Product Airtime Analysis

COLBY FORD, LISA GRIGGS, TAYLOR TILLINGER, KEVIN WOOD

PROJECT SUMMARY

QVC is the world's leading video and eCommerce retailer, offering a curated collection of desirable brands to millions of customers around the globe each day through broadcast, Internet, and mobile sales platforms. QVC is the world's top multimedia shopping company in terms of viewers and revenue and ranks among the top online mass merchandise retailers. QVC's 2014 sales generated $8.8B in annual revenues, $3.5B of which came from eCommerce.[1]

In order to maintain their position as market leader, and grow their bottom line, QVC must continuously evaluate their product offerings to ensure they are providing items their customers want and that they are broadcasting them for the right durations at the right times.

To help them better understand their current performance, we examined the past 6 month customer order history along with high-level customer demographic information and product airtime data to provide an analytical snapshot of purchasing trends and future buying behavior predictions.

- Is there a best time of day to sell a particular product or product category?
- Which categories and Brands do certain customers buy?
- Which days and seasons do certain products sell the best and what are their trends?

Overall, we were able to use:

- Regression analysis in SAS Enterprise Guide and Miner, and Excel pivot tables to determine the effect that time of day and airtime has on each product and product category
- Segmentation in SAS Enterprise Guide to develop three unique customer segments based on purchasing frequencies
- SAS Forecasting to predict seasonal, holiday, and day of week trends for each product category

In addition, we have provided suggestions for data collection and product identification that will assist with making future analyses more robust and beneficial.

[1] QVC, Inc. About Us, About QVC. Retrieved 06 May 2015 from http://www.qvc.com/AboutUsAboutQVC.content.html

ANALYSIS PROCESSES & STEPS

IS THERE A BEST TIME OF DAY TO SELL A PARTICULAR PRODUCT OR PRODUCT CATEGORY?

First Approach

We first cleaned the data relative to nomenclature of brand, merchandising division and item. Several items in the Orders dataset had commas in the Packing Slip Description, and so were separated incorrectly when they were transformed into CSVs. Seen below, the items' Merchandise Division Description and Brand Name were mislabeled. In several places, quotations were tagged to the end of descriptions as well, thus further mislabeling the product categories.

These columns had to be concatenated and trimmed in Excel before they were used for analysis.

PRODUCT_	PACKING_SLIP_DESC	MERCH_DIV_DESC	BRAND_NAME			
25238	HP 23 Touch All-in-One	Windows 8	6GB RAM	1T"	IQVC Divisional	HP
26039	HP 15.6 Notebook AMD A4	4GB RAM	500GB HD	an"	IQVC Divisional	HP
25311	HP 23 All-in-One Windows 8	6GB RAM	1TB	Beat"	IQVC Divisional	HP
25255	HP G6 15.6 Laptop Windows 8	4GB RAM	500GB	I"	IQVC Divisional	HP
23961	Sony 9.4 Android Tablet	1GB RAM	32GB HD	Mus"	IQVC Divisional	Sony
22754	HP 15 or 17" Laptop	Win 8	AMD A8 Quad Core	,Electronics"	Not Known	
22857	Dell 17 Laptop	Win 8	Intel Core i5	,Electronics"	Not Known	
23984	Acer 10.1 Netbook - 1GB RAM	320GB HD	Webcam	,IQVC Divisional"	Acer	
24700	Acer 15.6 LED Notebook - AMD Quad Core	4GB RA"	IQVC Divisional	Acer		
26336	Acer 11.6 Netbook - AMD Processor	4GB RAM 3 2"	IQVC Divisional	Acer		
26337	Acer Aspire 15.6 Notebook - AMD	4GB RAM 500G"	IQVC Divisional	Acer		
23985	Acer 17.3 Notebook - 6GB RAM	500GB HD w/Webca"	IQVC Divisional	Acer		
25286	Acer 15.6 Notebook - 4GB RAM	500GB HD and Bon"	IQVC Divisional	Acer		
24727	Acer 15.6 Notebook - 6GB RAM	500GB HD with 3U"	IQVC Divisional	Acer		

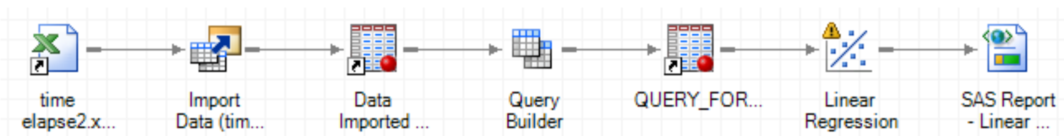
PRODUCT_	PACKING_SLIP_DESC	MERCH_DIV_DESC	BRAND_NAME
25238	HP 23 Touch All-in-One Windows 8 6GB RAM 1T"	IQVC Divisional	HP
26039	HP 15.6 Notebook AMD A4 4GB RAM 500GB HD an"	IQVC Divisional	HP
25311	HP 23 All-in-One Windows 8 6GB RAM 1TB Beat"	IQVC Divisional	HP
25255	HP G6 15.6 Laptop Windows 8 4GB RAM 500GB I"	IQVC Divisional	HP
23961	Sony 9.4 Android Tablet 1GB RAM 32GB HD Mus"	IQVC Divisional	Sony
22754	HP 15 or 17" Laptop Win 8 AMD A8 Quad Core	Electronics	Not Known
22857	Dell 17 Laptop Win 8 Intel Core i5	Electronics	Not Known
23984	Acer 10.1 Netbook - 1GB RAM 320GB HD Webcam Webcam	IQVC Divisional	Acer
24700	Acer 15.6 LED Notebook - AMD Quad Core 4GB RA"	IQVC Divisional	Acer
26336	Acer 11.6 Netbook - AMD Processor 4GB RAM 3 2"	IQVC Divisional	Acer
26337	Acer Aspire 15.6 Notebook - AMD 4GB RAM 500G"	IQVC Divisional	Acer
23985	Acer 17.3 Notebook - 6GB RAM 500GB HD w/Webca"	IQVC Divisional	Acer
25286	Acer 15.6 Notebook - 4GB RAM 500GB HD and Bon"	IQVC Divisional	Acer

