

Out Of Stock Patterns- Predictable or Not?

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Sponsor: a Global Consumer Packaged Goods company

Presented by:
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Agenda

- Company background & problem
- Data samples
- Methodology
- From 8 patterns to 3 patterns
- Pattern I and steep drops
- Future studies & Conclusion



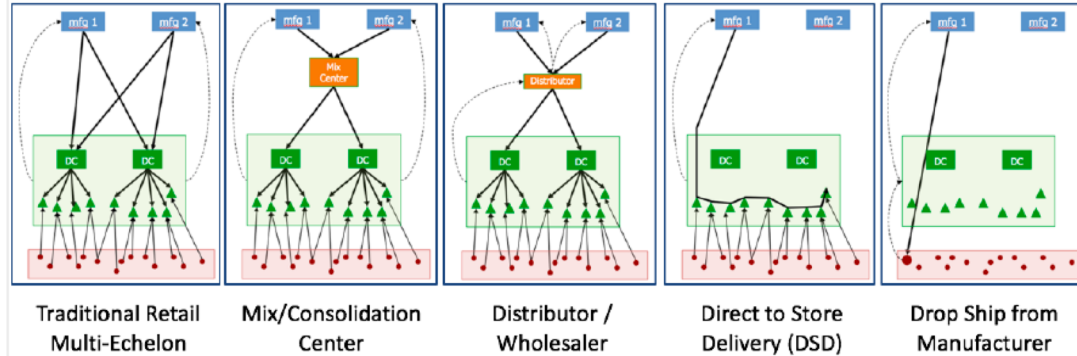
Company Overview – Industry & Distribution model

Industry

- Baby product
- HQ in NA
- Manufactures products and stores mainly in mixing centers

Mixing center

- Inbound shipments to mixing center
- From Mixing center to retailers' DCs
- From retailers' DCs to retailers' stores



OOS problem

- Repeated OOS events at retailers' DC
- There might be patterns for OOS
- Goal is to identify whether there is a pattern
- Sudden vs gradual drop in the last two days
- Actions to minimize the impact of OOS





Sample data

One SKU includes

- 42 DCs
- Each DC (one year)

