Forecasting Model for Sporadic Distributor based Markets

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Agenda

- Company Settings
- Motivation / Background
- Literature Review
- Methodology
- Results
- Conclusion

Company Settings

Company Information

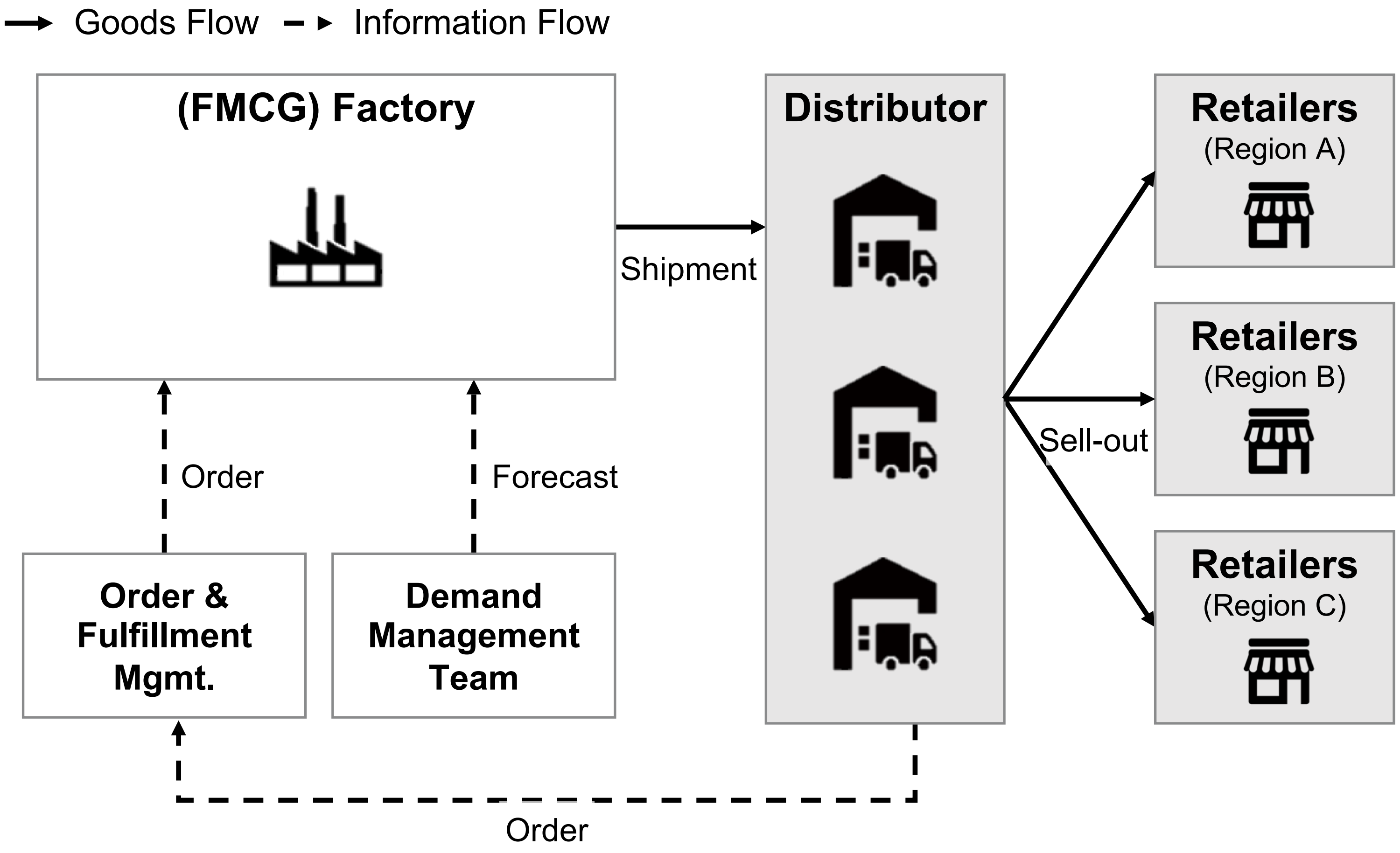
Industry

Fast Moving Consumer Goods (FMCG) Company

Geographical Operation

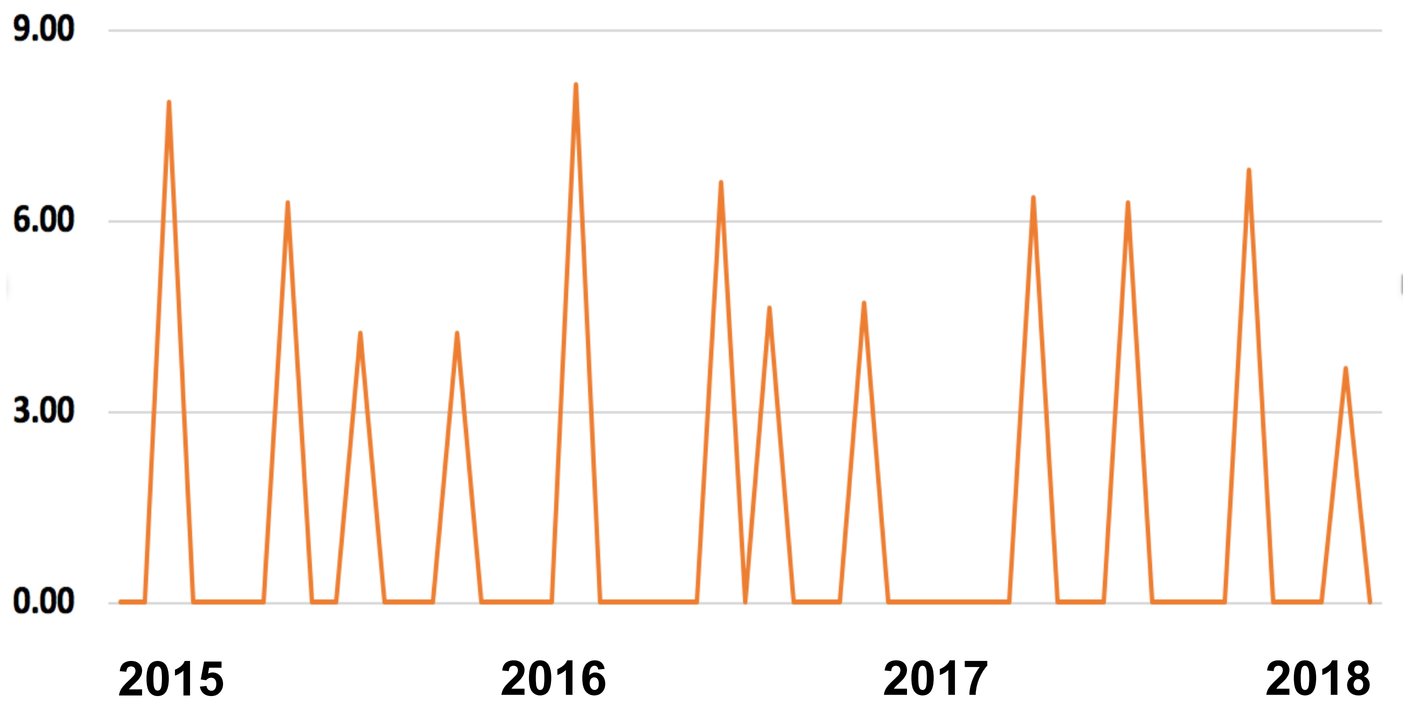
Global Region

Overall Process of Goods



Motivation / Background

Actual Shipment Volume[1] (in 1,000 units)