Using a Microsoft Azure database, we also cleaned the dates and times for the product airtime and order files. These were joined, and, using the LEAD function in SQL, showed which orders could be attributed to which airtimes for the product. For example, if ten orders came in after the product aired on the QVC channel, but *before the next* airtime for that product, it was attributed to the first airtime. This iteration was repeated for every customer order:

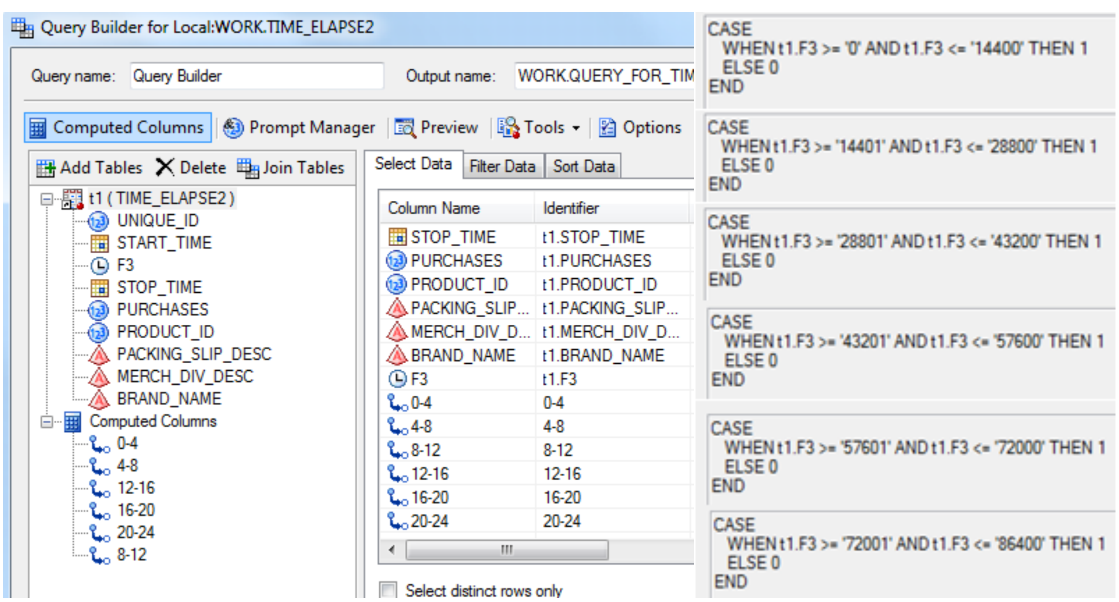
```sql
select a.product_id, a.product_airtime_mins, product_start_tms, product_stop_tms, end_date,
SUM(CASE when real_order_time between a.product_start_tms and end_date THEN 1 ELSE 0 END) as purchases

From
(SELECT *,
DATEADD(MINUTE, -1, LEAD(product_stop_tms, 1,'01-Jan-2100')
        OVER (PARTITION BY   product_id ORDER BY   product_stop_tms ASC))   AS end_date

FROM   dbo.qvc_product_airtime_master) as A

join

(select *,
DATEADD(DAY, +2, (order_date + order_time)) AS real_order_time

from dbo.qvc_order_master) as B
on a.product_id = b.product_id
group by a.product_id, a.product_airtime_mins, a.product_start_tms, a.product_stop_tms, a.end_date
order by a.product_id, product_start_tms asc
```

The results of the SQL query were imported into Excel and each of the revised airtime groups were then assigned a unique identifier and time formatting updated.

From there, the dataset was loaded into Enterprise Guide for time binning.



Computed columns were created to set min and max limits based on seconds corresponding to each 4-hour bin with resulting dummy variables. 4-hour time groupings were elected based on the regression results generated upon testing.



Linear Regression Results

The REG Procedure
Model: Linear_Regression_Model
Dependent Variable: PURCHASES

Number of Observations Read	55140
Number of Observations Used	55140

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	3415328	683066	669.41	<.0001
Error	55134	56258581	1020.39723		
Corrected Total	55139	59673909			

Root MSE	31.94366	R-Square	0.0572
Dependent Mean	17.86748	Adj R-Sq	0.0571
Coeff Var	178.78096		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	6.44330	0.36100	17.85	<.0001
4-8	1	2.07128	0.46896	4.42	<.0001
8-12	1	19.16811	0.49879	38.43	<.0001
12-16	1	14.74761	0.47624	30.97	<.0001
16-20	1	13.62636	0.49219	27.69	<.0001
20-24	1	21.14460	0.51408	41.13	<.0001

The binning results were then exported into Excel for further analysis.

Pivot tables were created for each of the 3 groups (brand, merchandising division and item) filtering which products were sold by time bin. It was then determined what % of the product's sales were in each bin, and which bin contained the largest %. The data was then normalized to account for products which were only on the air during one or two time periods and the same ranking process applied. The charts below show the top listings in each group.

CATEGORY	Adj % Sold	TIME SLOT
License Hardgds	70.9%	4pm - 8pm
PUBLIC RELATION	58.2%	4pm - 8pm
Collectibles	43.9%	4am - 8am
Health	36.3%	Noon - 4pm
IQVC Divisional	35.2%	4am - 8am
Health/Beauty	34.2%	8pm - Midnight
Apparel	33.3%	8am - Noon
Home Decor	30.3%	Noon - 4pm

BRAND	Adj % Sold	TIME SLOT
Verso	83.3%	8pm - Midnight
Lobster Gram	83.1%	4pm - 8pm
Olevano	81.7%	Noon - 4pm
NFL	77.3%	4pm - 8pm
Masterbuilt	77.2%	Noon - 4pm
Kansas City Steak	73.7%	4pm - 8pm
Belle Gray by Lisa Rinna	70.0%	4pm - 8pm

ITEM	Adj % Sold	TIME SLOT
Chrome Ceramic Stainless Steel Diamond Watch	87.5%	4pm - 8pm
Cottage Farms Bud 'N Flower Booster for Acid	84.8%	4pm - 8pm
Verso Versailles Large Universal Tablet Cover	83.3%	8pm - Midnight
Cottage Farms Bud 'N Flower Rose Booster	82.5%	4pm - 8pm
Bose CineMate Series II Digital Home Theater	80.0%	Midnight - 4am
Cottage Farms Bud 'N Flower Booster Fertilizer	76.9%	4pm - 8pm
Olevano 1L Olive Oil w/ Blue Jean Chef Cookbook	75.5%	Noon - 4pm
HP Photosmart Wireless Printer, Copier, Scanner	75.0%	8pm - Midnight
Boo The World's Cutest Dog" Life"	71.6%	8pm - Midnight
George Foreman 240 sq. in. Outdoor/Indoor Round	70.7%	Noon - 4pm

Second Approach

Once the airtimes were binned into time-slots (Step 6 in the First Approach), regressions were run in SAS for each product category air-times:

ProductSalesi = B1i + B2Airtimei + B3Time-Sloti + ui, where Time-Slot is a series of dummy variables for whichever 4-hour period the air-time falls under.

