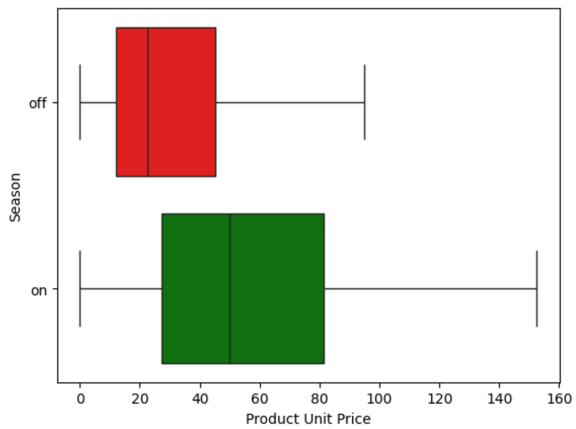


Figure 7: Distribution of Item Unit Price by Seasonal Popularity

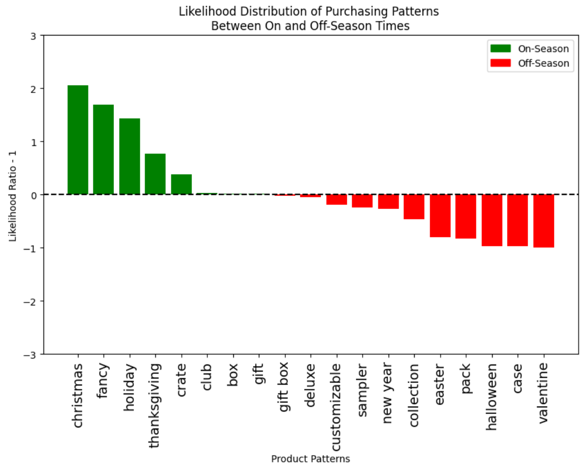


Figure 8: Likelihood of Products in Certain Categories being Purchased During On and Off Seasons based on Domain Knowledge

the null in favor of the alternative that the average price of a product purchased more frequently during 'peak' season is significantly different than the cost of an item purchased more often during the off season. This confirmed our intuition that products more commonly ordered during the holidays generally cost more, possibly due to the indulgent attitude that surrounds the holiday season.

Additionally, we noticed some potential trends among product names when comparing the products more popular during the off season to items that are more prevalent in the peak season. To investigate this phenomenon further, we tokenized each product name and applied some domain knowledge to look for specific words and patterns we deemed insightful. We then normalized these pattern counts by the total number of purchases made on and off-season and computed the likelihood ratio (on-season/off-season) in an attempt to understand what products are more likely to be purchased during each season.

Doing so left us with a table of likelihood ratios for each item token where a likelihood greater than 1 suggests that a product with this token is more likely to be purchased during the 'on-season'; likelihood less than 1 suggests that the product is more likely to be purchased during the 'off-season'; and likelihood equal to 1 suggests equal likelihood between seasons. We proceeded to graph the likelihood ratio distribution to visualize where the differences in purchasing behaviors may lie. As demonstrated by Figure 8, there appears to be a significant difference in likelihood of an item being purchased on or off season based on its naming convention or product type.

In our method outlined above, we suggested a list of keywords to identify among the two distinct lists of items that were more popular during either season and proceeded to compare the purchasing season likelihood of each word. Although this analysis leads to interesting results, they are limited to purely observational findings and domain knowledge. Instead of basing our curated list of words on intuition and notable patterns, we also implemented a more systemic, data-driven approach to identifying keywords.

We began with our two distinct tables of products that are more popular during the off season and on season that we constructed in section 3.2. We then processed these tables by splitting every stock name in each table into lists of individual words, converting them to lower case, combining all words into one long list and removing stop words. Next, we counted the number of times each word occurred in this list, sorted the resulting dictionary in descending order of frequency and stored the sorted dictionary in a dataframe for easier manipulation. Finally, we returned the top n most frequent words and their counts, along with the top words stored as a set.