Forecast vs Actual Error

+487%

Forecast

- 20%

- **Wide discrepancy between forecast and actual shipment impacts business (ex. missing sales, high inventory costs)**

1. Sample of one SKU

Key Question

- **What is the best model to forecast long & short term shipments for sporadic distributor based markets?**

- **How can we link distributor data to improve the E2E (End to End) supply network?**

Literature Review – Croston's Method

Traditional Forecasting method

Moving Average

- The method forecasts based on average of most recent observations
  (ex. 3MA observes 3 weeks of demand to forecast)
- Weight is same to each observation

Exponential Smoothing

- The forecast uses "Alpha" factor, which indicates the value of new information
- Put more weight to recent observation
  - If Alpha increases, more weight on new information

Since there are too many zero values in demand, it could lead to poor forecast

Croston's Method

Intro

- 1972, Croston JD developed the forecasting method
- Developed to forecast demands that have multiple 0 values

Approach

- Forecast two data independently and aggregates in order to determine average demand per period

Non-zero demand time series → **Demand size**

Zero demand time series → **Inter-arrival time**

Demand size + **Inter-arrival time** → **Average Demand per time period**

Literature Review – Multi-Tier Regression Analysis

- Demand-Driven Forecasting: A Structured Approach to Forecasting, Charles W. Chase, Jr.
- Methods of linking downstream data into forecasting model
- CPG Industry Case
- Demand & Supply Model Through Using Linear Regression
- Demand Forecast → Supply Forecast

$$(1)\ Demand\ (D) = \beta_d 0\ Constant + \beta_d 1\ Trend + \beta_d 2\ Seasonality + \beta_d 3\ Price + \beta_d 4\ Advertising + \beta_d 5\ Sales + \beta_d 6\ \%\ ACV\ Feature + \beta_d 7\ FSI + \beta_d 8\ Store\ Distribution + \beta_d 9\ Competitive\ Price + \cdots \beta_d n$$

$$(2)\ Supply\ (S) = \beta_s 0\ Constant + \beta_s 1 D(lag 1 - n) + \beta_s 2 Trend + \beta_s 3\ Seasonality + \beta_s 4\ Gross\ Dealer\ Price + \beta_s 5\ Factory\ Rebates + \beta_s 6\ Cash\ Discount + \beta_s 7\ Coop\ Advertising + \beta_s 8\ Trade\ Promotions + \ldots \beta_s n$$

Method – Downstream Data Acquisition

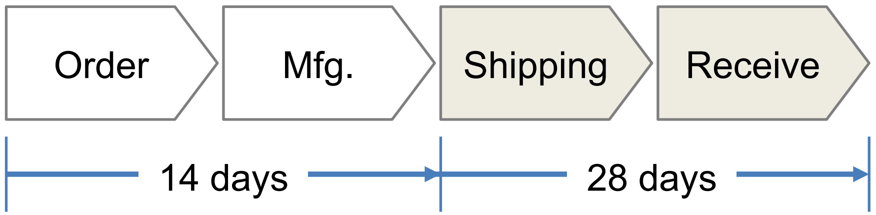
Category	Data Point	Note
Manufacturer / Distributor	Sell-out	Shipments from distributor to retailer
	Inventory level	Inventory level of distributor
	Customer Fill Rate	Satisfied orders / Requested orders
	Sales Target (or Building Block)	Sales target set by manufacturer
Retailer	Price	Not available
	POS data	Not available
	Competition Prices	Not available
	Premium Displays	Not available
	Advertising	Not available
General	Events	National events

Method – Multi-Tier Regression Model

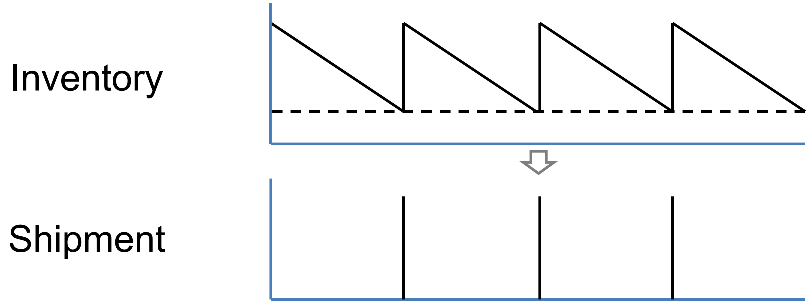
Regression Analysis

Dependent Variables (=y)	• Shipments
Independent Variables (=x)	• Sell-out • Inventory level • Customer Fill Rate • National holiday or event ⋮
Metrics	• RMSE[1] / A-MAPE[2] / MD[3]

- Apply various lag time between shipment and sell-out
  - Since there is lead time of approx. 1 month in shipping, the distributor might ship 1 month prior
  - The team applied lag time of 1 ~ 3 month



- Analyze the relationship between distributor's inventory and shipment
  - Identify how inventory level affects the shipment



1. Root Mean Square Error 2. Mean Absolute Percentage Error 3. Adjusted Mean Absolute Percentage Error 4. Mean Deviation

Method – Metrics

Approach #1 :
Multi-regression Analysis

Approach #2 :
Croston Method

Internal Method

1. $\text{RMSE}^1 = \left(\frac{1}{n}\sum_{t=1}^{n}(Y_t - F_t)\right)^{1/2}$

2. $\text{MAPE}^2 = \frac{1}{n}\sum_{t=1}^{n}|Y_t - F_t|/Y_t$

$$\text{A-MAPE}^3 = \frac{\frac{1}{n}\sum_{t=1}^{n}|Y_t - F_t|}{\frac{1}{n}\sum_{t=1}^{n}Y_t}$$