432 unique SKUs

- DC data
- Store data

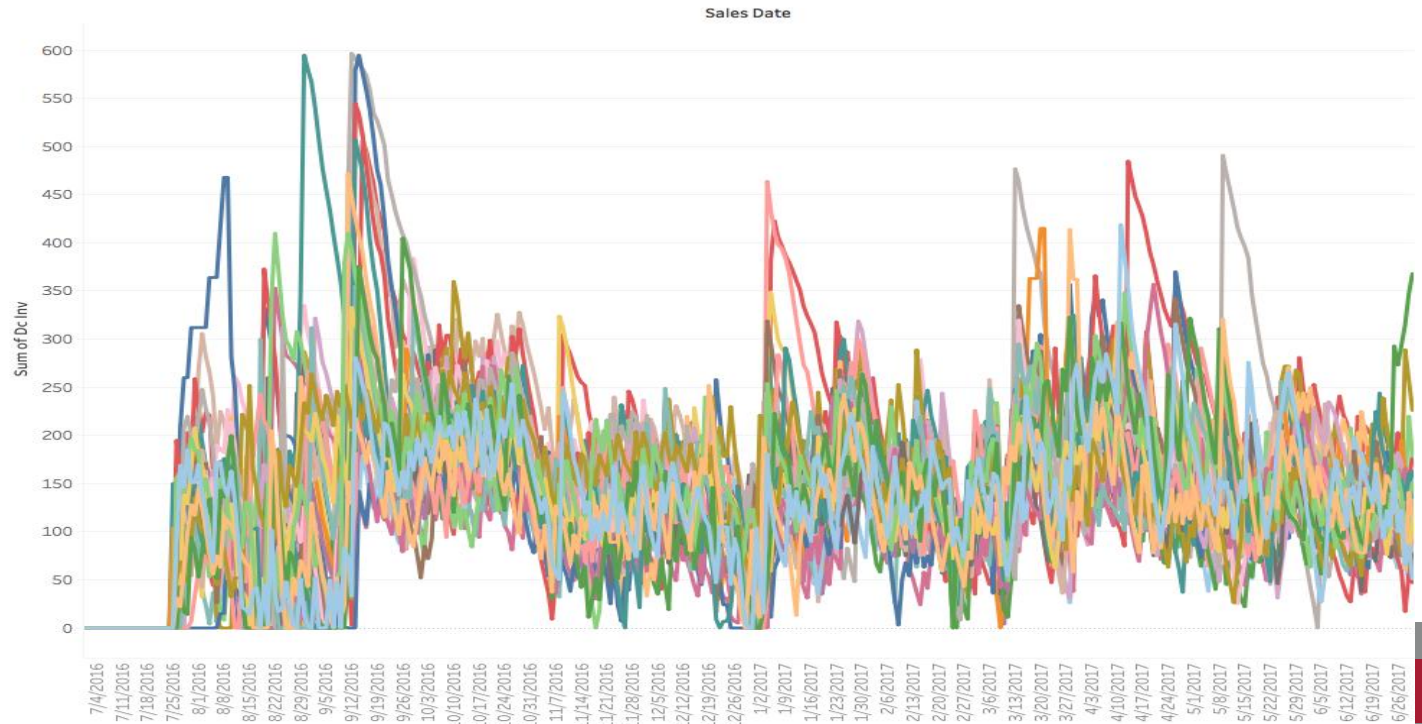
5 demand signals

- Base Demand
- Unexpected Demand
- Phase In
- Promotion
- Phase Out

20 SKUs are selected:

- High volume (65%)
- Demand signals mix

959991





Methodology – Index for three patterns

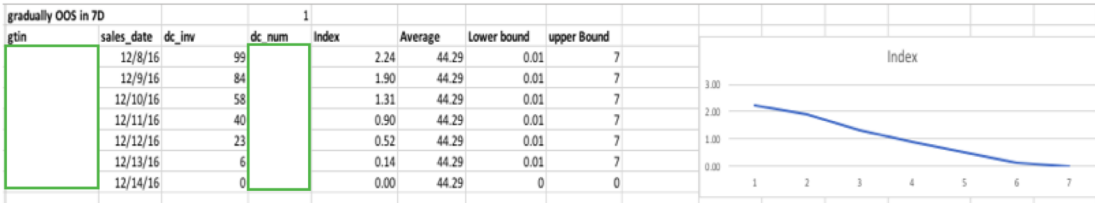
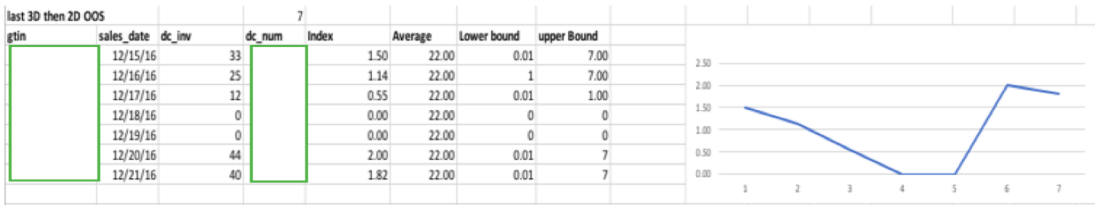
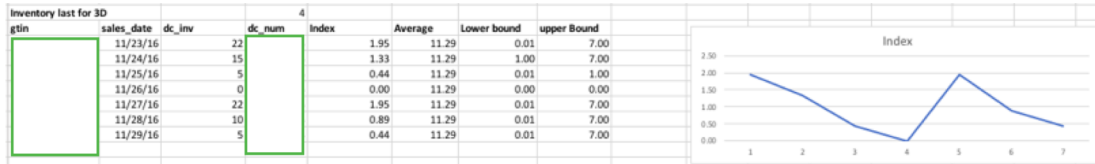


Figure 7 Pattern 1 gradually OOS in 7 Days



- Normalize data
- Matrix Profile
- Interval $m=7, 6, 5$ or 4 Days
- $Index = \frac{INVT_i}{AveINV(T_i \text{ to } T_i+7)}$
- Lower bound and upper bound