Upon comparing the top 20 most popular words among products most popular during the peak and outside of the peak, we created a new list of words to identify likelihoods based on the symmetrical difference of both sets. Similar to Figure 8, Figure 9 demonstrates a significant difference in likelihood of an item being purchased on or off season based on its naming convention or product type; however, the word tokens differ significantly.

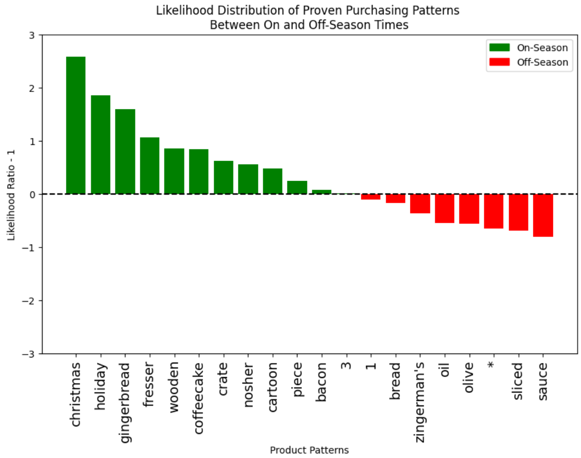


Figure 9: Likelihood of Products in Certain Categories being Purchased During On and Off Seasons based on Data-Driven set of Words

3.4 Lifestyle Segmentation

The goal of the customer 'lifestyle' segmentation is to highlight groups of products that were bought together to then identify groups of customers based on their lifestyles. This method utilizes the amount purchased of each product a customer bought in a two-year span as a proxy for their lifestyle. The products are then clustered using a variable clustering algorithm that is based upon PCA with additional steps. The input is a matrix of each row corresponding to a customer and each column is a quantity of that product purchased. The analysis outputs a set of cluster assignments that each product belongs to.

Due to the computational complexity of this task, we were only able to conduct this analysis on the sales data from 2020-2023. This left us with roughly 300,000 customers and 2,900 unique products, which required us to further shrink the size of the data for this algorithm. To address these issues, we retained only the products with sales counts within the 25th percentile, which returned 1,582 products.

We utilized the variable clustering algorithm to identify 10 groups of products commonly purchased together. Once the clustering was completed, we then graphed the sales trend of each cluster of products to see if there were differences between them. For each cluster/lifestyle, we extracted the customers who ordered a product from it (partaking in this lifestyle), and counted how many orders the customers made from each of the clusters. Using this information, we also graphed the overall sales count for customers of each lifestyle over time to analyze their shopping behaviors throughout the years and if they shopped from different clusters/lifestyles during those years. Finally, we investigated the distribution of product prices in each cluster. If products had different prices, we used the median price. For products excluded from the clustering approach, we grouped them into an additional cluster to conduct the same analysis.

4 Analysis - Findings

Seasonal decomposition analysis in section 3.1 revealed an interesting trend as sales increased during 2020 and remained elevated in the following years. Furthermore, peak analysis via the SARIMA algorithm verified consistent spikes in sales each year and predicted the peak start and end dates and duration for the next year. This multi-faceted analysis of the sales time series provides robust evidence of both long-term growth trends and pronounced seasonal fluctuations. These findings have significant implications for inventory management, staffing decisions, and strategic planning in anticipation of cyclical demand patterns. By leveraging this comprehensive understanding of sales dynamics, Zingerman's can optimize their operations to meet anticipated surges in customer demand, particularly during high-volume periods such as the holiday season. This data-driven approach to forecasting and planning can potentially lead to improved efficiency, customer satisfaction, and overall business performance in an increasingly competitive market landscape.

Refining the seasonal spike in section 3.2 suggests that the duration of 'peak seasons' in weeks remains consistent from year to year. In general, a 20% increase in sales from the previous week seems to be an appropriate threshold for defining a 'peak' season week, narrowing the length of on-season sales to 4 weeks (instead of 6) in most scenarios. More accurately defining peak-season weeks invited further aggregation and deeper analysis to determine if there is a difference among the average cost of an item and the types of products most commonly purchased during these two seasons.

Upon performing our hypothesis test in section 3.3, products purchased more frequently during peak season do appear to be more expensive on average than their off-season counterparts, suggesting that consumers are more likely to splurge during the three or four peak-season weeks every year.

