

Using Multi-tiered Causal Analysis to Synchronize Demand and Supply

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ABSTRACT

The two primary objectives of multi-tiered casual analysis (MTCA) are to support and evaluate business strategies that are based on the effectiveness of sales and marketing actions in both a competitive and holistic environment. By tying the downstream data—point-of-sale (POS) or syndicated scanner data—and the performance of a market, channel, brand, product, or SKU (or some combination) at retail to internal upstream replenishment shipments (or sales orders) across time, you can simulate and evaluate the outcome of making a change to sales and marketing programs (demand) in order to determine the full impact on supply (shipments). MTCA enables you to capture the entire supply chain by using predictive analytics to sense sales and marketing strategies, and then use “What If” scenario analysis to shape future demand. Finally, by linking future shaped demand to supply (shipments), you can arrive at a most realistic supply response (shipment forecast).

INTRODUCTION

Over the past several years, integrating consumer demand into the demand forecasting and planning process to improve shipment (supply) forecasts has become a high priority in the consumer packaged goods (CPG), automotive, pharmaceutical, over-the-counter (OTC) drug products, appliance, high-tech, and many other industries. Until recently, many factors, such as data collection and storage constraints, poor data synchronization capabilities, technology limitations, and limited internal analytical expertise, have made it impossible to integrate consumer demand with shipment forecasts. Consumer demand data include point-of-sale (POS) data and syndicated scanner data from The Nielsen Company, Information Resources, Inc. (IRI), and Intercontinental Marketing Services (IMS). This paper outlines a process that uses multi-tiered causal analysis, a process of nesting advanced analytical models, to link consumer demand to supply (that is, to link downstream data to upstream data). Although this process is not new in concept, it is new in practice. With improvements in technology, data collection and storage, processing, and analytical knowledge, companies are now looking to integrate downstream consumer demand with their upstream shipment (supply replenishment) forecasts to capture the impact of marketing activities (sales promotions, marketing events, in-store merchandising, and other related factors) on supply. (In-store merchandising includes primarily floor displays, features in store circulars, and temporary price reduction.) MTCA is a process that considers marketing and replenishment strategies jointly rather than creating two separate forecasts, one for consumer demand and another for shipments. MTCA also has implications on furthering the sales and operations planning (S&OP) and integrated business planning (IBP) processes.

OVERVIEW OF MTCA

MTCA is a process that links downstream and upstream data by using a series of quantitative methods together to measure the impact of sales and marketing strategies on consumer demand. Then, using the demand model coefficients, MCTA executes various what-if scenarios to shape and predict future consumer demand. Finally, it uses data and analytics rather than “gut feeling” judgment to link demand (POS/syndicated scanner data) to supply (sales orders or shipments).

In industries where downstream data is available, MTCA is used to model the push and pull effects of the supply chain by linking a series of quantitative models together based on marketing investment strategies and replenishment policies to retailers. The theoretical design applies in-depth causal analysis to measure the effects of the sales and marketing programs on consumer demand at retail (pull), and then links it, via consumer demand, to supply (push). This is known as a two-tiered model. For companies that have more sophisticated distribution networks, a three-tiered (or more) model could incorporate wholesalers (that is, consumer to retailer to wholesaler to manufacturing plant) or distributors, or both.

After the causal factors that influence consumer demand are determined and business drivers of consumer demand are sensed (measured) and used to shape future demand, a second model is developed by using consumer demand as the primary explanatory variable (or lead indicator) to link consumer demand to supply (shipments). The supply model can also include factors such as trade promotions, gross dealer price, factory dealer rebates, cash discounts (or off-invoice allowances), co-op advertising, and seasonality to predict supply (shipments). In many cases, consumer demand is lagged forward one or more periods to account for the buying (replenishment) patterns of the retailers. For example, mass merchandisers, such as Walmart, buy in bulk prior to high periods of consumer demand, usually one or more periods (months or weeks) prior to the sales promotion. Other retailers, such as Publix, carry large varieties of products and hold small inventories. This practice shortens their purchase cycle and requires them to purchase products more frequently with virtually no lag on consumer demand when introduced into the supply model. Other variables, such as price and advertising, also need to be lagged and transformed (using transfer functions) to account for the lagged decay effects and the cumulative aspects of consumer awareness.