3. $\text{MD}^4 = \sum_{t=1}^{n}\frac{Y_t - F_t}{n}$

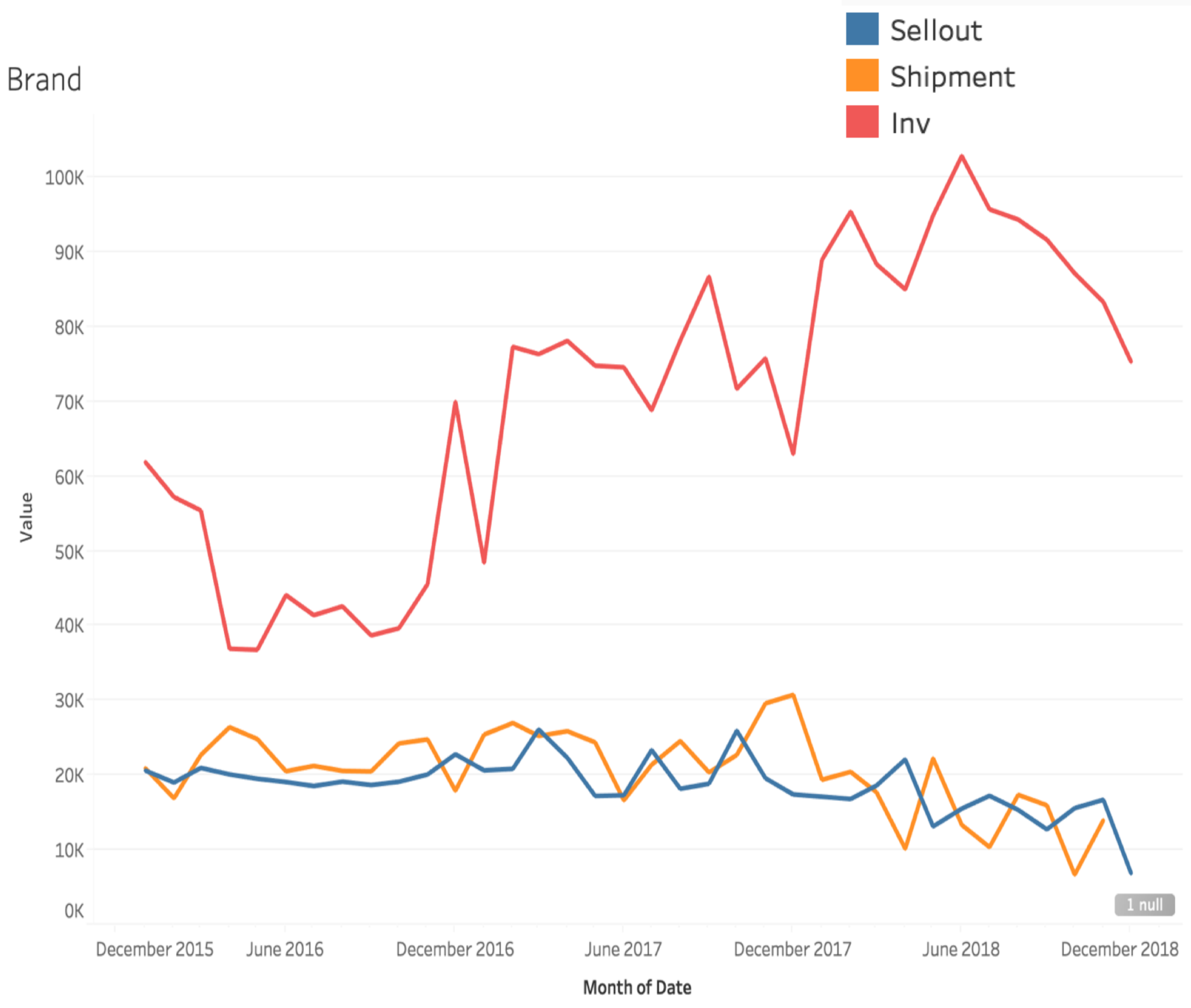
1. Root Mean Square Error 2. Mean Absolute Percentage Error 3. Adjusted Mean Absolute Percentage Error 4. Mean Deviation

Results- Regression Analysis on Brand Level

Objective:
Understand the behavior of explanatory variables overtime

Results:

1. There is a lag between Sellout and shipment
2. Distributor Inventory increased at the end of the time horizon due to sellout decrease.



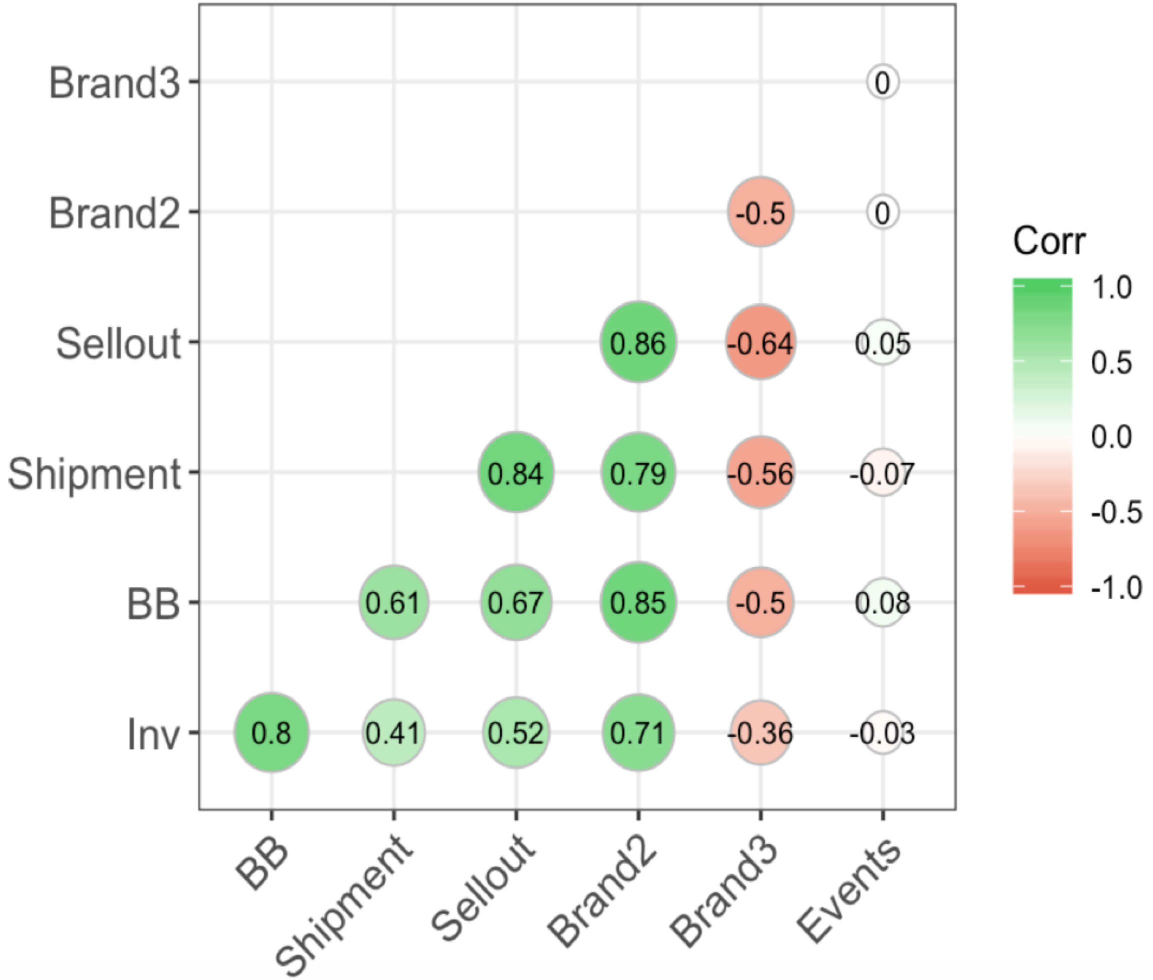
Results- Regression Analysis on Brand Level