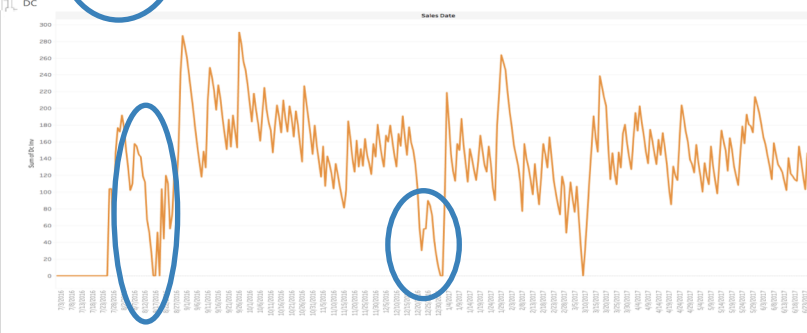
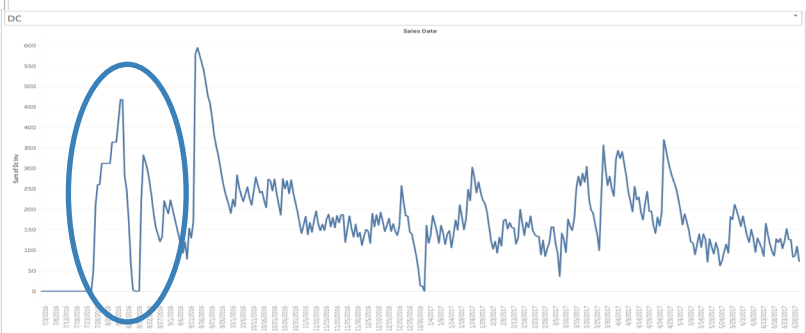
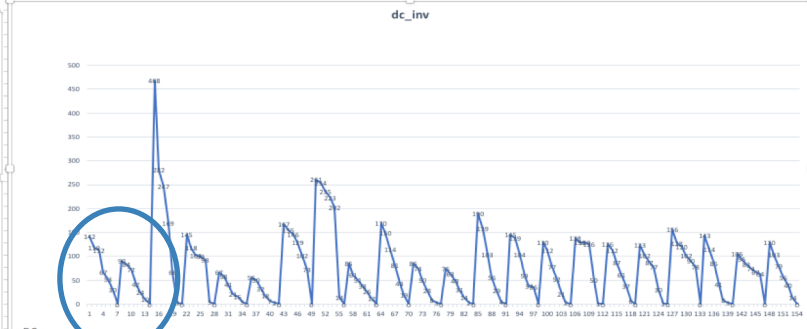
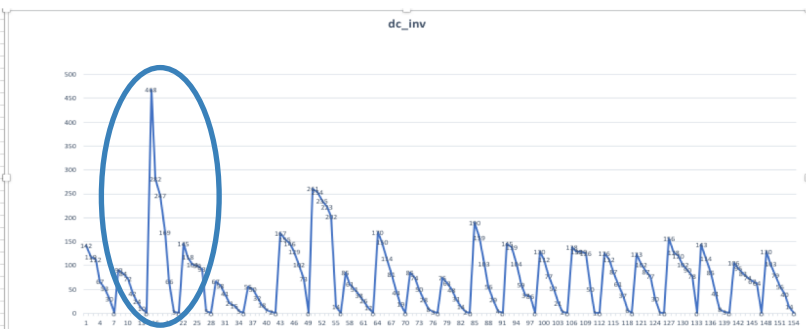
Methodology – Similarity search

- Calculate the average inventory level within each subset of time series (length of subset= m);
- Divide each inventory level by the average inventory level in order to obtain the index for each row;
- Compare each index to the interval of the predefined index range: If each index is within the lower bound and upper bound of the predefined index range, then a pattern is identified, indicated, and recorded in the new dataset;
- Slide the subset until the end of the time series in the same DC data;
- Repeat the same steps for all 42 DCs' data.