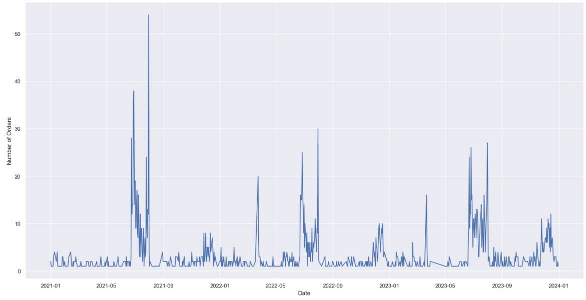


Figure 10: Daily Sales Count within First Lifestyle: 'Vintage Fish Connoisseurs'

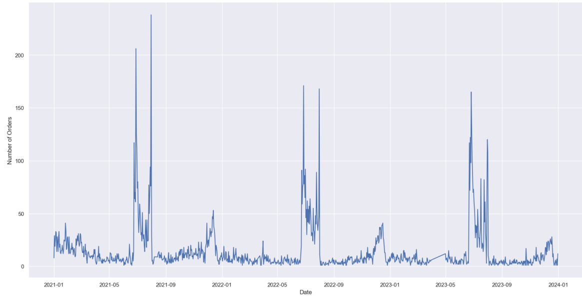


Figure 11: Daily Sales Count within Second Lifestyle

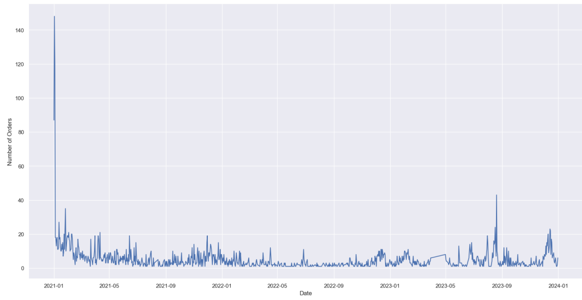


Figure 12: Daily Sales Count within Low Sale Volume Products

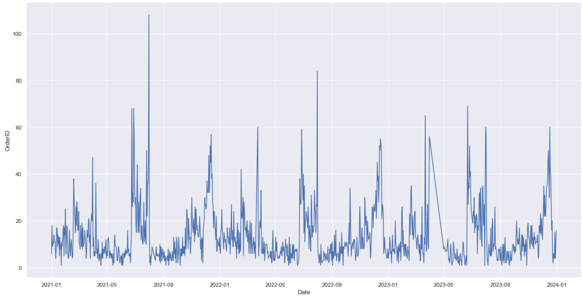
This trend remains consistent with product name pattern recognition as it seems that more indulgent products such as curated crates and items that are considered 'fancy' are more popular during Zingerman's on season while more generic items, possibly purchased in larger quantities like cases, packs and collections are more likely to be purchased during the company's off season. Additionally, the presence of words like 'valentines' suggests that perhaps there are products that are still concentrated in particular peaks but do not coincide with the traditional 'holiday season' most commonly celebrated in America.

To go beyond our prior understanding of the product space, we also compared product type popularity on and off season using a data derived list of words. Although using the words most frequently found in popular on- and off-season item names led to some similar results (e.g., products with words such as 'Christmas', 'holiday', and 'crate' are more likely to be purchased during the peak season), other more unexpected trends were uncovered. Given that products with stock names containing 'bread', 'oil', 'olive', and 'sauce' are more commonly purchased during the off-season, we can conclude that customers are more likely to use Zingerman's to supply their everyday pantry staples outside of the peak season. Additionally, the popularity of 'Zingerman's' in product names during the off season may suggest that consumers gravitate more toward the other brands that the e-commerce platform procures during the holiday season; however, customers rely on Zingerman's Mail Order for Zingerman's branded products throughout the rest of the year.