Objective:
Understand correlation between explanatory variables

Observations in the underlying dataset :

1. Events doesn't correlate with number of shipments
2. Number of shipments is highly correlated with sellout (.84) and Inventory (.41)
3. Building block and inventory are highly correlated which may cause multicollinearity

Correlogram of shipments and distributor data



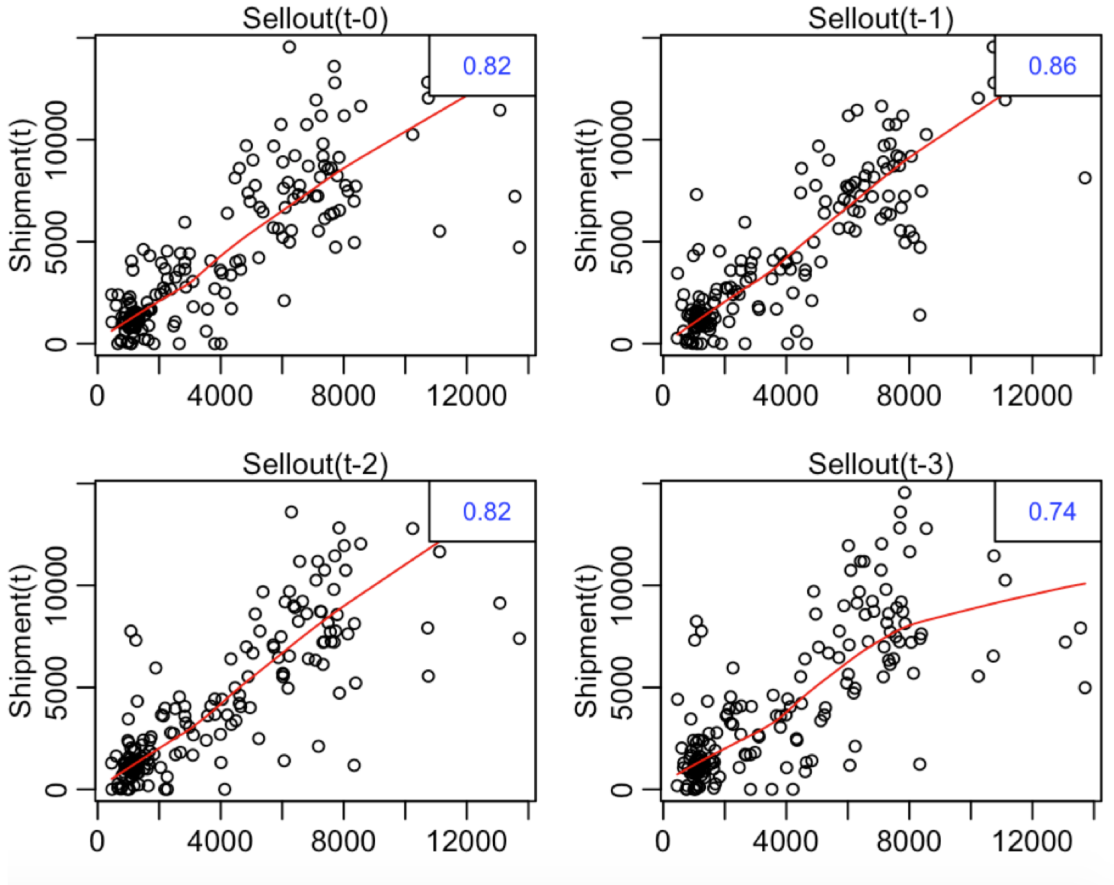
Results- Regression Analysis on Category Level

Objective:

Identify the lag between Shipment and sellout

Results:

1. Shipments are more correlated with sellout of t-1
2. There are some outliers, we flagged them as an event to see their effect on the model

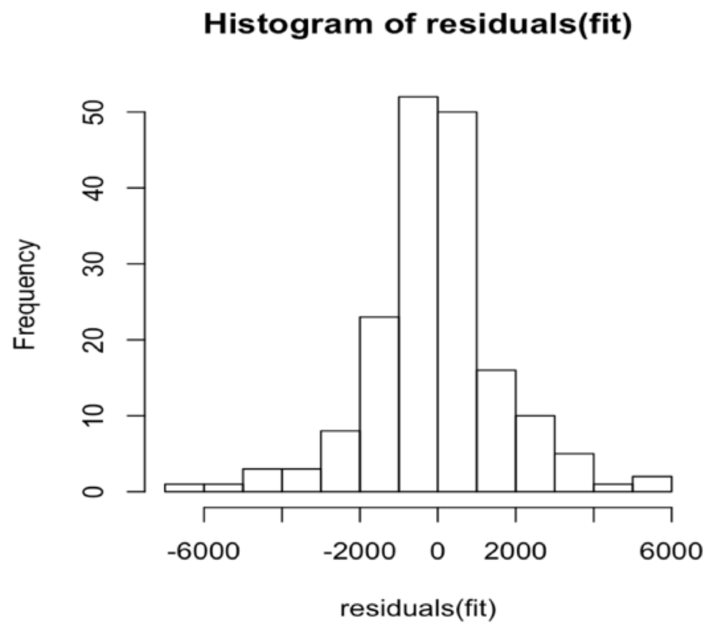


Results- Category level Model

1. We predicted sellout using the following equation
2. Model can predict up to building block availability date
3. We used the predicted sellout as an independent variable to predict shipments
4. Used a simulated inventory value as an explanatory variable
5. Flagged event dates, and added it as another independent variable
6. Predicted Sellout with an 83% R^2, and shipments with 78% $\mathbf{R^2}$

$$Sellout = 8291.22 - 45.18 * log(BB+1) - 6818.99 * (Category\ 2) - 1788.95 * (Category\ 3) - 7033.47 * (Category\ 4) - 5170.5 * (Category\ 5)$$