■ Five steps approach
■ Python



Example of pattern recognition for Pattern I



Original time series vs aggregated Pattern I

Use both index and inventory on hand value



From 8 Patterns to 3 patterns

GTIN 1 1211 OOS event		Initiative		7 days		6 days		5 days		4 Days	
Pattern #	Frequency	% compared	Frequency	% compared	Frequency	% compared	Frequency	% compared	Frequency	% compared	to OOS
Pattern 1 gradually OOS in 7D	7	0.00578	15	0.01239	22	0.01817	49	0.04046			
Pattern 1 half <1 half>-1	3	0.00248	11	0.00908	15	0.01239	48	0.03964			
Pattern 2	0	0.00000	0	0.00000	0	0.00000	0	0.00000			
Pattern 3	2	0.00165	2	0.00165	2	0.00165	2	0.00165			
Pattern 4 Inventory last for 3D half <1 half>-1	29	0.02395	30	0.02477	33	0.02725	40	0.03303			
Pattern 5	1	0.00083	1	0.00083	1	0.00083	1	0.00083			
Pattern 6	0	0.00000	0	0.00000	0	0.00000	47	0.03881			
Pattern 7 last 3D then 2D OOS	4	0.00330	6	0.00495	20	0.01652	20	0.01652			
Pattern 8	0	0.00000	0	0.00000	0	0.00000	0	0.00000			
GTIN 2 1381 stock out event		Initiative		7 days		6 days		5 days		4 Days	
Pattern #	Frequency	% compared	Frequency	% compared	Frequency	% compared	Frequency	% compared	Frequency	% compared	to OOS
Pattern 1 gradually OOS in 7D	32	0.02317	40	0.02896	59	0.04272	85	0.06155			
Pattern 1 half <1 half>-1	21	0.01521	23	0.01665	34	0.02462	85	0.06155			
Pattern 2	1	0.00072	1	0.00072	1	0.00072	1	0.00072			
Pattern 3	1	0.00072	1	0.00072	1	0.00072	1	0.00072			
Pattern 4 Inventory last for 3D half <1 half>-1	30	0.02172	32	0.02317	40	0.02896	69	0.04996			
Pattern 5	3	0.00217	3	0.00217	3	0.00217	3	0.00217			
Pattern 6	0	0.00000	0	0.00000	0	0.00000	54	0.03910			
Pattern 7 last 3D then 2D OOS	18	0.01303	23	0.01665	54	0.03910	103	0.07458			
Pattern 8	0	0.00000	0	0.00000	0	0.00000	0	0.00000			
GTIN 3 1219 stock out event		Initiative		7 days		6 days		5 days		4 Days	
Pattern #	Frequency	% compared	Frequency	% compared	Frequency	% compared	Frequency	% compared	Frequency	% compared	to OOS
Pattern 1 gradually OOS in 7D	16	0.01313	28	0.02297	28	0.02297	62	0.05086			
Pattern 1 half <1 half>-1	4	0.00328	21	0.01723	22	0.01805	61	0.05004			
Pattern 2	0	0.00000	0	0.00000	0	0.00000	0	0.00000			
Pattern 3	2	0.00164	2	0.00164	2	0.00164	2	0.00164			
Pattern 4 Inventory last for 3D half <1 half>-1	29	0.02379	31	0.02543	31	0.02543	43	0.03527			
Pattern 5	1	0.00082	1	0.00082	1	0.00082	1	0.00082			
Pattern 6	0	0.00000	0	0.00000	0	0.00000	42	0.03445			
Pattern 7 last 3D then 2D OOS	30	0.00820	14	0.01148	54	0.04430	65	0.05332			
Pattern 8	0	0.00000	0	0.00000	0	0.00000	0	0.00000			
GTIN 4 3548 stock out event		Initiative		7 days		6 days		5 days		4 Days	
Pattern #	Frequency	% compared	Frequency	% compared	Frequency	% compared	Frequency	% compared	Frequency	% compared	to OOS
Pattern 1 gradually OOS in 7D	1	0.00028	6	0.00169	22	0.00620	260	0.07328			
Pattern 2	0	0.00000	0	0.00000	0	0.00000	0	0.00000			
Pattern 3	0	0.00000	2	0.00056	2	0.00056	2	0.00056			
Pattern 4 Inventory last for 3D half <1 half>-1	68	0.01917	82	0.02311	94	0.02649	124	0.03495			
Pattern 5	0	0.00000	1	0.00028	1	0.00028	1	0.00028			
Pattern 6	0	0.00000	0	0.00000	0	0.00000	42	0.01184			
Pattern 7 last 3D then 2D OOS	23	0.00648	28	0.00789	417	0.11753	528	0.14882			
Pattern 8	0	0.00000	0	0.00000	0	0.00000	0	0.00000			

