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Research

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New Normal Weather Breaks a Traditional Clothing Retail Calendar

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Abstract

Background: Clothing businesses have complained of sluggish sales because of new normal weather, an increased variation of temperature and precipitation and the higher occurrence of extreme weather events. Traditionally, the business runs tied to calendar dates or retailing events, and the previous year's sales draw up a sales plan. This study questioned whether the sales planning method of the clothing business is valid and reliable for today.

Results: Using weather observation data and Google Trends for the past 11 years, consumers' responses to weather changes were analyzed through the decision tree to learn about consumer insights. The month is the most significant predictor of seasonal clothing demand during a season, and consumers' responses to weather vary from month to month. Minimum temperature and maximum temperature were significant predictors in a particular month.

Conclusions: Our results have important managerial implications. Rapid weather changes affect consumers' demand. Clothing retailers can apply the predictive model to quickly respond to unexpected weather changes, prepare products with rapidly increasing demand not to miss sales opportunities, and adjust quantities and prices for products with sharp declines in demand.

Keywords: Seasonal clothing, Retail calendar, Google trends, Decision tree

Background

Unseasonable warm winter, worst heatwaves, cold and wet springs, and cooler and longer summers become new normal weather. It is frequently cited in numerous publications to show the effects of unpredicted weather factors on clothing sales. The demand forecasting of seasonal clothing is an extreme challenge because the clothing industry runs its business tied to a calendar date or a retailing event and develops a sales plan based on last year's sales. The clothing industry is a highly fragmented global value chain, encompassing textiles producers, designers, manufactures, specialized factories, branded markers, and retailers [26]. Thus, the clothing product procurement requires long lead times and lesser flexibility cause overstocking and understocking problem.

Summer clothes are introduced in mid-April at the store, and hot weather appears to encourage sales. Most consumers purchase summer clothes from May to July. Even though the temperature is continuously high in August, consumers hesitate to purchase new summer clothes at full prices because the new fall clothes are introduced in August. Winter clothes are introduced in October, and the cold temperature encourages winter clothing sales. Before the end of the season, all stocks sell with deep price reductions called the end-of-season clearance sales to liquidate all items. The ideal weather conditions for clothing retailers seem to be one where the seasons exert themselves early, and thus new seasonal products sell quickly with full price.

There is a large body of evidence in clothing retailers to have challenges from unseasonal weather events. In 1995, estimates of the impact of the anomalous climate of heat sources in the UK on retail showed that the clothing and footwear retail market has the highest weather sensitivity [1]. A record-breaking El Nino event marked the winter of 1997-1998, and retailers in the northern states in the US suffered from a lack of winter clothing sales [12, 25]. Gap Inc. reported poor sales in the first quarter of 2019 because of unseasonable cold and wet weather [39]. The leading US clothing retailers observed depressed sales for the winter clothing due to unseasonably warm temperatures into the high of about 15°C and some parts of the East Coast in the US [37]. While many professionals acknowledge the importance of weather as a sale forecasting factor [8, 13, 17, 30, 37], very few companies such as ZARA utilize weather information in the sales plan.

Since the retail clothing market is the most sensitive to weather change [1], it is questionable whether clothing retailers' traditional merchandising planning methods are valid and reliable today in new normal weather. In this study, we tested consumers' seasonal clothing demand using data from the past decade to develop the foundation for a predictive model that clothing

retailers can predict a seasonal sales plan and respond to weather changes that can support supply chain activities. Therefore, this research proposed to answer the following questions: 1) when do consumers search for seasonal clothes? 2) how do weather factors affect consumers' seasonal clothing searches? 3) What are the essential predictors, and how the predictors interact with consumers' seasonal clothing searches?

Temperature leading to clothing sales up to a certain period of a season Researchers have long recognized that clothing sale depends on unique aspects of clothing, including trend, quality, and price, and is related to the interaction of several weather situations. While the objectives of studies are various, and the results of studies are inconsistent, numerous studies investigated the impact of temperature changes on clothing sales [1, 2, 3, 4, 6, 7, 22]. Warmer temperature increases sales of the clothing item (i.e., dress) in Spring and Summer and decreases clothing items (i.e., winter jacket) in fall and winter [6, 7, 22]. Specifically, when the temperature is 1°C warmer in Spring, there is a three percent increase in sales. In fall, the opposite applies; when temperature is up by 1°C, there is a three percent drop in sales [6]. The maximum temperature fluctuations are insignificant in clothing sales, but the sales increase when the temperature increases to some extent and then decreases [2]. Sunshine [1], Snow depth [2], and rain [22] were considered to be the significant factors in buying clothes. Consumers are physically and psychologically inconvenient to go to a clothing store to buy clothes during harsh weather such as snow or rain, resulting in decreased sales. An inch of snowfall reduces sales by 17%, but the snowfall effect is weak if the snowfall is historically common [32]. On a rainy day, store traffic is reduced by 7.4 % in street stores, increasing by 5.2 percent in a shopping mall [22].