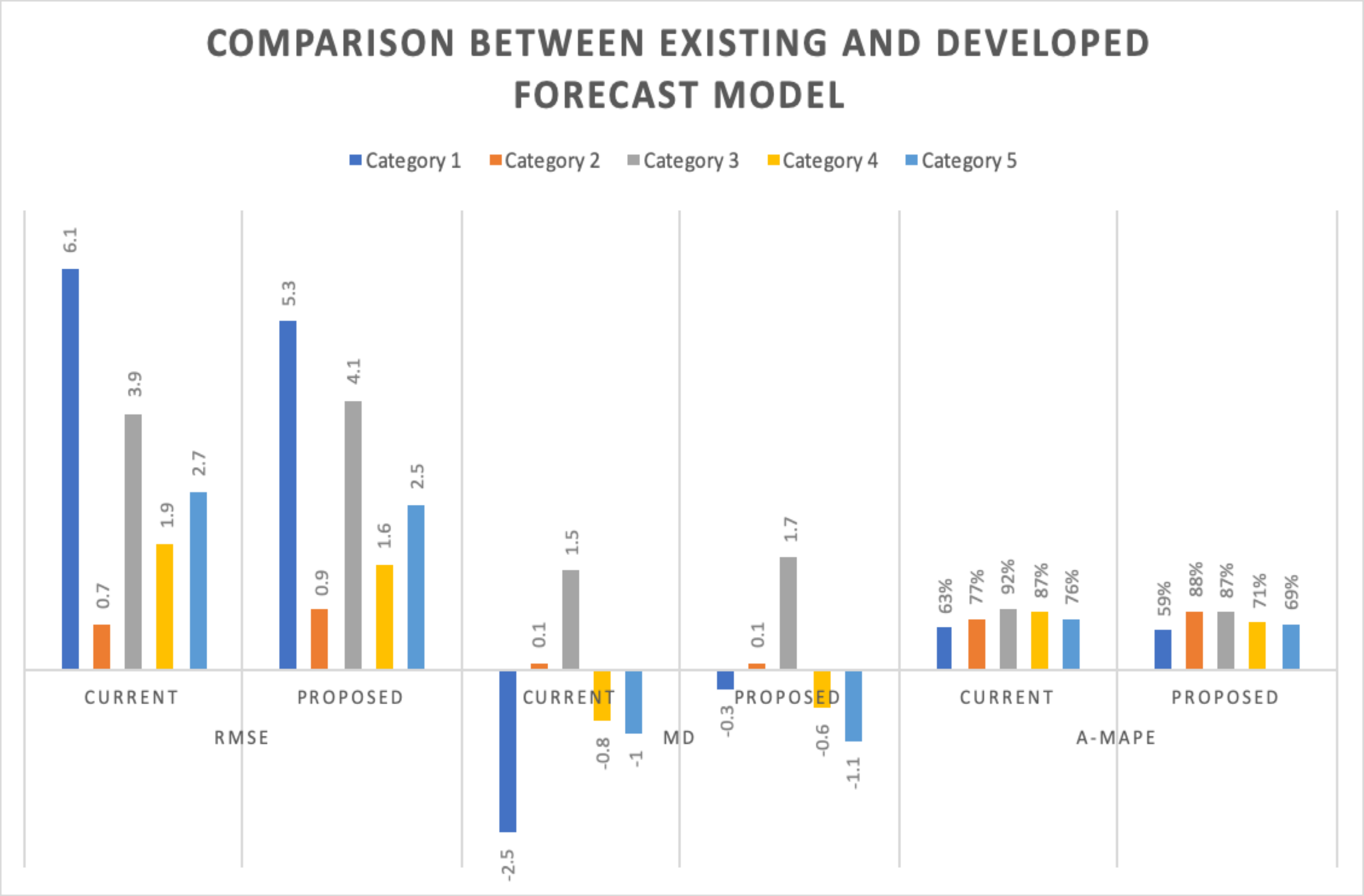
$$Shipment\ volume = 8.399e+03 + 2.552e-01 * (Sellout\ t-1) - 6.535e-02 * (Inventory\ t-1) - 7.957e+02\ (Events) - 7.228e+03 * (Category\ 2) - 1.691e+03 * (Category\ 3) - 6.978e+03 * (Category\ 4) - 5.023e+03 * (Category\ 5)$$



Results- Measuring Accuracy on Category Level

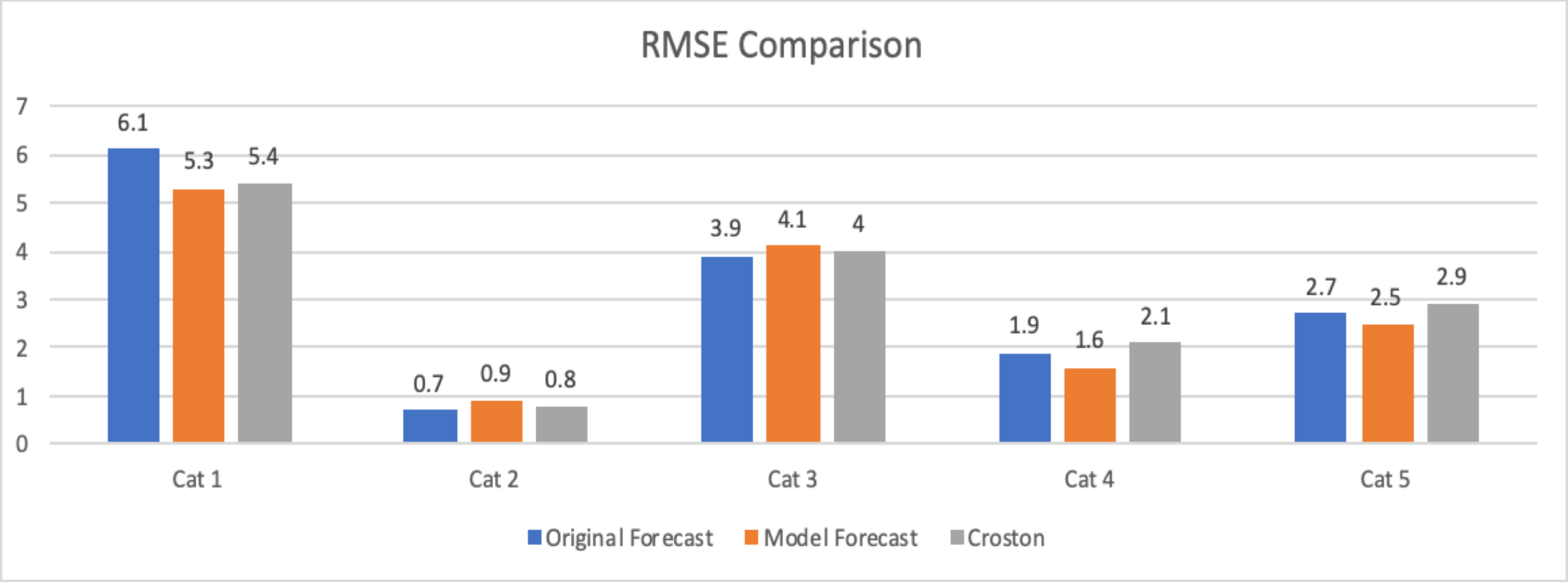
Category Results Summary:

1. Model REMSE has decreased for 3 out of 5 categories
2. Proposed model is less biased in some categories than original forecast
3. Since the model is taking building block as main variable, it's all dependent on its accuracy.