Suppose that the retail consumer demand (D) of Product A is defined as follows, where Distribution is the percentage of stores in which the product will be sold:

$$\text{Demand (D)} = \beta_0 \text{ Constant} + \beta_1 \text{ trend} + \beta_2 \text{ Seasonality} + \beta_3 \text{ Price} + \beta_4 \text{ Advertising} + \beta_5 \text{ Sales Promotion} + \beta_6 \% \text{ ACV Feature} + \beta_7 \text{ Store Distribution} + \beta_8 \text{ Competitive Price} + \dots \beta_n$$

Then Product A's supply (S) would be

$$\text{Supply (S)} = \beta_0 \text{ Constant} + \beta_1 D (\text{lag1+n}) + \beta_2 \text{ trend} + \beta_3 \text{ Seasonality} + \beta_4 \text{ Gross Dealer Price} + \beta_5 \text{ Factory Rebates} + \beta_6 \text{ Trade Discounts} + \beta_7 \text{ Co-op Advertising} + \beta_8 \text{ Trade Promotions} + \dots \beta_n$$

For MTCA, you can use a "What If" scenario analysis to hold some of the explanatory variables (key business indicators) static while changing others to simulate the impact of alternative marketing strategies on consumer demand. The impact of the selected scenario is linked to supply (shipments). The goal here is to simulate the impact of changes in key performance indicators (those that shape future demand) that can be changed, such as price, advertising, in-store merchandising, and sales promotions (or events); determine their outcomes (predict demand); and choose the optimal strategy that produces the highest volume and revenue. The key assumption is that "if all things hold true" based on the model's parameter estimates when the level of pressure on any one or group of explanatory variables is changed, it will have "X" impact on future consumer demand, resulting in "X" change in supply (shipments). The most difficult explanatory variables to simulate are those related to competitors and to factors over which companies have little or no control (such as weather, economy, and local events).

STEP-BY-STEP PROCESS

This step-by-step process is an actual application of MTCA that uses downstream (POS and syndicated scanner) data and upstream (shipment) data at a large CPG manufacturer to sense, shape, and predict demand and supply. A brand manager, demand analyst (statistical modeler), and demand planner all work together to evaluate the efficiency and productivity of the company's sales and marketing efforts (sense the demand signal by measuring the impact of business drivers that influence demand), take actions (shape future demand) with the goal of driving more profitable volume growth, and then proactively predict future consumer demand (POS and syndicated scanner data). Then they link predicted demand to supply to create a supply plan (shipment forecast). The brand manager has the domain knowledge of the market, category, channel, brand, products, SKUs, and marketplace dynamics; the demand analyst has the statistical experience and knowledge to apply the appropriate quantitative methods; and the demand planner has the demand planning (supply planning) expertise. This process raises three major questions:

1. What tactics in the sales and marketing programming are working to influence the demand signal within the retail grocery channel? Identifying and measuring the key business indicators (KBIs) that influence demand is called sensing demand.

2. How can they use “What If” analysis to put pressure on those key business indicators to drive more volume and profitability? In other words, what alternative scenarios can be identified to maximize their market investment efficiency? This is shaping future demand.
3. How does the final shaped demand influence supply (shipments)?

These three questions can be answered by the following six steps:

Step 1: Gather all the pertinent data for consumer demand and shipments. In this example, POS syndicated scanner data (153 weeks, starting January 1996) was downloaded from the Nielsen database at the brand, product group, product, package size, and SKU levels for the entire grocery channel. The example focuses on the brand's weekly case volume, non-promoted price, in-store merchandising vehicles (displays, features, features and displays, and temporary price reduction), and distribution percentages by product, which were downloaded along with major competitor information. The calendar for marketing events (sales promotions and marketing events) from the sales and marketing plan was also downloaded along with weekly advertising “targeted rating points” (TRPs) that are managed by their advertising agency. TRPs are similar to “gross rating points” (GRPs) except they target certain age and/or gender groups rather than all groups. Finally, weekly supply volumes (shipments) were downloaded along with wholesale price, case volume discounts (off-invoice allowances), trade promotions/events, and local retailer incentives being offered by the CPG manufacturer.