The weather generally has a complex effect on daily sales in a brick-and-mortar store. In contrast, the degree and direction of weather effects depended on the store location and the sales promotion such as promotion theme [3]. Consumers' online searches and online shopping activities are a significant part of the market; consumers may shop through online stores when faced with unfavorable weather for clothing shopping to physical stores. Two studies showed contradictory findings. One study found that online clothing sales had a very positive relationship with rain [35], but another study did not provide evidence of bad weather online clothing sales [32].

Maybe retailers wished for supernormal weather that was warmer than average in spring and cooler than average in fall [28]. Early weather changes in the new season are significant because rapid weather changes increase new season clothing sales. However, towards the middle of the season, the weather, especially the temperature, does not spur sales[1, 2, 4, 6]. Determining when to purchase when the weather is consistently hot or cold involves the possibility of comparison performance, and consumers hesitate to buy seasonal items at the end of the season because consumers feel bored with the clothes they are wearing now and want to change to the clothes of the new season to come.

Seasonal clothing search on Google Clothing is the human's most immediate environment associated with an individual's biologically protective functions. Weather changes are the most dominant exogenous factor and influence an individual's everyday clothes choices [20]. Consumers recognize the need for new seasonal clothes concerning physical and psychological comfort. The recognition of needs results in the creation of information search activities. The determination of an information search by a consumer before a purchase is either to enhance the quality of the purchase outcome or pleasure [9]. Online retailing has grown over the past decade. According to the US Census Bureau News [41], online sales were 10.2 % of total sales in the first quarter of 2019, and clothing consumers use Google to search for ideas, find the best designs, and buy new clothes [10]. In this study, Google Trends (GT) was employed. GT is an extensive real-time dataset and indicates consumers' seasonal demand for any given product [34]. GT is not familiar with the clothing and textiles field, but it has gained popularity in various research areas such as finance, health care, hospitality, and tourism [15, 29, 31]. GT and complement survey data such as Consumer Index and Consumer Sentiment are positively associated [27]. There is a need for more study that provides conclusive evidence to confirm that GT can predict clothing purchase. This study used GT, the volumes of search queries on a product, as a consumers' demand indicator because an online search for information is the strongest predictor of online purchase intention [33], and consumers may combine online and offline channels to search for information and to purchase seasonal clothes.

Rationale of the study The studies mentioned above have provided a useful contribution to understanding the usefulness of weather in the clothing market. However, there are limitations in

developing a prediction of clothing demand that responds to weather changes over a single season. First, most of the studies mentioned above have found the relationship between weather factors and clothing sales in brick-and-mortar stores. Consumers feel that unpleasant weather conditions (i.e., rain, snow, snow depth) are a physical and psychological obstacle to traveling to a brick-and-mortar store. It is reasonable to use Google Trend, consumers' online search, as an indicator of consumer demand in today's society dominated by online search and online shopping. Second, most previous studies have tested clothing sales in one season or year. However, this study tested each month during the winter months. Since extreme weather is getting more frequent and severe, and the lifecycle of clothing is getting shorter, not only the overall winter retail months need to test, but each month during the season needs to test. Third, under new normal weather, it is crucial to identify the predictable factors for consumers' seasonal clothes demand and reveal the relationship among the predictable factors during a season from a managerial perspective. Clothing sales increased when the temperature increased to some extent and then decreased [2]. Without considering nonlinear effects, the impact of extremely bad and good weather occurrences could be misestimated [3]. Therefore, the study used a decision tree, one of the most popular data science techniques, to understand consumer insight, the nonlinear effect of weather variables on clothing sales.

