Predictive Analytics, Big Data, and Abnormal Purchasing Patterns in the Pharmaceutical Supply Chain
“Big Data” and “Predictive Analytics” dominate discussion within the boardroom, are often featured panel discussions at business conferences, and are plastered across marketing documents; however, it can be difficult to define what these phrases entail and even more demanding to determine how they might be of use to an organization – particularly within the pharmaceutical industry.

The Council of Supply Chain Management Professionals (CSCMP) details the widespread misapplication of Big Data in their Q3 2014 issue of Supply Chain Quarterly: “Although widely used, the term ‘big data’ is poorly defined. This lack of a clear definition may be the reason why some supply chain managers make the mistake of thinking that big data has little relevancy to their work …”

The CSCMP warns that those supply chain managers who view Big Data as “just an IT storage issue” may overlook the inherent value of the data they’re collecting. Many executives fail to take advantage of the data at their fingertips, and fewer think of creative applications that might benefit their organization.

### Predictive Analytics and the Pharmaceutical Industry

The use of analytics and behavioral intelligence tools has exploded with the market speculated to grow to $17 billion by 2016 (Gartner, Inc., 2012). Even so, trying to define predictive analytics is almost as nebulous a task as defining Big Data; indeed,
the pharmaceutical industry has leveraged predictive analytics for years in the form of forecasting (e.g. inventory levels, product demand). Why then has predictive analytics emerged as a particularly potent buzzword in recent years?

In a survey of leading American businesses, Dresner Advisory Services found that less than 30% of organizations currently deploy advanced and predictive analytic tools; however, another 30% plan to deploy some such service in the next 18 months (Dresner Advisory Services, 2014). Despite most organizations being slow to adopt, almost 90% of respondents attach some importance to predictive and advanced analytics.

The demand for predictive analytics should not be attributed to one source, but rather to a number of congruent factors that have made new analytics possible:

- Intuitive user interfaces (e.g. SPSS, SAS) have lowered the technical barriers to end users
- Rise of the Hadoop platform, an alternative to SQL capable of processing vast quantities of data
- Increasing popularity of R Language, a free, open source alternative to SAS and SPSS with powerful analytic capabilities
- Improving data collection and custodial efforts, coupled with the falling cost of storage has led to the increased availability of “good” data
- Advances in machine learning algorithms and speed of computation have expanded what is possible with predictive analytics

Predictive tools will continue to provide new functionality and see more widespread deployment. As the market grows, so too does the need to differentiate between different forms of analytics; “predictive analytics” has become a catchall term, similar to Big Data, that encompasses a number of potential meanings. Experts tend to group analytics into several different categories (CSCMP, 2014):

- **Descriptive Analytics**: Reporting and score carding that describe the state of some industry, product, etc.
- **Predictive Analytics**: Refers to the idea of predicting future behavior or improving a forecast.
- **Prescriptive Analytics**: An extension of predictive analytics; a form of analysis that recommends a certain action to take. Alternatively referred to as optimization, these analytics can tell a trade manager the ideal range for performance metrics.

Novel applications of advanced analytics are necessary to effectively manage your supply chain and diagnose the correct course of action. When leveraged effectively, Big Data and predictive analytics can lead to a competitive advantage in the industry.

Having defined what these terms entail, we explore how predictive analytics have been used to great effect in pharmaceutical manufacturing. Industry experts are concerned that an old issue is on the rise again: abnormal purchasing patterns around product price changes, exacerbating variability within the pharmaceutical supply chain.
This restructuring was largely due to instances of speculative buying, wherein a wholesaler would hoard product in anticipation of a price increase, benefiting from the increased market value following the price change. Critics of investment buying claimed the practice introduced variability to the supply chain thereby reducing the effectiveness of forecasts and the ability to gauge market health.

ValueCentric was a pioneer firm in helping manufacturers to manage their FFS agreement-related data and their relationships with wholesalers. Recently, manufacturers have approached ValueCentric because they believe investment buying is on the rise again, this time further downstream at the outlet level.

The pharmaceutical manufacturing industry is particularly vulnerable to investment buying due to the relative predictability of potential product price changes. Almost 31% of price changes occur January 1st, and 15% occur sometime in July (Figure 1). Further analysis of price change data reveals that the same manufacturer/product combinations tend to perform their price changes on the same date each year.

Leveraging R’s suite of predictive analytics and machine learning algorithms, data scientists at ValueCentric have put together a solution that identifies unusual buying patterns at the outlet level. ValueCentric calculates candidate locations by measuring manufacturer post-price change revenue at risk and the likelihood of investment buying behavior. This predictive algorithm is run across a manufacturer’s universe of 867 data, returning the most affected products at the outlet location level.

Recently, ValueCentric partnered with a top US pharmaceutical manufacturer to investigate suspicious downstream purchasing patterns. Investment buying patterns are identifiable by atypical purchasing increases preceding a price change, followed by a subsequent dip in product orders (i.e. peaks and valleys surrounding a price change). High cost, low volume products are most at risk, though low cost, high volume products are also attractive investment buying candidates; this manufacturer’s product falls into the former category.

Figure 2 depicts one such result of that investigation: an outlet location with over $20 million in annual product sales. We observe that sales increased from an average of 300 units to a peak 700 in December, 2012 – more than a hundred percent increase from baseline sales. Those

<table>
<thead>
<tr>
<th>Month</th>
<th>Price Increase</th>
<th>Sum of Sales Units</th>
<th>Average Sales Units</th>
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<tbody>
<tr>
<td>Jan</td>
<td>31%</td>
<td>300</td>
<td>300</td>
</tr>
<tr>
<td>Feb</td>
<td>24%</td>
<td>350</td>
<td>350</td>
</tr>
<tr>
<td>Mar</td>
<td>12%</td>
<td>400</td>
<td>400</td>
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<tr>
<td>Apr</td>
<td>9%</td>
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<tr>
<td>May</td>
<td>8%</td>
<td>500</td>
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<td>Jun</td>
<td>7%</td>
<td>550</td>
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<td>Jul</td>
<td>6%</td>
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<td>Nov</td>
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<tr>
<td>Dec</td>
<td>1%</td>
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Speculative investment purchasing is most prevalent when the date of a price change is easily predicted; randomizing this date would make product hoarding a higher risk, lower return endeavor for outlets (Robert C. Blattberg, 2010).

ValueCentric, on behalf of their client, was able to detail over thirty outlets engaged in suspicious buying with over one hundred million dollars in at-risk inventory. Armed with knowledge of the extent of the problem, the manufacturer was able to make adjustments to their forecasts, weigh the pros and cons of randomizing their future price increases, and more closely monitor downstream orders.

Novel applications of predictive analytics are necessary to effectively manage your supply chain and diagnose the correct course of action. Leveraging Big Data and predictive analytics, although difficult, can be lucrative and provide an advantage over your competitors. ValueCentric data scientists are available to transform your data into prescriptive metrics, and can help you identify the Big Data tools necessary for your organization.

With over ten years of experience managing pharmaceutical supply chain data, ValueCentric is uniquely positioned to offer unprecedented insights into Big Data and predictive analytics. ValueCentric data scientists can help solve novel problems in your supply chain with its experience in using tools such as R, Hadoop, SQL, SAS, and SPSS. ValueCentric is committed to researching breakthroughs in Big Data and to empowering your organization through joining ValueTrak data with 3rd party sources to best solve your supply chain problems.

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REFERENCES

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