It made more sense to model at the product group level (middle-out) rather than at the individual SKU level (bottom-up) and disaggregate the product group case volume down to the individual SKU level, using the bottom-up statistical demand forecasts, which build in the trends that are associated with the lower-level SKU mix. This particular CPG brand is nationally distributed with several size and package configurations.

The brand hierarchy is as follows:

- Total market area
 - Total grocery channel
 - Total brand
 - **Product groups (use demand shaping at this aggregate level)**
 - Group 1
 - Group 2
 - Products
 - Product 1
 - Product 2
 - Product 3
 - SKUs

The product group case volume projections are disaggregated down across all the lower levels to the SKUs based on their historical demand and supply (shipments), including any trends that are established using basic time series methods (for example, Holt-Winters exponential smoothing and others). The SKU forward forecasts provide a mechanism to build in trends that are associated with those lower SKU levels, and the brand level forward projections reflect sales and marketing investment activities and seasonality. In other words, we build models at every level (bottom-up), but run our “What If” scenarios at the middle-out product group level. Finally, we use the lower-level SKU forecasts to disaggregate the middle-out product group forecast volumes down to the SKU level. This method of disaggregation builds in the lower-level trends and creates a more dynamic result; this method is more accurate than using a static disaggregation. Figure 1, which shows consumer demand and shipments at the product group level, indicates that there is a strong correlation between demand and supply.

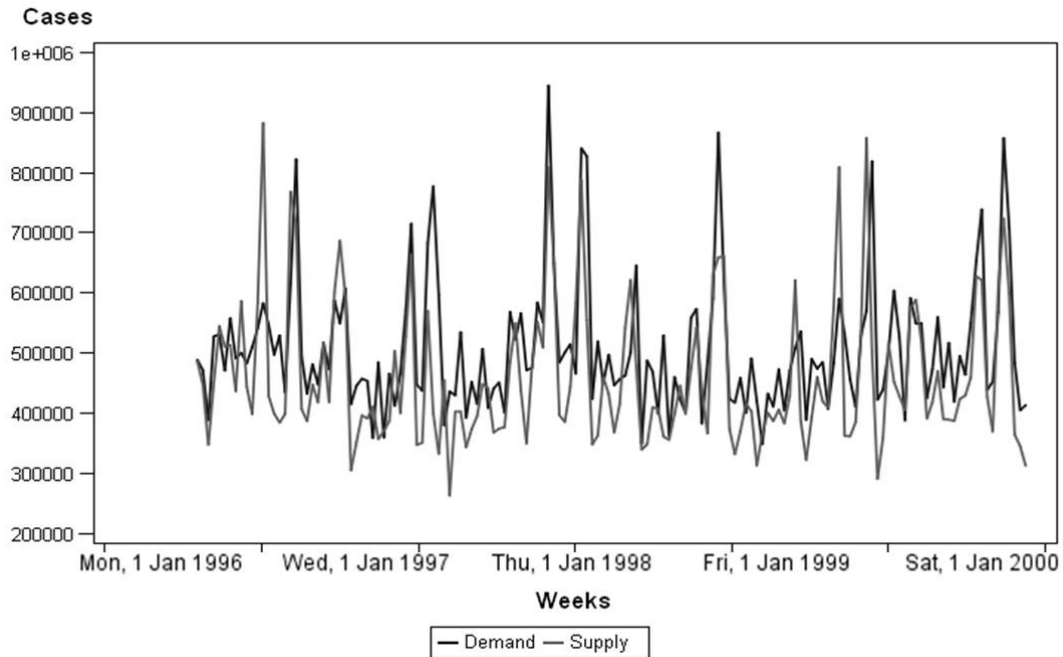


Figure 1. Consumer Demand Compared to Shipments

Step 2: Build the consumer demand model by using downstream data to sense demand. The demand analyst runs the company forecasting system to create the business hierarchy and then uses time series and causal models and the Nielsen data from their demand signal repository (DSR) to investigate all the data to create statistical consumer demand forecasts at all levels of the hierarchy. The DSR is a centralized database that stores, harmonizes, and normalizes data attributes and organizes large volumes of demand data—such as point-of-sale (POS) data, wholesaler data, electronic data interchange (EDI) 852 and 867, inventory movement, promotional data, and customer loyalty data—for use by decision support technologies, category management, account team joint value creation, shopper insight analysis, demand planning forecast improvement, inventory deployment, replenishment, and transportation planning. Then at the Product Group level in the hierarchy, create consumer demand models to sense, shape, and predict demand (D), which is the first tier in the MTCA process. Demand drives supply, not the reverse, so it is important to model demand before supply. The demand forecast serves as the primary lead indicator or explanatory variable in the supply (S) model. The selected model is an ARIMAX model (ARIMA model with causal variables) that uses causal factors that are significant in influencing demand. See Table 1 for model results.