From there, the parameters from each regression were listed in a cross-sectional table and normalized. We derived a matrix to weight the best and worst times to air each category, based on each time-slots' performances within the category and relative to the performances of the time-slots for every other category.

	4am - 8am	8am - Noon	Noon - 4pm	4pm - 8pm	8pm - Midnight
Accessories	3.974871685	1.177311187	-0.095758379	-0.133795386	-0.222671911
app/access event	0	0.554940471	0.490645006	-0.07689999	-0.972368065
apparel	0	0.744473208	-0.035098337	0.174128677	0.828701661
collectibles	0	0	0	0	0
costume jewelry	0	0.318425711	-0.506414264	-0.700155577	0.969087469
electronics	0	0.520033919	0.731546499	-0.307391766	0.192003545
entertainment	0	0.812755061	1.015430703	2.498701486	1.840522485
fun & leisure	0	0.360913545	-0.417947115	1.272338957	0.245595375
health	0	1.435892772	1.754528298	3.997633614	3.876713286
health/beauty	4.467204987	-0.05234697	0.093769732	0.077961986	0.826485231
home décor	0	0.397298236	1.157498616	-0.160157071	0.851436856
housewares	3.468687428	0.397365784	0.281100937	0.808764419	0.645651806
IQVC Divisional	0	0	0	0	0
jewelry	0	-0.175257503	-0.763559333	-0.750736162	0.138931114
license hardgds	0	0	0	0	0
public relation	0	0	0	0	0
textile/furnit	0	0.642297884	-0.136800428	-0.093547002	1.559255621

This led to a "Sell / Do Not Sell" calendar for the daily QVC airings:

Sell List	Midnight - 4am	4am - 8am	8am - Noon	Noon - 4pm	4pm - 8pm	8pm - Midnight
1st		Health/Beauty	Health	Health	Health	Health
2nd		Accessories	Accessories	Home Décor	Entertainment	Entertainment
3rd		Housewares	Entertainment	Entertainment	Fun and Leisure	Textile/Furnit
4th			Apparel	Electronics	Housewares	Costume Jewelry
5th			Textile/Furnit	App/Access Event		Home décor
6th			App/Access event			Apparel
7th			Electronics			Health/Beauty
8th						Housewares

Do Not Sell List	Midnight - 4am	4am - 8am	8am - Noon	Noon - 4pm	4pm - 8pm	8pm - Midnight
1st			Jewelry	Jewelry	Jewelry	App/Access Event
2nd			Health/Beauty	Costume Jewelry	Costume Jewelry	Accessories
3rd				Fun and Leisure	Electronics	
4th				Textile/Furnit	Home Décor	
5th				Accessories	Accessories	
6th				Apparel	Textile/Furnit	
7th					App/Access Event	

No relation to Time of Day
License Hardgds
Public Relation
IQVC Divisional
Collectibles

The above calendar shows when each product category should be sold, not sold, or if the time of day is irrelevant. If an airtime planner is looking for proper airtimes for several product categories, they can follow this process:

1. Place the categories on the Sell List first. These are beneficial time-slots that will increase sales for that category.

2. If there isn't a "good" time-slot for a category, simply avoid "bad" time-slots using the Do Not Sell List.

3. If there still is not a suitable time-slot for a category, or if the category is on the No Relation to Time of Day List, then fill them into any remaining time-slots, because it makes no difference.

Comparison

Relative to the merchandising division, the two approaches aligned well. Excluding product categories that were too small to determine using the matrix, the categories with high “Adj % Sold” corresponded with the same bins reported by the matrix. Farther down the list, the correlation between Bin and product category success diminishes. The "No"s are marked as such because the % sold is not strong enough to trump *other* product categories being sold in that time-slot.

MERCH_DIV_DESC	Adj % Sold	Bin	Matrix
License Hardgds	70.90%	16-20	Sample size too small
PUBLIC RELATION	58.20%	16-20	Sample size too small
Collectibles	43.90%	4-8	Sample size too small
Health	36.30%	12-16	Yes
IQVC Divisional	35.20%	4-8	Sample size too small
Health/Beauty	34.20%	20-24	Yes
Apparel	33.30%	8-12	Yes
Home Decor	30.30%	12-16	Yes
App/Accss Event	28.10%	8-12	Yes
Textile/Furnit	26.80%	8-12	Yes
Fun & Leisure	26.70%	8-12	No
Accessories	26.70%	12-16	No
Housewares	26.10%	8-12	No
Electronics	26.10%	8-12	Yes
Jewelry	24.50%	16-20	No
Entertainment	23.90%	8-12	Yes
Costume Jewelry	23.40%	20-24	Yes

CUSTOMER CLUSTERING: WHICH CATEGORIES AND BRANDS DO CERTAIN CUSTOMERS BUY?

First, this following query was executed on the dataset in Azure SQL:

```
SELECT [CUSTOMER_NBR],
COUNT(ORDER_LINE_NUMBER)/COUNT(DISTINCT(ORDER_DATE)) AS
Average_Nbr, COUNT(ORDER_LINE_NUMBER) AS Freq
FROM QVC_ORDER_MASTER
GROUP BY [CUSTOMER_NBR];
```

This yields the average number of orders for each customer and the total number of items that they purchased during the 6-month period of the dataset. [See the *Query* tab in the Excel file.]