- 5 GTINs were tested with 8 patterns
- as the m value decreases from 7 days to 4 days, similar pattern shapes happen more often,
- 3 higher frequency patterns were selected for further research



Step drops for Pattern I

7 Days		6 Days		5 days	
Bin	Frequency	Bin	Frequency	Bin	Frequency
0%	0	0%	0	0%	0
20%	2	20%	5	20%	5
40%	4	40%	5	40%	4
60%	0	60%	4	60%	10
80%	0	80%	0	80%	2
100%	0	100%	0	100%	0
More	0	More	0	More	0
	6		14		21
Average drop		Average drop		Average drop	
Per day	17%	Per day	20%	Per day	25%
For the last 2 days	33%	For the last 2 days	40%	For the last 2 days	50%
>70%	0	>70%	0	>80%	0
>70%	0%	>70%	0%	>80%	0%
7 Days		6 Days		5 days	
Bin	Frequency	Bin	Frequency	Bin	Frequency
0%	0	0%	0	0%	0
20%	8	20%	6	20%	5
40%	14	40%	17	40%	19
60%	4	60%	9	60%	21
80%	5	80%	6	80%	8
100%	0	100%	1	100%	5
More	0	More	0	More	0
	31		39		58
Average drop		Average drop		Average drop	
Per day	17%	Per day	20%	Per day	25%
For the last 2 days	33%	For the last 2 days	40%	For the last 2 days	50%
>70%	1	>70%	4	>80%	5
>70%	3%	>70%	10%	>80%	9%

7 Days		6 Days		5 days	
Bin	Frequency	Bin	Frequency	Bin	Frequency
0%	0	0%	0	0%	0
20%	5	20%	6	20%	7
40%	6	40%	8	40%	13
60%	5	60%	12	60%	10
80%	0	80%	2	80%	9
100%	0	100%	0	100%	1
More	0	More	0	More	0
	16		28		40
Average drop		Average drop		Average drop	
Per day	14%	Per day	17%	Per day	20%
For the last 2 days	29%	For the last 2 days	33%	For the last 2 days	40%
>70%	0	>70%	1	>80%	1
>70%	0%	>70%	4%	>80%	3%
7 Days		6 Days		5 days	
Bin	Frequency	Bin	Frequency	Bin	Frequency
0%	0	0%	0	0%	0
20%	4	20%	3	20%	4
40%	8	40%	7	40%	9
60%	1	60%	10	60%	14
80%	1	80%	2	80%	4
100%	0	100%	0	100%	0
More	0	More	0	More	0
	14		22		31
Average drop		Average drop		Average drop	
Per day	14%	Per day	17%	Per day	20%
For the last 2 days	29%	For the last 2 days	33%	For the last 2 days	40%
>70%	0	>70%	1	>80%	1
>70%	0%	>70%	5%	>80%	3%

- 70% drop for 7, 6 and 5 days; 80% drop for 4 days
- 20 SKUs were tested
- step drops seems to be infrequent events (less than 10%)
- OOS pattern doesn't seem to be predictable solely based on DC data