Consumer Demand Model Results					
ARIMAX Model (0,1,1)(0,1,1)					
	R ² = .8478	Adj. R ² = .8071			
Component	Parameter	Coefficient	Standard Error	t-Value	P-Value
Demand	MA1	0.85394	0.0715	11.94	0.001
Demand	MA2_52	0.1849	0.2024	1.91	0.001
Product 1 Price	Scale	-117306.2	25221	-4.65	0.001
Product 1 Price	Den1	-0.05512	0.2104	-0.26	0.7942
Product 2 Price	Scale	11081.5	3262.8	3.4	0.0012
Product 2 Price	Num1	1672.2	3823.6	0.44	0.6633
Product 2 Price	Num2	14293.5	3406.7	4.2	0.001
Product 3 Price	Scale	-78099.8	21161.9	-3.69	0.0005
Product 3 Price	Num1	12398.1	24064.1	0.52	0.6081
Product 2 Display	Scale	-2992.6	710.5	-4.21	0.001
Product 2 Display	Den1	-0.2992	0.2237	-1.34	0.1863
Competitor 1 Promo	Scale	-1003	1102.4	-0.91	0.3662
Competitor 1 Promo	Num1	-831.63	1085.9	-0.77	0.4465
Competitor 1 Promo	Num2	-979.55	1056.5	-0.93	0.3572
Memorial Day	Scale	110891.2	28181.9	3.93	0.0002
Competitor 1 Display	Scale	-1796.6	531.75	-3.38	0.0012
Competitor 1 Display	Den1	-1.02	0.0795	-12.84	0.001
Competitor 1 Display	Den2	-0.8005	0.0817	-9.8	0.001
Competitor 2 Price	Scale	134118.1	58706.8	2.28	0.0255
Competitor 2 Price	Den1	-0.61	0.2767	-2.18	0.0329

Fitted MAPE = 7.23% 13WK Holdout MAPE = 7.48%

Table 1. Consumer Demand Model Results at the Aggregate Product Group Level

Step 3: Test the predictive ability of the model by using out-of-sample data. Figure 2 compares model projections against the actual results. The model was tested with a 13-week out-of-sample forecast (holdout sample). Overall, the predictability of the model is very good with a fitted MAPE of 7.23% and a holdout MAPE of 7.48%. Even on a week-to-week basis, the model is fairly good (well below the industry average of 22–35%, which is based on benchmarking surveys published in the *Journal of Business Forecasting*). If the demand analyst finds a week or more in the holdout sample test that are outside the 95% confidence level range, the brand manager knows what happened by identifying inputs that can be added to the model. This is where domain knowledge, not “gut feeling,” can help. The demand analyst might identify additional explanatory variables that should be incorporated into the model or might point out sales and marketing events that were overlooked. In our example, each of the holdout-sample forecasts was within the 95% confidence level (not uncommon for consumer demand models) because most of the POS and syndicated scanner data at the aggregate level is very stable. Plus, there was no change in the customers’ inventory replenishment policies. The core reason why shipment data is unstable is changes in the manufacturer’s replenishment policy or load practicing (or both).

Step 4: Refit the model by using all the data. After identifying and verifying the consumer demand model parameter estimates for all the explanatory variables and testing the model’s predictive capabilities, the modeler refits the model with the 13-week out-of-sample data (using all 153 weeks of data). See Figure 2 for the final model fit and forecast, which use the entire data set.