Results- Comparing with Croston

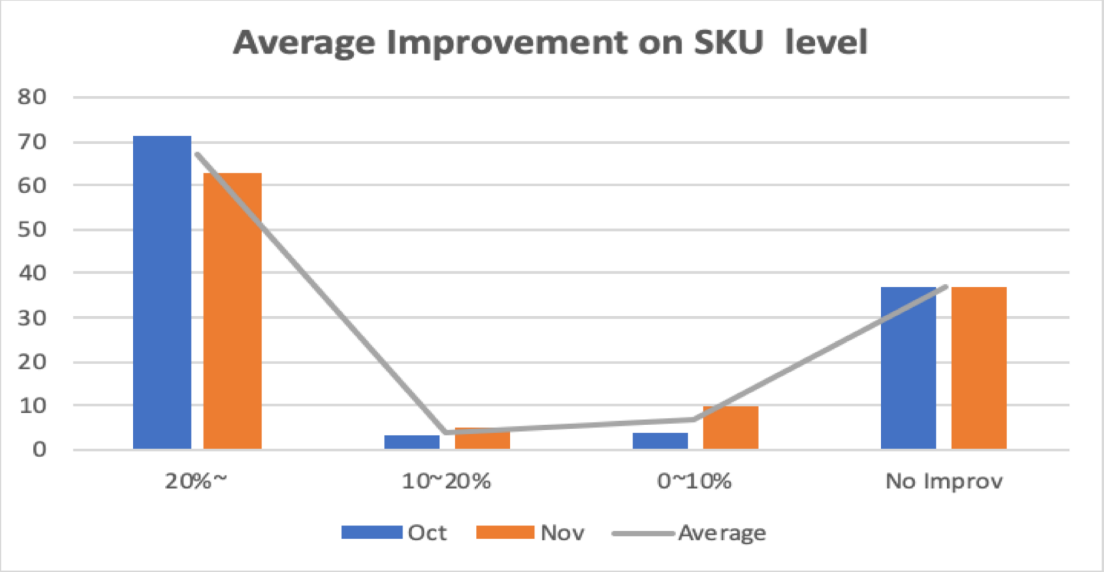
- ➢ Ran Croston Method on category level
- ➢ Compared results over three month
- ➢ Improvement in 3 out of 5 categories



	RMSE			MD			A-MAPE		
	Original Forecast	Model Forecast	Croston	Original Forecast	Model Forecast	Croston	Original Forecast	Model Forecast	Croston
Cat 1	6.1	5.3	5.4	-2.5	-0.3	-1.3	63%	59%	54%
Cat 2	0.7	0.9	0.8	0.1	0.1	0.3	77%	88%	78%
Cat 3	3.9	4.1	4	1.5	1.7	1.9	92%	87%	89%
Cat 4	1.9	1.6	2.1	-0.8	-0.6	-1.5	87%	71%	95%
Cat 5	2.7	2.5	2.9	-1	-1.1	-1.5	76%	69%	81%

Results- Split on SKU level

- ➢ Used demand model to predict expected sellout
- ➢ Predicted shipment using supply model
- ➢ Split Category value on SKU based on how each SKU represents in total category
- ➢ On the shaped demand; on average 67 SKU improved more than 20% in terms of RMSE



	Oct	Nov	Average
20%~	51	44	48
10~20%	3	5	4
0~10%	4	10	7
-20%~0%	37	37	37
Total	95	96	96

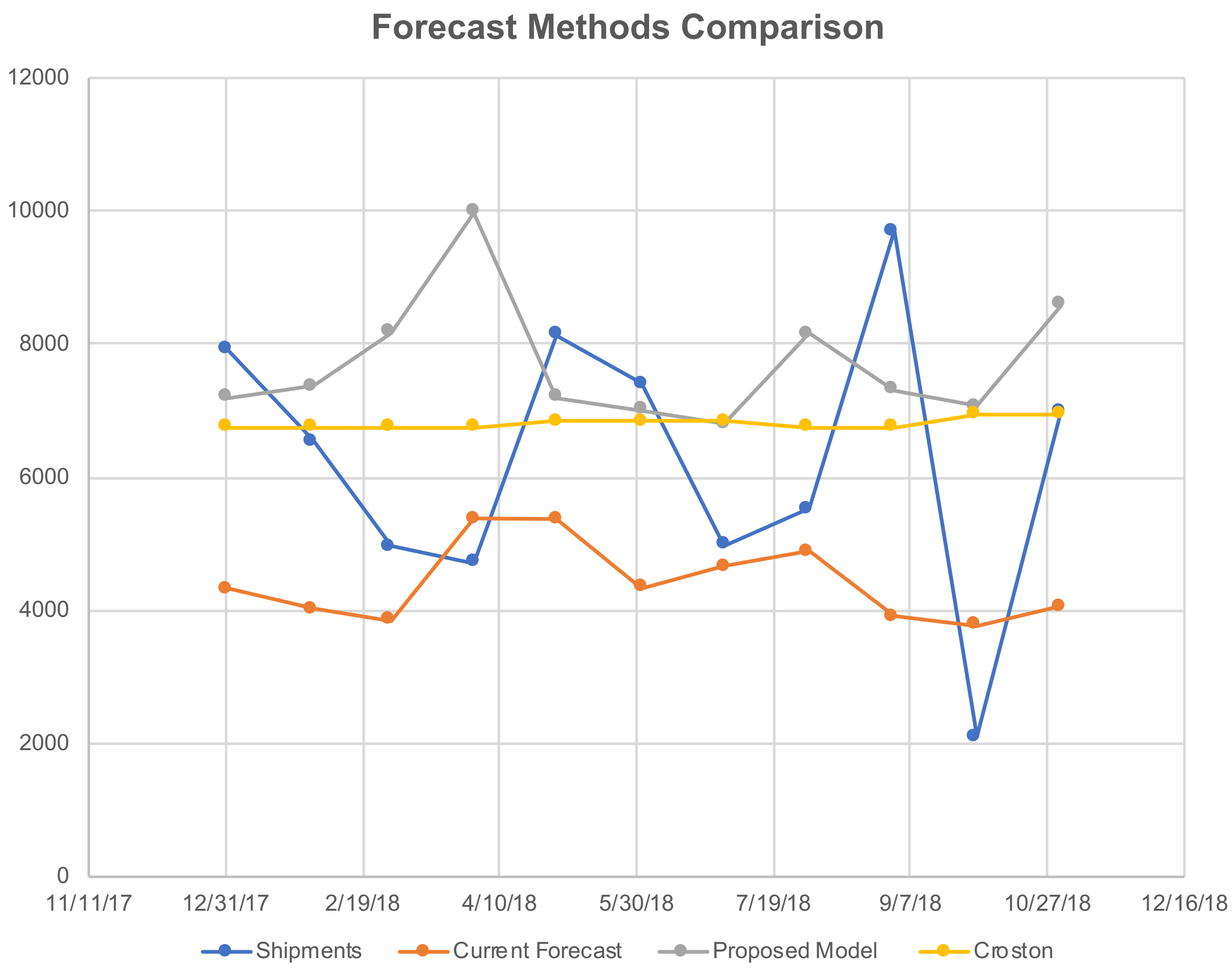
Supply Chain MANAGEMENT

Conclusion

- With the underlying dataset, Multiple regression analysis shows
- Collaboration with distributor is an imperative factor of the success of this method of linking downstream
- Croston method helps setting a smooth inventory level.