From this, k-means cluster analysis was run on the data, trying 2,3,…,10 clusters. We found that at around 3 clusters, the 95% confidence levels for the clusters seemed to overlap the least and give the most distinct groups based on purchase frequency.

Using 3 clusters, there are 3 groups of customers where one group buys ~2 items during a 6-month period, another that buys ~20 items in a 6-month period, and lastly, a group that buys ~60 items in a 6-month period. [See the *Clusters* tab in the Excel file.]

Joining the query above with the ORDER_MASTER and PRODUCT_MASTER, we wanted to see the differences in what customers in each cluster but based on product category and brand. So, by running the Summary Table Wizard in SAS Enterprise Guide, it generates the charts you see in the *By Merch Div* and *By Brand tabs* in the Excel file.

Lastly, by using conditional formatting and identifying the popular categories and brands by cluster, we can tell what kinds of items (or brands of items) people in each cluster generally buy.

By Merch Div (Category):

	Cluster (Row %)		
MERCH_DIV_DESC	1	2	3
Average Purchase Frequency	2	60	20
Accessories	35.57	23.42	41.01
App/Accss Event	38.71	23.96	37.33
Apparel	23.15	32.46	44.38
Collectibles	27.67	29.35	42.98
Costume Jewelry	27.11	32.52	40.37
Electronics	61.77	10.58	27.65
Entertainment	55.58	11.89	32.53
Fun & Leisure	42.57	18.93	38.51
Gift Cards	77.52	4.33	18.15
Health	43.39	17.4	39.21
Health/Beauty	39.45	20.98	39.57
Home Decor	42.25	19.19	38.56
Housewares	47.33	15.68	36.99
IQVC Divisional	62.6	11.21	26.19
Jewelry	30.42	29.27	40.31
License Hardgds	55.78	13.38	30.84
PUBLIC RELATION	33.38	22.42	44.21
Returns	63.28	10.16	26.56
Textile/Furnit	45.04	17.09	37.87

	Cluster (Column %)		
MERCH_DIV_DESC	1	2	3
Average Purchase Frequency	2	60	20
Accessories	9.22	10.5	10.46
App/Accss Event	0.4	0.43	0.38
Apparel	11.18	27.14	21.11
Collectibles	0.21	0.38	0.32
Costume Jewelry	0.93	1.94	1.37
Electronics	10.32	3.06	4.55
Entertainment	3.52	1.3	2.03
Fun & Leisure	1.08	0.83	0.96
Gift Cards	0.2	0.02	0.05
Health	0.7	0.49	0.63
Health/Beauty	19.3	17.77	19.07
Home Decor	24.92	19.59	22.4
Housewares	7.07	4.05	5.44
IQVC Divisional	1.24	0.38	0.51
Jewelry	5.66	9.44	7.39
License Hardgds	0.39	0.16	0.21
PUBLIC RELATION	0.2	0.24	0.27
Returns	0.02	0.01	0.01
Textile/Furnit	3.42	2.25	2.83

	Cluster (Row %)		
MERCH_DIV_DESC	1	2	3
Average Purchase Frequency	2	60	20
Accessories	35.57	23.42	41.01
App/Accss Event	38.71	23.96	37.33
Apparel	23.15	32.46	44.38
Collectibles	27.67	29.35	42.98
Costume Jewelry	27.11	32.52	40.37
Electronics	61.77	10.58	27.65
Entertainment	55.58	11.89	32.53
Fun & Leisure	42.57	18.93	38.51
Gift Cards	77.52	4.33	18.15
Health	43.39	17.4	39.21
Health/Beauty	39.45	20.98	39.57
Home Decor	42.25	19.19	38.56
Housewares	47.33	15.68	36.99
IQVC Divisional	62.6	11.21	26.19
Jewelry	30.42	29.27	40.31
License Hardgds	55.78	13.38	30.84
PUBLIC RELATION	33.38	22.42	44.21
Returns	63.28	10.16	26.56
Textile/Furnit	45.04	17.09	37.87

	Cluster (Column %)		
MERCH_DIV_DESC	1	2	3
Average Purchase Frequency	2	60	20
Accessories	9.22	10.5	10.46
App/Accss Event	0.4	0.43	0.38
Apparel	11.18	27.14	21.11
Collectibles	0.21	0.38	0.32
Costume Jewelry	0.93	1.94	1.37
Electronics	10.32	3.06	4.55
Entertainment	3.52	1.3	2.03
Fun & Leisure	1.08	0.83	0.96
Gift Cards	0.2	0.02	0.05
Health	0.7	0.49	0.63
Health/Beauty	19.3	17.77	19.07
Home Decor	24.92	19.59	22.4
Housewares	7.07	4.05	5.44
IQVC Divisional	1.24	0.38	0.51
Jewelry	5.66	9.44	7.39
License Hardgds	0.39	0.16	0.21
PUBLIC RELATION	0.2	0.24	0.27
Returns	0.02	0.01	0.01
Textile/Furnit	3.42	2.25	2.83

By Brand:

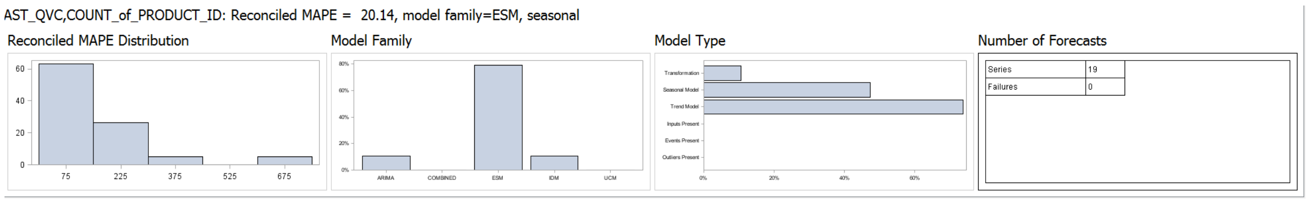
	Cluster (% by Row)		
BRAND_NAME	1	2	3
Average Purchase Frequency (out of 182)	2	60	20
100% Pure	66.67	11.11	22.22
180 Snacks	21.43	42.86	35.71
1800baskets.com	100	0	0
180s	53.45	13.79	32.76
21 drops	25	37.5	37.5
3 Custom Color Specialists	0	100	0
32 Brand	20.4	33.78	45.82
35 Degrees Below	38.43	15.57	46
360 Degrees	0	0	100
3M	58.33	8.33	33.33
505 Games	33.33	0	66.67
7 Gypsies	100	0	0
A Cheerful Giver	13.13	44.44	42.42
A&E	49.09	9.09	41.82

FORECASTING: WHICH DAYS AND SEASONS DO CERTAIN PRODUCTS SELL THE BEST AND WHAT ARE THEIR TRENDS?