Future studies-POS & weekends

gtin	brand	sales_dt	dc_nm	dc_nm	indicat	Average	Index	weekday	weekend	Days withi	num_sls	Total Store invent	Total Store POS	num_it_cox_0	num_it_cox_1	Comments
		5/10/16	142		1		1.90	4 Weekdays		1	101	253	17	5	19	POS=109 inventory=142
		5/11/16	119		0		1.59	5 Weekdays		2	101	243	14	6	23	
		5/12/16	112		0		1.50	6 Weekdays		3	101	229	24	7	30	
		5/13/16	67		0	74.71	0.90	7 Weekend		4	101	209	12	10	39	
		5/14/16	53		0		0.71	1 Weekend		5	101	194	21	16	45	
		5/15/16	30		0		0.40	2 Weekdays		6	101	201	14	23	46	
		5/16/16	0		0		-	3 Weekdays		7	101	201	7	27	47	
		5/25/16	90		1		1.96	1 Weekend		1	103	310	0	10	14	POS=112 inventory=90
		5/26/16	84		0		1.83	2 Weekdays		2	103	309	33	9	16	but tota store inventory 3107
		5/27/16	72		0		1.57	3 Weekdays		3	103	311	12	10	15	
		5/28/16	42		0	46.00	0.91	4 Weekdays		4	103	311	14	8	13	
		5/29/16	24		0		0.52	5 Weekdays		5	103	316	15	8	12	
		5/30/16	10		0		0.22	6 Weekdays		6	103	314	39	8	13	
		5/31/16	0		0		-	7 Weekend		7	103	317	39	9	12	
		5/9/16	468		1		2.65	3 Weekdays		1	140	232	0	44	77	POS= 35 inventory=468
		5/10/16	282		0		1.60	4 Weekdays		2	140	197	0	46	79	
		5/11/16	247		0		1.40	5 Weekdays		3	140	172	0	54	86	
		5/12/16	169		0	176.43	0.96	6 Weekdays		4	140	195	1	54	83	
		5/13/16	64		0		0.37	7 Weekend		5	140	312	7	41	68	
		5/14/16	3		0		0.02	1 Weekend		6	140	334	18	41	66	
		5/15/16	0		0		-	2 Weekdays		7	140	372	9	47	71	
		5/11/16	145		1		1.81	5 Weekdays		1	82	163	18	27	18	POS= 71 inventory=145
		5/12/16	118		0		1.47	6 Weekdays		2	82	139	18	39	18	
		5/13/16	101		0		1.26	7 Weekend		3	82	126	14	42	14	
		5/14/16	99		0	80.14	1.24	1 Weekend		4	82	120	3	47	3	
		5/15/16	93		0		1.16	2 Weekdays		5	82	116	11	48	11	
		5/16/16	5		0		0.06	3 Weekdays		6	82	125	3	49	3	
		5/17/16	0		0		-	4 Weekdays		7	82	133	4	49	4	
		5/1/16	67		1		2.27	5 Weekdays		1	82	215	23	17	23	POS= 107 inventory=67
		5/2/16	58		0		1.96	6 Weekdays		2	82	201	16	18	16	
		5/3/16	41		0		1.39	7 Weekend		3	82	190	21	21	21	
		5/4/16	21		0		0.71	1 Weekend		4	82	186	12	22	12	
		5/5/16	15		0		0.51	2 Weekdays		5	82	194	10	21	10	
		5/6/16	5		0		0.17	3 Weekdays		6	82	190	16	23	16	
		5/7/16	0		0		-	4 Weekdays		7	82	198	9	19	9	
		5/29/16	55		1		2.35	2 Weekdays		1	98	309	14	10	18	POS= 147 inventory=55
		5/30/16	50		0		2.13	3 Weekdays		2	98	307	15	8	16	
		5/31/16	32		0		1.37	4 Weekdays		3	98	285	25	8	18	
		5/1/16	18		0	23.43	0.77	5 Weekdays		4	98	256	29	11	24	

- POS>inventory starting point
- Total store inventory > POS
- Weekday vs weekends
- Safety stock
- Collaborative planning



Conclusions and Recommendations

- Using the index and similarity search methods, a series of OOS patterns can be identified and aggregated in a large scale. This method could possibly be scaled to all 432 GTINs to aggregate patterns from 4 million transactions.
- Stock outs don't seem to be predictable based solely on the DC data.
- Store data could be incorporated to connect the POS and OOS events, in order to identify the drivers of out of stocks.

Thank you and questions