Methodology

Study area and study period There are three reasons to select one study area: First, individuals living in different cultures and environments show different psychological evaluations related to weather despite similar climate conditions [19]. Second, clothing reflects a wide range of individual psychological and physiological needs, so individual heterogeneity is relatively high. Third, since this study is about seasonal clothing demand, a region of Google Trends where long-term data are available, and areas with seasons were selected. New York City, which has a significant influence on global fashion trends and is a significant center of the clothing industry, was selected as the study area. The summer months in New York City are warm and humid, while the winter months in New York City are frigid and windy. According to the Climate Normals: 1981-2010 in NYC [42], the highest temperature in early October is over 12°C, and the lowest temperature is 15°C. The trend of temperature is dropped until late January and is increased in early February. The average annual temperature has increased about 1.1 over the last two decades,

and the polar jet stream has brought the number of extreme precipitation events during the winter [14].

Data The coldest months in New York City are from January to February, and the cold winter lasts until early March. Clothes are usually displayed in stores from October to early November and sold during winter. Winter clothing is sold at all price points in October, and after Holidays, retailers generally lower prices to stimulate more sales. This study analyzed the data from October 1 to January 31, as winter clothing sales after January do not generate enough revenue for retailers, and retailers make an effort to try to introduce spring clothing products. Therefore, the data were obtained from October 1 to January 31 for the past 11 years. The data set was combined with two data sources. Consumers' seasonal clothing search data was from GT, and weather data was from NOAA. Table 1 shows the definitions of each variable in this study.

The winter jacket was employed for a seasonal clothes query—winter jacket GT in NYC for the past 11 years, from 2008 to 2019 (<https://trends.google.com/trends/?geo=US>). Considering a retail calendar in the clothing business and a weather pattern in NYC, this study obtains data from October 1 to January 31. Being connected with the previous findings, the focus of this analysis was based on daily observations of maximum temperature (MAXT), minimum temperature (MINT), precipitation (PRCP), snowfall (SNOW), snow depth (SNWD), wind movement (WIND). The data from October 1, 2008, to January 31, 2019, are obtained through email from NOAA (<https://www.ncdc.noaa.gov/cdo-web/>). There are six observation sites in NYC. Considering data availability and continuity from 2008 to 2019, we obtained data from one observation site, John F. Kennedy Airport, NY. Weather factors, MAXT, MINT, PRCP, SNOW, SNWD, and WIND, were collected, and temperature data were converted to Celsius degree (C°).

Table 1. Variables

Factors		Descriptions
WGT	Winter jacket google trend	Winter jacket in NYC was searched as terms within the shopping category, and results were filtered through Google Shopping.
MONTH	Months of the winter season	October, November, December, January
MAXT	Maximum temperature (C°)*	The highest temperature recorded during a specified period of time; The most common reference is to the daily maximum temperature.
MINT	Minimum temperature (C°)*	The lowest temperature recorded during a specified period of time; The most common reference is to the daily minimum temperature.
PRCP	Precipitation(inch)*	The process where water vapor condenses in the atmosphere to form water droplets that fall to the Earth as rain, sleet, snow, hail, etc.
SNOW	Snowfall (in)*	The amount of snow that falls there during a particular period.
SNWD	Snow depth (in)*	The combined total depth of both the old and new snow on the ground
WIND	Wind movement (mi)*	The prevailing direction from which the wind is blowing with speed given usually in miles per hour or knots.

*National Oceanic and Atmospheric Administration (NOAA) National Weather Glossary (<https://w1.weather.gov/glossary/>)

Method The data were analyzed using ANOVA and Pearson correlation. To find the pattern of consumers' seasonal clothes search behavior during the winter months, WGT was compared by the months of the winter retail season (MONTH) using ANOVA and Games-Howell post hoc test. With Pearson correlation tests, the relationship between WGT and weather factors were investigated. Then, to develop a predictive model's foundation, the critical predictors for consumers' seasonal clothes search were identified through the decision tree regression model. A decision tree is a popular data science technique for discovering the consumers' decision process [16, 21, 23]. It is to find and describe structural patterns in data as tree structures, explaining data, and making predictions using the data [40]. The primary purpose of using the decision tree is to achieve a more concise and perspicuous representation of the relationship between a target variable and predictor variables. This study used the classification and regression tree (C&RT) algorithm with WGT as a target variable and all other variables (i.e., MAXT, MINT, PRCP, SNOW, SNWD, & WIND) as predictors. C&RT is a recursive partitioning method used for both classification and regression. It is configured by dividing a subset of a data set using all predictors, creating two child nodes repeatedly, starting with the entire data set [11].