Merchandise category was used as the classification or BY variable. The number of purchases per day (count of product ID), category of purchases, and order date were used for forecasting. The following table shows a representative sample of this data. The time interval was set to day and the seasonal cycle length was set 7. The role for purchases was set to dependent. The forecast produces predictions for 12 days.

	ORDER DATE	MERCH DIV DESC	COUNT of PRODUCT ID
1	01OCT2012	Accessories	1025
2	01OCT2012	Apparel	6155
3	01OCT2012	Collectibles	4
4	01OCT2012	Costume Jewelry	203
5	01OCT2012	Electronics	52
6	01OCT2012	Entertainment	14
7	01OCT2012	Fun & Leisure	4
8	01OCT2012	Gift Cards	1
9	01OCT2012	Health	29
10	01OCT2012	Health/Beauty	281
11	01OCT2012	Home Decor	239
12	01OCT2012	Housewares	49
13	01OCT2012	IQVC Divisional	23
14	01OCT2012	Jewelry	194
15	01OCT2012	License Hardgds	3
16	01OCT2012	PUBLIC RELATION	13
17	01OCT2012	Textile/Furnit	26
18	02OCT2012	Accessories	134
19	02OCT2012	App/Accss Event	2
20	02OCT2012	Apparel	593
21	02OCT2012	Collectibles	4
22	02OCT2012	Costume Jewelry	20
23	02OCT2012	Electronics	76
24	02OCT2012	Entertainment	8
25	02OCT2012	Fun & Leisure	3
26	02OCT2012	Gift Cards	3
27	02OCT2012	Health	12
28	02OCT2012	Health/Beauty	563
29	02OCT2012	Home Decor	594

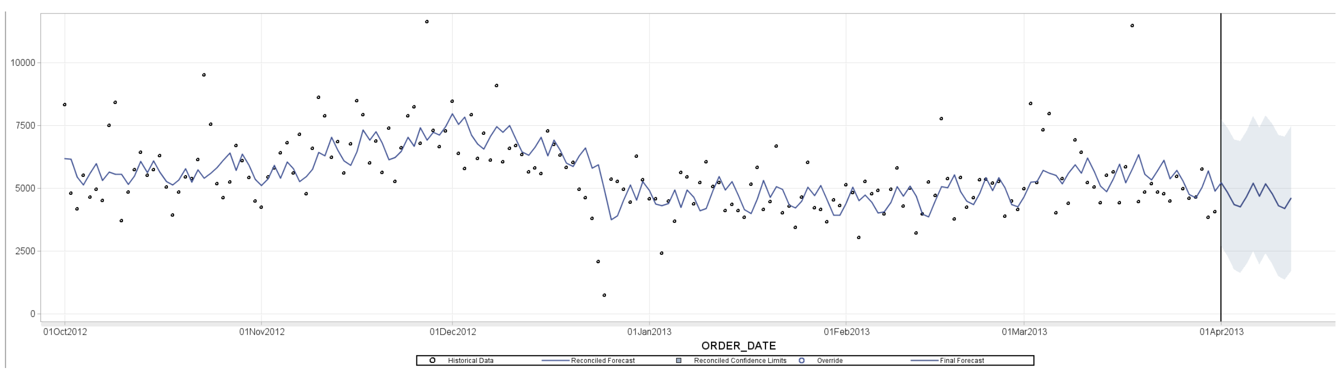
Representative Data used for SAS Forecast Studio



ESM Model was produced

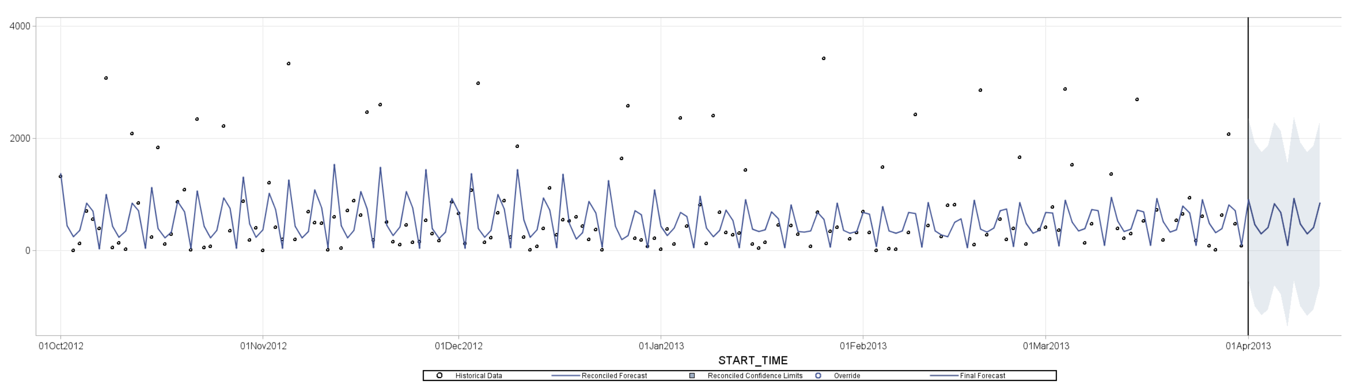
Component	Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|
COUNT_of_PRODUCT_ID	Level Weight	0.16488	0.02945	5.60	<.0001
COUNT_of_PRODUCT_ID	Trend Weight	0.0010000	0.01371	0.07	0.9419
COUNT_of_PRODUCT_ID	Seasonal Weight	0.0010000	0.02607	0.04	0.9695