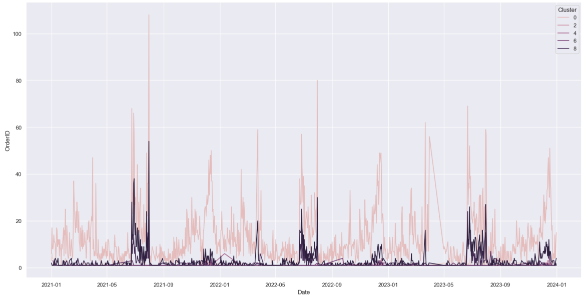
The lifestyle segmentation approach from section 3.4 yielded some encouraging results. We identified two clusters of products that were typically bought during the months outside of the peak, with high sales occurring during the holiday months (November and December). Figures 10 and 11 highlight the order counts throughout the years for the two clusters. The figures show only one annual spike from June through August. The lifestyle we deemed for the first cluster of products was the 'Vintage Fish Connoisseurs', where 7 of the 8 products in this cluster included vintage tuna or sardines. When evaluating the customer behavior from this cluster, of the customers who ordered a products from it, 14.3% of orders contained a product from the cluster. Overall, customers only shopped for products from this cluster 0.4% of the time.

We could not place a name on the second lifestyle because the 14 products in this cluster did not have an explicit theme among them. When evaluating the customer behavior from this cluster, of the customers who ordered a product from it, 16.7% of orders contained a product from the cluster. Overall, customers only shopped for products from this cluster 2.1% of the time. For the other 8 clusters, the sales trends follow the overall seasonal trend around the peak season, however, some interesting information was provided from them. The remaining clusters contained 1323, 30, 58, 51, 36, 16, 29, and 17 products respectively.

For the clusters with under 1,000 products in them, most of the products contained subscription-