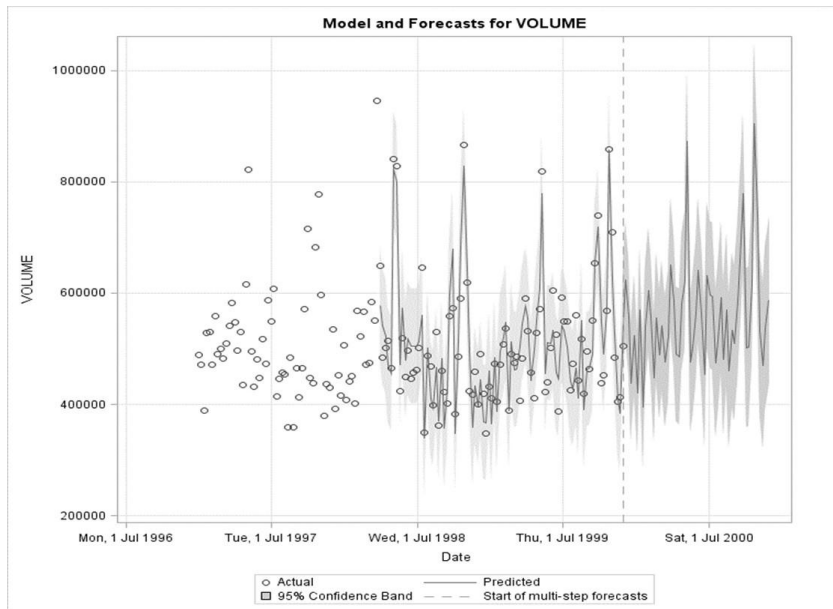


Figure 2. Consumer Demand Model Fit and Final Forecast

Step 5: Run what-if scenarios to shape future demand. Using the consumer demand model, the product manager can shape demand by conducting several what-if simulations by varying future values of different explanatory variables that are under his or her control. Upon completion of the simulations, the product manager chooses the optimal scenario that generates the most case volume and profitability; that scenario then becomes the consumer demand future forecast for the next 52 weeks. The optimal model can be selected in matter of minutes with the right technology. After the optimal scenario (model) is chosen based on available marketing expenditure, document the assumptions.

In many cases, the marketing budget constraints play a key role in the number and type of sales promotions the company can execute. Finance also plays a role in assessing the financial impact on a revenue and profitability basis. It is recommended that post-analysis assessments be conducted prior to updating the model and regenerating a new forward consumer demand forecast to identify opportunities and weaknesses in the sales and marketing investment plan. In other words, a post-reconciliation of the actual execution of the final scenario should be conducted after each weekly or monthly update to determine deviation of the actual from the forecast so that corrective action can be taken.

Step 6: Link the consumer demand forecast to supply (shipments). The process just described is now applied to develop a model for supply (shipments) by using demand (D) as the key independent variable along with its forward forecast based on the final scenario chosen by the product manager in the demand-shaping phase of the process. As a result, the demand analyst links the first tier (demand) to the second tier (supply) of the supply chain by incorporating consumer demand (D) as one of the explanatory (predictor) variables in the supply (S) model. The results in Table 2 show demand along with several other trade variables that influence supply (for example, average wholesale price, trade promotions, off-invoice allowance, trade discounts, and inventory). The most significant variable in the supply model is consumer demand (0.37739), which indicates that 37.75% of shipments are being pulled through the grocery channel by consumer demand at the product group level. Conversely, approximately 62% of shipments are being pushed through the channel by offering trade incentives to retailers.

Shipments (Supply) Model Results					
ARIMAX (0,1,1)(0,1,0)					
	$R^2 = .7257$	$\text{Adj. } R^2 = .69.32$			
Component	Parameter	Coefficient	Standard Error	t-Value	P-Value
Shipments	Constant	-1804233.7	724840.7	-2.49	0.0146
Shipments	MA1	0.33201	0.10352	3.21	0.0018
Demand	Scale	0.37739	0.10304	3.66	0.0004
Wholesale Price	Scale	-26196.5	14685.2	-1.78	0.0778
Trade Inventory	Scale	-25045.2	11170.1	-2.24	0.0274
Trade Promo 1	Scale	1408147.7	565403.2	2.49	0.0145
Off-Invoice Allowance	Scale	2768.5	1302.6	2.13	0.0362
Trade Discount	Scale	1536.7	749.16	2.05	0.0431

Fitted MAPE = 10.57% 13WK Holdout MAPE = 12.64%

Table 2. Shipment (Supply) Model Results at the Aggregate and Product Group Level

Note that the fitted MAPE of supply is 10.57% and the holdout MAPE of the 13-week out-of-sample is 12.64%, which is well below the industry average of 15.0–25.0%. Keep in mind that the industry average is based on one-month-ahead monthly forecasts, whereas the MTCA model is of 1–13 weeks out. These results are not uncommon when the MTCA process is used.