Results

When do consumers search for seasonal clothes? Consumers' seasonal clothes searching pattern during the four winter months is shown in Figure 1. The overall average of WGT is 32.87 (SD =

19.09). Consumers' searching was increased in late October, and the peak was in mid and late November. Then, consumers' searching was declined in early January. A one-way between-subjects ANOVA was conducted to compare the effect of the months of the winter retail season on consumers' seasonal clothes search. Welch's test showed $F(3, 743.989) = 30.351, p < .000$, and the Games-Howell test indicated that the mean scores for monthly demand were significantly different (See Table 2). The highest WGT is November ($M = 39.81, SD = 21.53$), and December ($M = 34.63, SD = 17.99$), October ($M = 30.59, SD = 18.21$), and January ($M = 26.67, SD = 15.86$) was followed. November was the decisive period for winter clothing sales, and December was the second most important period. Retailers have traditionally shown winter clothing in October, so consumers are looking for new winter clothing from October. The demand for winter clothing gradually declines in January.

Figure 1. Average Winter Jacket Goggle Trends

Table 2. Winter Jacket Google Trend differences according to the months of the winter season

	Sum of Squares	Df	Mean Squares	F	Sig.
Between Groups	31820.659	3	10606.886	31.052	.000
Within Groups	460793.706	1349	341.582		
Total	492614.365	1352			

Traditional clothing retailers bring their new winter clothes to market in October, based on the sales plan. There are three holidays, such as Thanksgiving Day, Christmas, and New Year's

Day in the winter months. Holiday sales in November and December represent about 20% of annual retail sales based on the report of National Retail Federation [24], and seasonal winter clothes usually go on end-of-season sales in January after the Winter Holidays. Black Friday and Cyber Monday are the most profitable shopping events in the winter season [36]. WGT on the highest demand date in November and WGTs for Thanksgiving Day through Cyber Monday were listed (See Appendix 1). Except for winter 2015/16 and 2018/19, the highest demand days were not during the 5-days shopping event period. The result was expected because the constant sales promotions from retailers are available throughout the years. One recent study reported that as more shopping moves online, the brick-and-mortar store events are less essential to the consumer [38]. Since clothing retailers rely on winter clothing sales to boost annual profit, selling without deep markdowns is a key driver of clothing business success.

How do weather factors affect consumers' seasonal clothing searches? Pearson correlation coefficient computed to assess the relationship between consumers' seasonal clothing buying and elements such as MAXT, MINT, PRCP, SNOW, SNWD, and WIND. There was a significant negative association between WGT and temperature, MINT ($r = -.175$, $n = 1353$, $p = .000$), MAXT ($r = -.167$, $n = 1353$, $p = .000$), and WIND ($r = -.049$, $n = 2002$, $p = 0.030$). However, consumers' demand did not have a significant relationship with PRCP, SNOW, and SNWD. Overall, there were negative relationships between consumers' winter clothes searching behavior and temperatures and wind. An increase in winter clothes demand was correlated with decreases in maximum and minimum temperatures and wind movement. Since there was a significant weather variation in four winter months, Pearson correlation was computed each month. WGT has a negative relationship with MAXT and MINT throughout all the months. In October, SNOW ($r = .186$, $n = 341$, $p = .001$) and SNWD ($r = .147$, $n = 341$, $p = .006$) positive relationship with WGT. In November, WGT showed a strong correlation with temperature [MAXT ($r = -.507$, $n = 330$, $p = .000$); TMIN ($r = -.555$, $n = 330$, $p = .001$)] and SNWD ($r = .149$, $n = 341$, $p = .007$) and WIND ($r = .176$, $n = 330$, $p = .001$) showed a positive relationship with WGT.

Table 3 summarizes the results. Overall, there was a negative relationship between consumers' winter season clothes search activity and temperature. Increases in consumers' winter season clothing demand were correlated with decreases in maximum and minimum temperature and increased wind movement. In October and November, when snow depth increases, winter

clothing searching behavior is increasing. Snowfall in October is a very unusual event in NYC. Snow is an external stimulus to consumers, motivating consumers to prepare winter clothes. Weather factors impacted consumers' seasonal clothing throughout the season. The results were supported by previous studies [1, 3, 4, 6, 7, 22, 32].