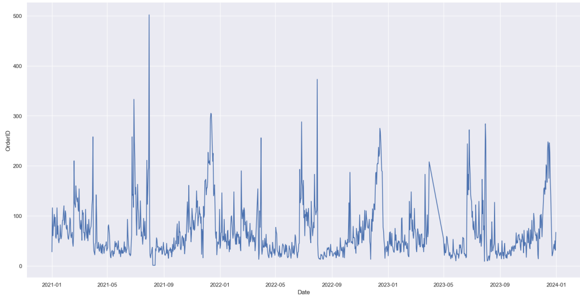


(a) Overall

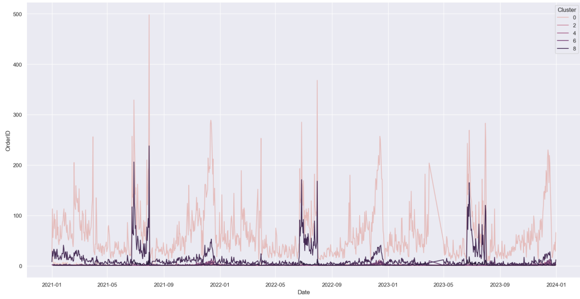


(b) By Lifestyle

Figure 13: Daily Sale Counts by Customers from First Lifestyle



(a) Overall



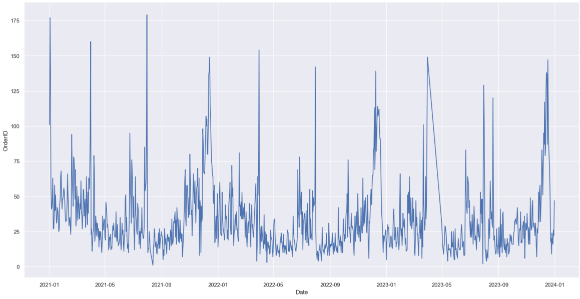
(b) By Lifestyle

Figure 14: Daily Sale Counts by Customers from Second Lifestyle

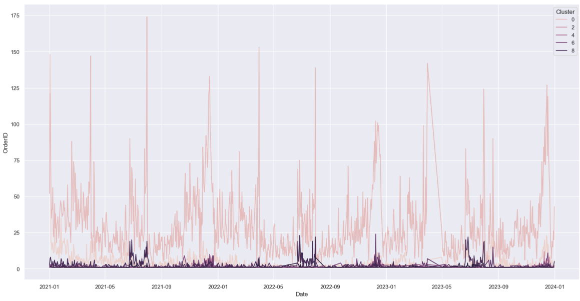
based deliveries for a variety of foods. Given that most of the sales of these subscriptions take place during the peak season, there seems to be a clear set of Zingerman's customers who order subscription-based items as gifts, referred to as clubs. These subscriptions cover a variety of products, including bread, sauces, deli items, coffee, cheese and many more. Interestingly, the product types for the subscriptions within a cluster are closely related. For example, one of the clusters included mainly bread clubs or pastry clubs, while another had cheese, meat and cheese, cured meats, and bacon clubs. These products are offered for three to twelve month periods. This is confirmed by some of the clusters in which these subscriptions are joined by other gift boxes or gift cards. When grouping the products that were excluded from the clustering analysis, it was found that the sales counts over time for this group remained consistently low, as shown by Figure 12. When evaluating the customer behavior from this cluster, of the customers who ordered a products from it, 11.7% of orders contained a product from the cluster. Overall, customers only shopped for products from this cluster 0.7% of the time.

The customer shopping behavior over time from our two key lifestyles, and low volume products are found in figures 13-15. For the 'Vintage Fish Connoisseurs' lifestyle (labeled as cluster 9), the sales trend indicates that these customers are ordering during both the summer spike between June and August and the holiday season, with the summer spikes being larger than the holiday peaks. The same pattern holds for the second lifestyle (labeled as cluster 8). As expected, when breaking down the sales counts by cluster/lifestyle, the customers from our two lifestyles shift to ordering from clusters 0-7, which are the lifestyles with a majority of orders occurring during the holiday season. Lastly, customers that ordered products from the low-sale volume category mainly purchase from Cluster 0, the largest cluster containing 1,323 products; however, it is worth noting the customers who order from these three groups seem to have similar shopping behavior throughout the year.

When analyzing the price distribution of our lifestyles, we found that the off-season lifestyles we highlighted had the lowest mean and median product price with a majority of the items (over 75%) being under \$10. The standard deviation in the prices of the products was \$5 and \$10. The other lifestyles, including the low sales volume products, had higher median prices ranging from \$30-\$50. The standard deviation of these lifestyles ranged from \$30-\$95.



(a) Overall



(b) By Lifestyle

Figure 15: Daily Sale Counts by Customers who bought Low Sale Volume Products

5 Discussion

5.1 Reflection & Application of Findings

Through our exploration and manipulation of Zingerman's Mail Order transaction data, we were able to pinpoint and predict yearly seasonal peaks through sales forecasting, compare trends among products across different variables, and segment sales based on the 'lifestyles' of the customers. This information can be strategically applied to inform off-season product offerings and promotions in an attempt to boost sales and mitigate the stress Zingerman's Mail Order continually faces every year around the holidays.

The SARIMA model forecast for 2024 predicted a pronounced peak season from early November through December, with maximum intensity in the first week of December. This seasonal trend, consistent across years but amplified since 2020, suggests a cyclical component in customer behavior that Zingerman's can leverage for strategic planning. Although our model estimated a lower size peak when tested on prior years, its insights can still provide valuable guidance for inventory management, staffing, and logistical preparations, enabling Zingerman's to anticipate and meet the heightened demand during peak seasons, particularly in the evolving post-pandemic retail landscape.

Given the significant difference in the average cost of an item purchased during peak season compared to the rest of the year and the likelihood of buying various product categories between these two time periods, it appears that customers do seem to be attracted to different items and utilize Zingerman's Mail Order for different purposes throughout the year. Since customers seem to be more likely to purchase everyday goods during the off-season, perhaps Zingerman's could begin emphasizing their pantry essentials near the end of the peak season. Alternatively, Zingerman's could offer customers who made a purchase during the holiday season a discount on everyday or Zingerman-branded items, beginning in the new year.

Through performing lifestyle segmentation, we identified a qualifiable niche customer lifestyle that typically orders products during the off-season months. We found that customers typically ordered vintage tins of aged sardines and tuna together throughout the off-season months; thus, it is evident that Zingerman's is able to cater to a group of individuals that are connoisseurs of a specific type of product. Although these customers make up a small number of orders, marketing and customer acquisition efforts could be made to draw in different groups of customers who indulge in niche products. This could help address the seasonality of the business as customers who order from these groups do not order during the holidays.