ESM Model's Parameter Estimate



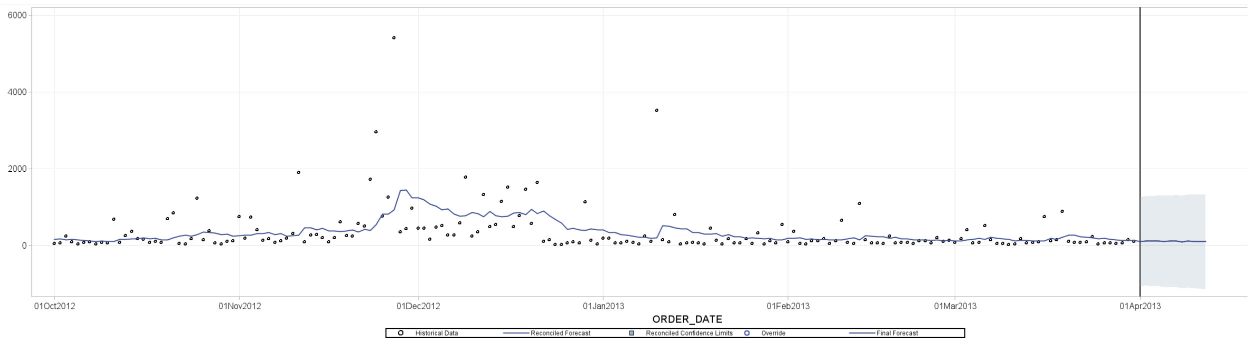
Overall Forecast

Forecasted sales are sloping downwards for the next 12 days.



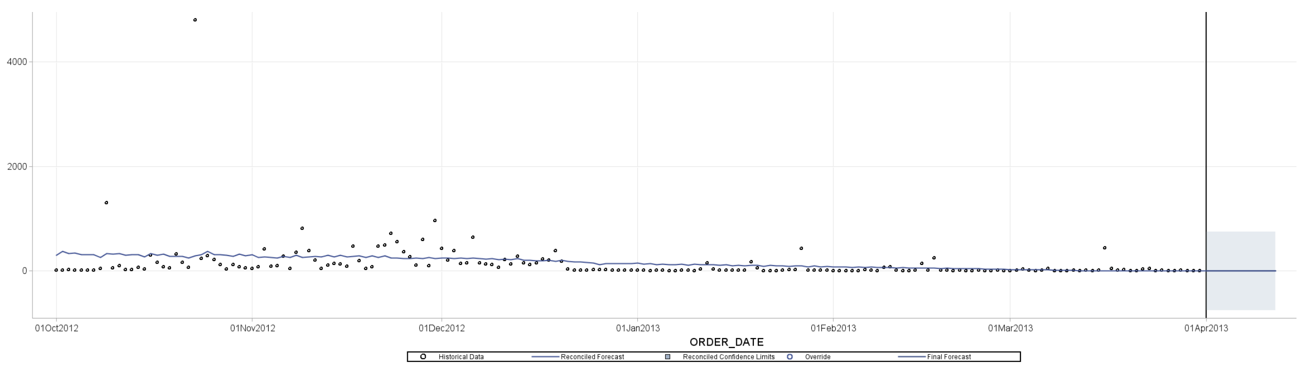
Accessories Forecast

Peaks on Wednesday and over the weekends. Overall, relatively stable trend.



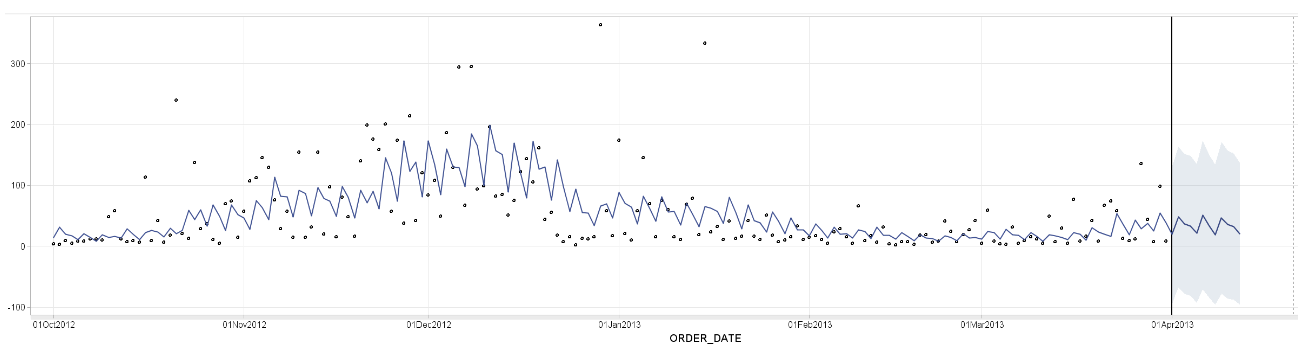
Electronics

Note there are many purchases over Christmas another hump in purchases over January (could be sales).



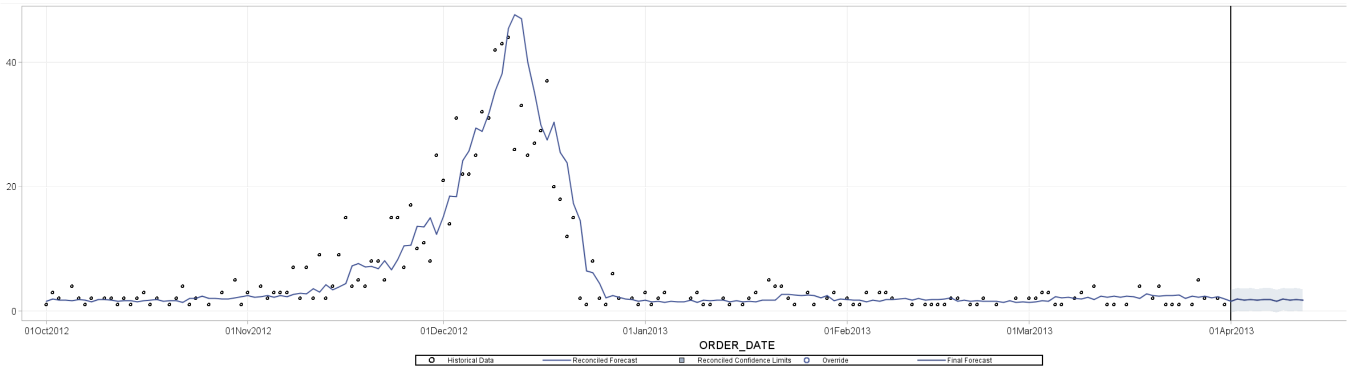
Entertainment

No peaks, but overall downward trend. Books and crafts are common products in this category.