Recommendation

- For Future research; Machine learning can be utilized to cluster items, and used different forecasting methods accordingly



Thank You

Final Results in $$

TC = Purchase Costs + Order Costs + Holding Costs + Stock Out Costs

$$TC = vD + A\left(\frac{D}{Q}\right) + \left(\frac{Q}{2} + k\sigma_L + DL\right)c_e + B_1\left(\frac{D}{Q}\right)p_{u\geq}(k)$$

Category	$/unit	RMSE Improvement (Unit)
Category 1	$ 20.00	800
Category 2	$ 48.36	-200
Category 3	$ 42.70	-200
Category 4	$ 56.71	300
Category 5	$ 53.20	200
RMSE difference in $		$25,442

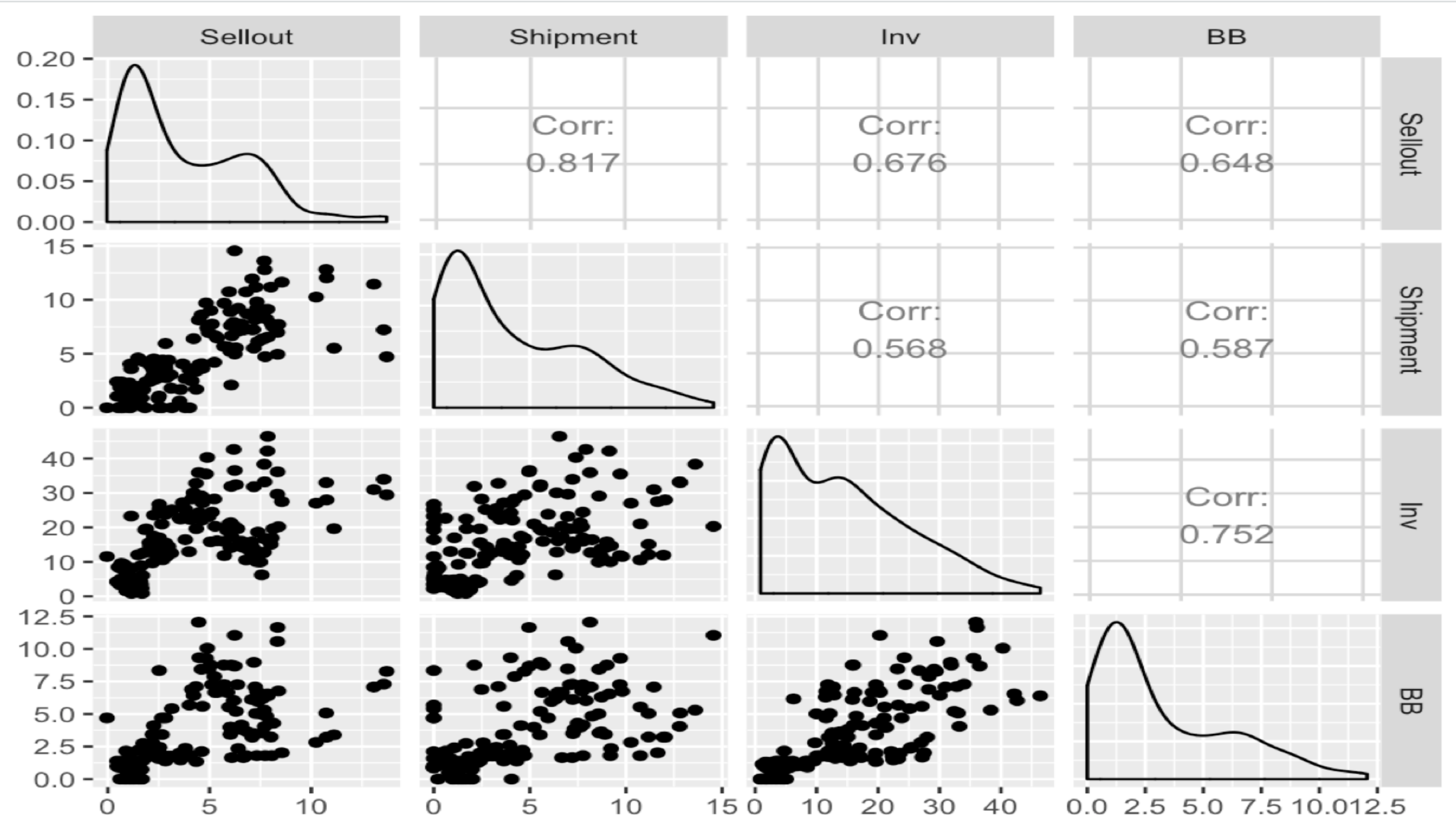
80 Countries **30+ Categories**

Forecast error difference of

> $80 million

* Assume 1 distributor in 1~2 countries (i.e. 40 countries for potential savings)
* Assume 20 categories

Scatter plot matrix for shipment and other three numeric predictors in 1,000 unit



Results- Simulation based on target inventory

Objective:

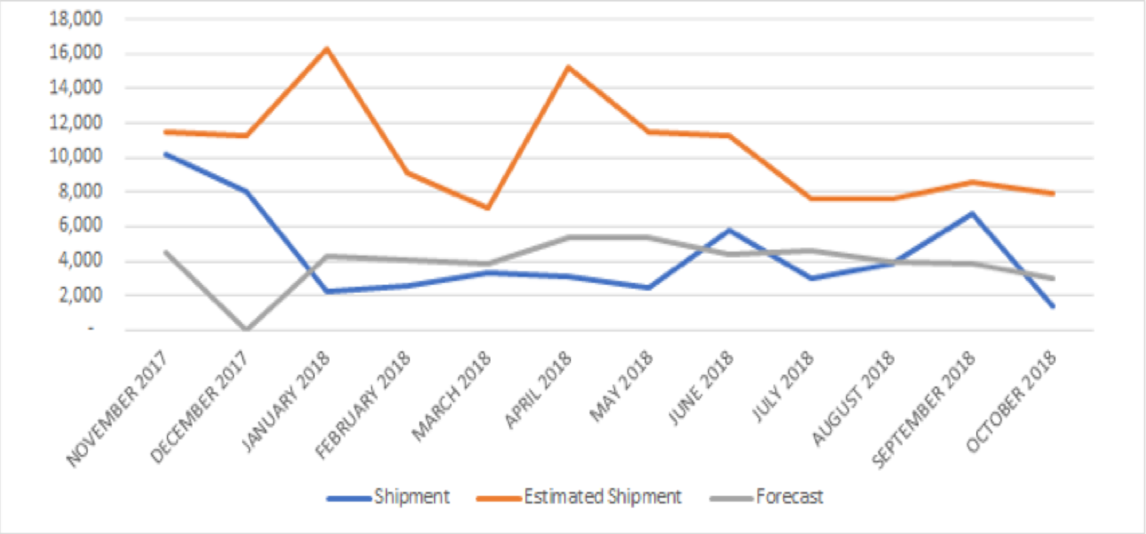
To investigate the replenishment the products that fall below the target inventory level