Table 3. Pearson Correlations

		WGT	MAXT	MINT	PRCP	SNOW	SNWD	WIND
All	WGT N	1 1353	-.167***	-.175***	-.019	.039	-.020	.073**
OCT	WGT N	1 341	-.380**	-.388**	.042	.186**	.147**	.093
NOV	WGT N	1 330	-.507***	-.555***	-.016	0.93	.149**	.176**
DEC	WGT N	1 341	-.239**	-.229**	-.072	.128	.043	-.036
JAN	WGT N	1 341	-.217**	-.271**	-.042	.066	.038	.112

*** Correlation is significant at the 0.001 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

What are the important predictors, and how the predictors interact with consumers' seasonal clothing searches? A decision tree identified the consumers' seasonal clothing predictors and the relationships among the predictors. All variables were used to construct a decision tree regression model to predict WGT as a continuous variable. The data (n=1353) were split by using the sampling technique of 80/20, partitioning 80% into a training set (n=1090) and 20% into a testing set (n=263). The result of the C&RT identified important predictors and showed the relative importance of predictors (see Figure 2). MONTH (47.83%) is the most important predictor, MINT (30.43%) is the second important factor, MAXT (27.08%) is the third, and PRCP (2.91%), WIND (1.50%), SNOW (0.16%), and SNWD (0.06%) are followed. It is consistent results compared to previous studies, where the temperature is the most important meteorological factor. The importance of temperature changes in the early season was confirmed by previous studies [1, 2, 4, 6], and the ineffectiveness of temperature changes in the late season[1, 2, 3]. However, the definition of early and late is vague and impracticable. Unlike previous studies, this study included the months of a retail season as a predictor and weather factors. The month of a season is a significant predictor of seasonal clothing demand, and temperatures next followed the

significant factors.

Figure 2. The relative importance of predictors to Winter Jacket Google Trends

Figure 3 shows a tree diagram. By the first root node, the months of the winter retail season (MONTH), WGT was split into November/December and October/January branch. The highest WGT (Node 7, M=61.367, n=109, 10.0%) was predicted by MONTH (November) and MINT (≤ 4.167). The second highest WGT (Node 9, M=37.058, n=158, 14.3%) was predicted by Month (October) and MAXT (≤ 18.611). The third highest WGT (Node 9, M=36.256, n=199, 18.3%) was predicted by MONTH (December) and MINT (≤ 4.167). The Lowest WGT (Node 6, M=24.015, n=131, 12%) was predicted by Month(October/December) and MAXT (> 18.611).

The results indicated that the month of the winter retail season, minimum temperature, and maximum temperature were significant predictors of consumers' searching for winter clothing. In November and December, the minimum temperature was the critical predictor, but the maximum temperature was the critical predictor in October and January. If the minimum temperature is higher than 4.167°C in November and December, the consumers' searching for winter clothing activity was relatively weak. When the minimum temperature in November and December is lower than 4.167°C , consumers search for winter clothing in November is the strongest, and December is also relatively strong. In October and January, when the maximum temperature is higher than 18.611°C , consumers' winter clothing search activity is the weakest.

However, in October, when the maximum temperature falls below 18.611°C, consumers' winter clothing search activities are relatively strong.

Figure 3. The results of the trained tree diagram.

Discussion

Since we have experienced new normal weather, increased the variation of temperature and precipitation and the higher occurrence of extreme weather events [18, 39], we initiated this study to question whether clothing retailers' traditional sales planning method is valid and reliable for today. From the findings of previous studies, this study built a predictive model in which a clothing retailer can control the seasonal sales plan in response to weather changes during a season. Unlike previous research, this study adopted four approaches: First, Google Trends is used as a consumer demand indicator. Although GT is a relatively new method to predict consumers' clothing demand, it provides new data sets to complement survey data [27]. Since online shopping is part of everyday life and clothing retailers run multichannel stores, GT provides more holistic

data, including brick-and-mortar stores, online stores, and omnichannel stores. Second, clothing retailers have suffered enormously from new normal weather over the past decade. This study used and analyzed weather observation data for the past 11 years to understand the historical consumers' response to weather changes. In carrying out place-specific research in NYC, we proposed a model for clothing retailers can develop a plan of action to deal with uncertainties. Third, consumer demand varies from month to month during a season, and the weather does not match the seasonality of temperature and the high incidence of extreme events. Thus, this study assessed the relationship between the whole winter retail month and monthly consumers' demand and weather factors to find the change in monthly consumers' demand during a season. Last, since the seasonal clothing demand associated with weather changes cannot be explained with a linear model [2, 3], this study used a decision tree to reveal all possible outcomes of a decision, trace each path to a conclusion, and assess the importance of predictor variables.