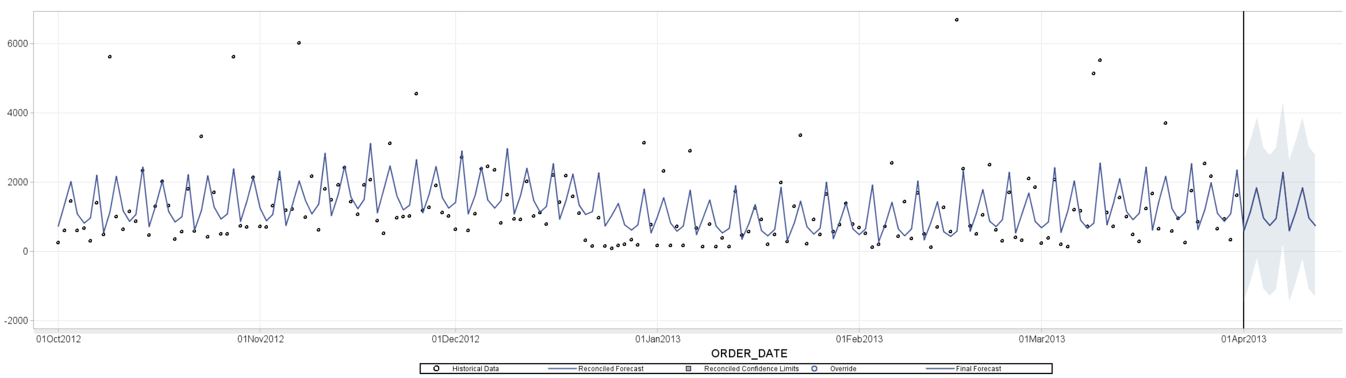
Fun & Leisure

This model has a seasonal trend with many purchases in the winter and over Christmas. Interestingly, more purchases in this category occur before the weekend (Thursday and Friday), while purchases dip over the weekend. Customers are most likely anticipating a weekend of "fun & leisure."



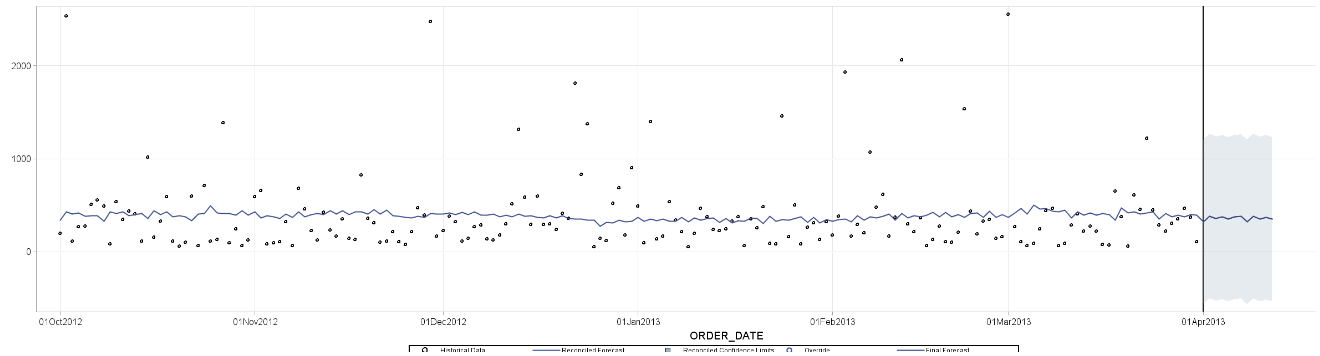
Gift Cards

Huge Peak at Christmas.



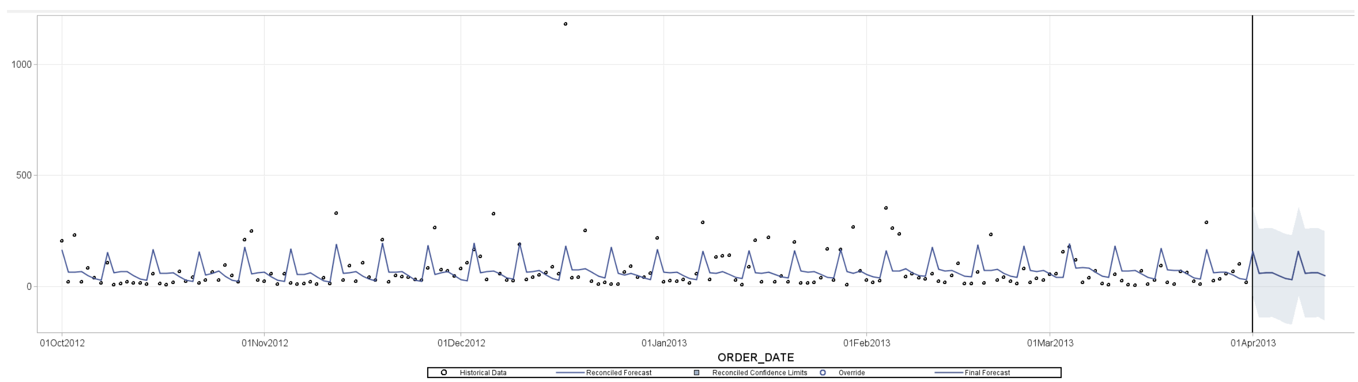
Home Décor

Peaks are at Fridays & Saturdays. Over the weekend, most people are at home more and generally do house related tasks. Therefore, it is intuitive, to reason why there are more purchases at this time.