5.2 Limitations & Future Works

Although we explored a variety of methods in an effort to create a comprehensive, data-driven approach to help Zingerman's Mail Order flatten the seasonal sales peak, we must acknowledge a number of limitations. While SARIMA is a robust method for time series forecasting, it can sometimes lead to over or underfitting when the model fits historical data too closely and fails to generalize or does not accurately capture the nuance and complexity of the data. Our model's poor performance in predicting the exact sales volume during peaks may imply that the SARIMA model does not fully capture the multifaceted variables that influence seasonal demand such as major events, brand promotions, new innovations and economic climate. Additionally, the limited amount of sales data after 2020, where there was a notable shift in consumer behavior due to the pandemic, made it difficult to train the SARIMA model on a dataset that is representative of the current online retail environment.

Although longer time spans (2013 to 2023) help identify seasonal patterns, recent events (such as the COVID-19 pandemic) can drastically alter consumer buying patterns which SARIMA may fail to predict if not adjusted for these changes.

Our method of defining a peak week is based on percentage change (20%) in weekly sales. We determine this threshold using statistical methods; however, it remains somewhat arbitrary. Varying this threshold can influence our results, leading to different definitions and lengths of the peak season. As we noted, the variability in the timing of Thanksgiving can affect when the peak occurs; however, we did not quantify how this factor impacts a peak's magnitude and intensity. A late Thanksgiving might shift the peak later and make it shorter yet more intense while an early Thanksgiving could result in an earlier spike that is more prolonged and tamer. As with the SARIMA model above, this fixed peak definition also fails to consider how seasonal patterns may differ depending on external factors, such as consumer confidence or global events.

Although intuitive, our assumption that higher-priced items are more popular during the peak season may be too simplistic as price is not the only determinant of purchasing behavior during this time; discounts, promotions, social media, and pop culture trends could also act as potential influences. By focusing on products with the most significant seasonal variations in our product purchasing analysis, we are potentially overlooking the broader inventory that could be key to flattening the seasonal peak. Furthermore, this method neglects niche items that may not be the top sellers but still have steady demand throughout the year; however, we tried to address this concern in our customer lifestyle segmentation.

By reducing the product dataset to only include the top 25% of products by sales in our customer lifestyle segmentation, we risk losing critical insights about less popular products, which could still have unique purchasing behaviors that are relevant to our analysis. Although we managed to identify some customer niches, excluding less frequent items might skew the results of our lifestyle clusters and leave out smaller niche consumer segments who buy specific products but do not contribute as much to the greater cluster. Additionally, the term 'lifestyle' is a complex and multifaceted concept that cannot be fully captured or qualified by product purchases alone. Perhaps incorporating more demographic, behavioral, or attitudinal data would provide a fuller picture of lifestyle segmentation; however, this information was unavailable to us. As another effect of computational complexity, we were only able to perform the segmentation on the three most recent years of data. This relatively small dataset (which may not accurately represent the entire customer base) coupled with the fact that clustering algorithms can be highly sensitive to data size and temporal changes can lead to unstable results and less generalizable findings.

Overall, our methodology relies heavily on historical data without explicitly incorporating external factors that may drive seasonal demand fluctuations. Variables such as economic climate, global events, ad campaigns, media attention, weather patterns, and more can lead to significant deviations from the patterns we reported and make any finding in this realm seem arbitrary and insignificant. In future works, we could address and account for the economic environment by joining external data related to the U.S. economy. Additionally, we could try to collaborate with the marketing team at Zingerman's to better understand how ads and a presence on social media platforms correspond to sales. Perhaps an improved approach might involve combining SARIMA with machine learning models, incorporating customer sentiment analysis, exploring other ways of aggregating products, adjusting for real-time market conditions, better handling of computational challenges, and collaborating with Zingerman's cross-functional teams to improve predictions and ensure a more dynamic, flexible strategy for managing seasonal sales fluctuations.

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