The results of the analysis of the past 11 years of data are as follows. First, month, minimum temperature, and maximum temperature were the significant predictors of consumers' search for winter clothes. Consumers' demand pattern for each month was identified. The coldest month in NYC is January, based on the 1981-2010 Climate Normals, but consumers' demand was the highest in November. December, October, and January followed. Second, overall, demand for winter clothing increases when the temperature drops, but the demand of consumers every month varies depending on the weather. While the minimum temperature is a key driver that increases consumers' demand in November, the maximum temperature is a key driver that increases consumers' demand in October, December, and January. Third, consumers' demand increased due to extreme weather, such as snowfall in NYC in October.

Conclusions

Our results have important managerial implications. Clothing retailers will be able to procure seasonal clothing products based on a long-term weather forecast. For example, clothing retailers choose materials, fabrics, and designs that appropriate the weather, especially the temperature. With a short-term weather forecast, the clothing retailers will able to determine when to launch new products with price competitiveness in stores and reduce prices according to weather changes in the middle of the season. Rapid weather changes affect consumers' demand. Clothing retailers can apply the predictive model to quickly respond to unexpected weather changes,

sufficiently prepare products with rapidly increasing demand not to miss sales opportunities, and adjust quantities and prices for products with sharp declines in demand. Thus, profit can be maximized, and unsold, excessive products can be minimized.

Even though we provide significant predictors and decision-making rules, consumer demand cannot predict with only weather factors. Consumers shop for new clothes for real needs and psychological enjoyment. Besides, clothing consumers' purchasing decision-making process depends on clothing characteristics such as style, quality, and price and is related to the interaction of various factors such as economy, society, and ecological environment. Hence, the results reduce the explanatory power of this study to describe considerable seasonal clothing demand. Since 11 years of data were used, it is insufficient to be used as a climate change model and inappropriate to apply to other places because this study is based on a place-specific case study. However, this study contributes to the building body of knowledge about weather changes in clothing sales by confirming the results of previous studies. It is also valuable to provide the importance of predictors and decision rules for new seasonal clothing demands in the new normal weather era.

Abbreviations

GT: Google Trends

NYC: New York City

MAXT: Maximum Temperature

MINT: Minimum Temperature

PRCT: Precipitation

SNOW: Snowfall

SNWD: Snow Depth

WIND: Wind Movement

WGT: Winter Jacket Google Trend

Month: Months of the Winter Season

C&RT: Classification and Regression Tree

Declarations**Ethics approval and consent to participate**

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding authors on request.

• Competing interests

The authors declare that they have no competing interests.

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Not applicable

• Authors' contributions

Conceptualization: OH, HA, and Jo. Investigations: OH and JO. Data analysis: OH and HA. Writing: OH, HA and JO. Review and editing: all. All authors read and approved the final manuscript.

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Appendix 1. The highest winter jacket GT in November and winter Jacket GT during the Thanksgiving holidays

	Highest Demand		5-days shopping events on Thanksgiving	
	Date	WGT	Date	WGTs
Winter 2008/09	11/23/08	100	11/27/08 ~ 12/01/08	70, 62, 0, 61, 0
Winter 2009/10	11/17/09	65	11/26/09 ~ 11/30/09	0, 0, 31, 34, 33
Winter 2010/11	11/11/10	65	11/25/10 ~ 11/29/10	48, 29, 62, 60, 40
Winter 2011/12	11/20/11	82	11/24/11 ~ 11/28/11	68, 58, 26, 76, 40
Winter 2012/13	11/04/12	100	11/22/12 ~ 11/26/12	49, 60, 47, 60, 55
Winter 2013/14	11/25/13	100	11/28/13 ~ 12/02/13	78, 48, 88, 42, 63
Winter 2014/15	11/19/14	100	11/27/14 ~ 12/01/14	42, 63, 55, 33, 31
Winter 2015/16	11/27/15	62	11/26/15 ~ 11/30/15	36, 62, 41, 40, 52
Winter 2016/17	11/21/16	100	11/24/16 ~ 11/28/16	43, 49, 66, 43, 59
Winter 2017/18	11/11/17	100	11/23/17 ~ 11/27/17	46, 62, 32, 37, 40
Winter 2018/19	11/23/18	100	11/22/18 ~ 11/26/19	16, 100, 80, 74, 51

Figures

Figure 1

Average Winter Jacket Goggle Trends

Figure 2

The relative importance of predictors to Winter Jacket Google Trends

Figure 3

The results of the trained tree diagram.