The demand planner then uses the supply model to create 52-week forward forecasts for supply. The demand planner can use “What If” analysis with different values of explanatory variables to perform additional supply shaping. Figure 3 is the final supply forecast (shipment plan). Prior to the pre-S&OP meeting, the demand planner disaggregates the product group level supply forecasts down across all the member SKUs and reconciles the supply forecast business hierarchy by using the company’s demand forecasting and planning system. In other words, the demand planner disaggregates the middle-out product group supply forecasts down the hierarchy to the SKU level mix and then summarizes the results to make sure the entire supply forecast is synchronized (summarized and balanced) up and down the business hierarchy.

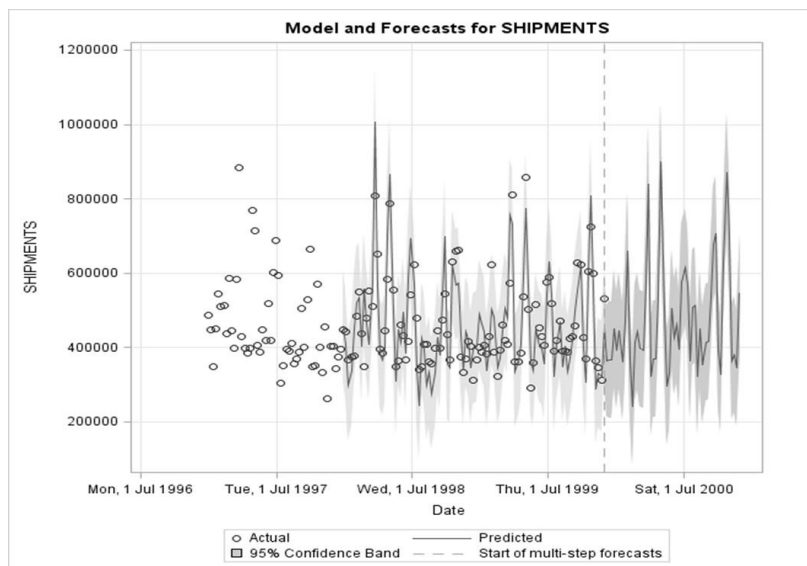


Figure 3. Shipment (Supply) Model Fit and Final Forecast

SUMMARY

Multi-tiered causal analysis (MTCA) is a simple process that links a series of causal models, in this case two ARIMAX models, through a common element (consumer demand) to model the push/pull effects of the supply chain. It is a decision-support system that is designed to integrate statistical analysis with downstream (POS or syndicated scanner or both) data and upstream (shipment) data to analyze the business from a complete supply-chain perspective. This process enables both brand management and demand planners to make better and more actionable decisions from multiple data sources (that is, POS/syndicated scanner, internal company, and external market data). The purpose of the process is to provide a distinct opportunity to address supply-chain optimization through the nesting (supply-chain distribution tiers) of causal models to sense demand signals and then use what-if simulations based on alternative business strategies (sales/marketing scenarios) to shape and predict future demand. Finally, the objective is to link consumer demand to supply (shipments) by using a structured approach that relies on data, analytics, and domain knowledge rather than on “gut feeling” judgment and manual manipulation (manual overrides).

The key benefit of MTCA is that it captures the entire supply chain by focusing on sales and marketing strategies to shape future consumer demand, and then uses a holistic framework to link demand to supply. These relationships are what truly define the marketplace and all marketing elements within the supply chain. Today, technology exists to enable demand analysts to use their data resources and analytics capabilities as a competitive advantage, offering a true, integrated supply-chain management perspective to optimize the value chain. Relying just on a demand (supply) model is like taking a picture of inventory replenishment through a narrow-angle lens. Although you can see the impact within your own supply replenishment network (upstream) with some precision, the foreground (downstream) is either excluded or out of focus. As significant (or insignificant) as the picture might seem, far too much is ignored by this view. To enable you to capture the full picture of the supply chain, MTCA provides a wide-angle telephoto lens to ensure clear resolution of where a company is and where it wants to go.

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