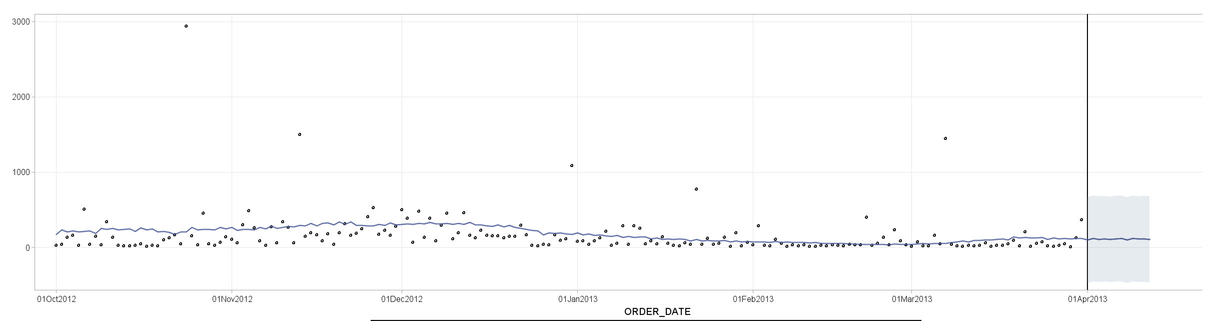
Jewelry

No apparent trend for this category. Reasoning could be that most people who need to buy Jewelry are either for Anniversary (no one date) and if need to buy last minute most will chose a brick and mortar store.



Costume Jewelry

Peaks on Wednesday drops Thursday and over the weekend.



Textile & Furniture

There is slight downward trend.

SUGGESTIONS TO ENHANCE OUR ANALYSIS

MARKET BASKET ANALYSIS

An attempt was made to perform market basket analysis on the QVC_ORDER_MASTER dataset using the Association node in SAS Miner. Despite filtering the dataset on multiple criteria, and adjusting the maximum items per rule set, support, and confidence level, SAS only discovered overwhelming rules for a few select items, with extraordinary lift and twin rules. After deliberation, our group came to the conclusion that these association rules may be the side effects of other, unknown relationships between the items that need to be explored further.

CONF	SUPPORT	LIFT	COUNT	RULE	_LHAND		_RHAND	
93.14	0.23	379.46	258	22904 ==> 22876	22904	PC Treasures Software Bundle w/ Anti-Virus	22876	Dell 15 or 17" Laptop Intel Core i5 8GB RAM"
95.56	0.23	379.46	258	22876 ==> 22904	22876	Dell 15 or 17" Laptop Intel Core i5 8GB RAM"	22904	PC Treasures Software Bundle w/ Anti-Virus
92.88	0.23	336.09	248	11018 ==> 11007	11018	New Beauty Test Tube with Magazine Ltd. Ed. A-D	11007	New Beauty 8-piece Test Tube with Magazine A-D
81.58	0.23	336.09	248	11007 ==> 11018	11007	New Beauty 8-piece Test Tube with Magazine A-D	11018	New Beauty Test Tube with Magazine Ltd. Ed. A-D
92.06	0.32	291.01	348	22652 ==> 22595	22652	Image Broadway & pcPhotos Digital Camera	22595	Canon Rebel T3i DSLR 18MP Digital Camera w/
100	0.32	291.01	348	22595 ==> 22652	22595	Canon Rebel T3i DSLR 18MP Digital Camera w/	22652	Image Broadway & pcPhotos Digital Camera
94.01	0.24	262.48	267	11585 ==> 11584	11585	WEN by Chaz Dean Spring Gardenia Green Tea 32	11584	WEN by Chaz Dean Winter Vanilla Mint 32 oz. A-D
67.77	0.24	262.48	267	11584 ==> 11585	11584	WEN by Chaz Dean Winter Vanilla Mint 32 oz. A-D	11585	WEN by Chaz Dean Spring Gardenia Green Tea 32
99.21	0.34	250.31	379	33006 ==> 33004	33006	Jim Shore Heartwood Creek Easter Basket with	33004	Jim Shore Heartwood Creek Harvest Basket with
86.93	0.34	250.31	379	33004 ==> 33006	33004	Jim Shore Heartwood Creek Harvest Basket with	33006	Jim Shore Heartwood Creek Easter Basket with

It would be necessary to know how QVC tied items together:

1. Bundles – the top rule associates a software package with a Dell laptop, and vice versa below it. This relationship will not show us a relevant consumer purchasing rule if they are forced to receive both products in a bundle.
2. Buy one, get another product at some sort of discount
3. QVC may already suggest items to purchase. In this dataset, phone chargers are associated with over 50 products. It may be that phone chargers are independently advertised to each consumer as they are checking out, so they are associated simply because QVC is further advertising them. Buying a phone charger probably does not lead to buying makeup simply because it is a phone charger, as the association rules suggest.

Having further knowledge of these issues would increase the confidence in the conclusions drawn from the market basket analysis. Knowledge of bundling could help us develop new business theories, such as distinguishing customers based on Memory-based or Sensory-based reasoning (for example, customers who are more prone to sales and bundles).

FUTURE WORK

Forecasting could be made stronger by increasing the data beyond 6 months. Having at least a full year worth of data will more strongly elucidate the seasonal trends of certain product categories. Increasing the data should also decrease the mean absolute error. It would also be beneficial to forecast the sales (in dollars) and not just units sold. Having this data would be beneficial across all of our analysis.

Interesting trends or findings could be discovered if we had % discount along with the products price. This could allow us to optimize at what % discounts products sell the best, while taking into account QVC's profits. Optimizing QVC's discounts would be paramount to its success because it prides itself in offering deep discounts that are unavailable in brick and mortar stores.

Another key piece of information which could be valuable in multiple areas of our analysis is profitability by item, brand and category. It is possible that the highest dollar or best-selling items may not yield the most profit in terms of percentage or true dollars. It may be more advantageous to use prime airtime windows for slower moving items in terms of units which generate more dollars to the bottom line.

One of the larger categories included was iQVC. As this is their internet site, it would be beneficial to have stronger, additional information regarding the relationship of these items to the TV sales. In only viewing the data and not being provided supporting context, there was a bit of ambiguity in interpreting if the times were when it was live online in general, spotlighted, linked to a TV ad, etc. It would also be helpful if those items were categorized in similar manner to the TV items instead of being lumped together under one grouping so a separate analysis could be conducted.