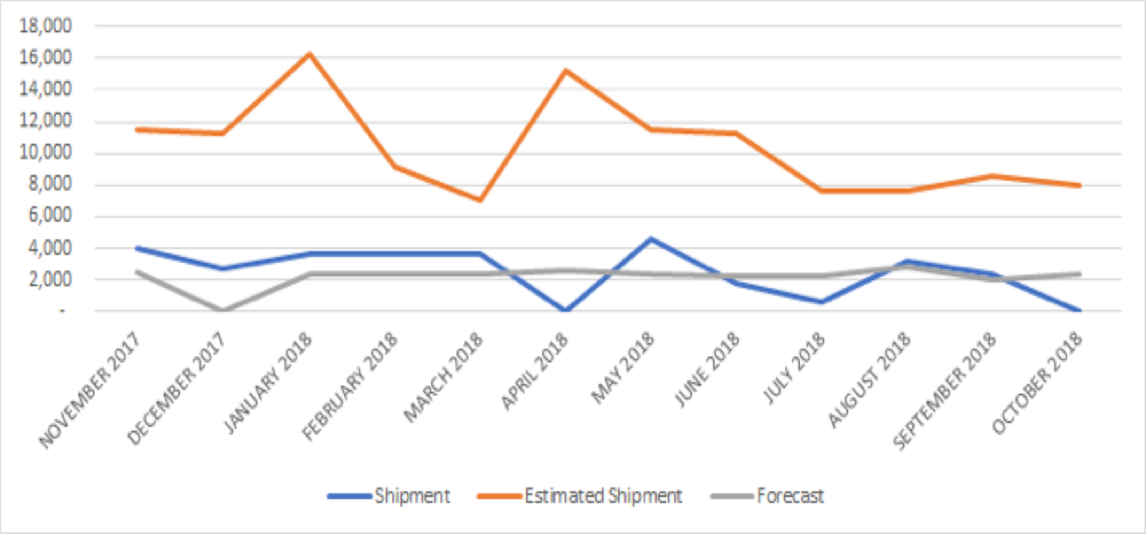
Result:

Brand 2 had improved by 33%

Other brands accuracy dropped significantly

	RMSE_Simulation	RMSE_Internal	Improvement
Brand1	7,094	3,311	-53%
Brand2	4,644	6,176	33%
Brand3	8,523	1,701	-80%





Model

1- Predicting distributor sellout

```
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)        8291.22     533.96  15.528  < 2e-16 ***
log(BB + 1)         -45.18      58.13  -0.777    0.438    
CategoryCategory2 -6818.99     314.82 -21.660  < 2e-16 ***
CategoryCategory3 -1788.95     301.25  -5.938 1.59e-08 ***
CategoryCategory4 -7033.47     416.75 -16.877  < 2e-16 ***
CategoryCategory5 -5170.50     303.98 -17.009  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1258 on 169 degrees of freedom
Multiple R-squared:  0.8308,    Adjusted R-squared:  0.8258 
F-statistic:   166 on 5 and 169 DF,  p-value: < 2.2e-16
```

2- Predicting company shipment

```
Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)        8.399e+03  1.141e+03   7.361 7.88e-12 ***
CategoryCategory2 -7.228e+03  1.047e+03  -6.906 9.95e-11 ***
CategoryCategory3 -1.691e+03  5.081e+02  -3.327  0.00108 ** 
CategoryCategory4 -6.978e+03  1.029e+03  -6.778 2.00e-10 ***
CategoryCategory5 -5.023e+03  7.546e+02  -6.657 3.85e-10 ***
Sellout            2.552e-01  1.101e-01   2.319  0.02161 *  
Inv               -6.535e-02  2.255e-02  -2.898  0.00427 ** 
Events            -7.957e+02  3.605e+02  -2.207  0.02867 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1792 on 167 degrees of freedom
Multiple R-squared:  0.7563,    Adjusted R-squared:  0.7461 
F-statistic: 74.03 on 7 and 167 DF,  p-value: < 2.2e-16
```

Forecasting Techniques

- ➢ **Simulation**
- ➢ **Croston and it's variation**
- ➢ **Multi-Tiered Causal Analysis**

$$(1)\ Demand\ (D) = \beta 0\ Constant + \beta 1\ Trend + \beta 2\ Seasonality + \beta 3\ Price + \beta 4\ Advertising + \beta 5\ Sales + \beta 6\ \%\ ACV\ Feature + \beta 7\ FSI + \beta 8\ Store\ Distribution + \beta 9\ Competitive\ Price + \cdots \beta n$$

$$(2)\ Supply\ (S) = \beta 0\ Constant + \beta 1\ D(lag1 - n) + \beta 2\ Trend + \beta 3\ Seasonality + \beta 4\ Gross\ Dealer\ Price + \beta 5\ Factory\ Rebates + \beta 6\ Cash\ Discount + \beta 7\ Coop\ Advertising$$

Model with building Block

```
Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)         8.434e+03  1.183e+03   7.131 2.93e-11 ***
CategoryCategory2 -7.256e+03  1.076e+03  -6.745 2.42e-10 ***
CategoryCategory3 -1.673e+03  5.310e+02  -3.151  0.00193 ** 
CategoryCategory4 -7.012e+03  1.073e+03  -6.534 7.52e-10 ***
CategoryCategory5 -5.056e+03  8.065e+02  -6.269 3.02e-09 ***
Sellout             2.532e-01  1.118e-01   2.266  0.02477 *  
Inv               -6.373e-02  2.647e-02  -2.408  0.01714 *  
BB                -1.148e-02  9.736e-02  -0.118  0.90632    
Events            -7.879e+02  3.676e+02  -2.143  0.03355 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1798 on 166 degrees of freedom
Multiple R-squared:  0.7563,    Adjusted R-squared:  0.7446 
F-statistic:  64.4 on 8 and 166 DF,  p-value: < 2.2e-16
```