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Analytics is not of course profitable, it's a cost. However, converting analysis into more effective decisions, is the way to potentially improve revenue and profitability. This is the only role for analytics, and the reason we invest time, money and effort in the analytical process - to make better decisions. Anything else is navel gazing or technology for its own sake.

Since analytics break down into several well defined domains, it is useful to consider the types of decisions each can affect.

- Business Intelligence provides a look in the rear-view mirror and supports diagnostics of prior performance. As such it is most useful for tactical decision making. We might use BI to determine whether greater production capacity is needed, or whether sales people should be divided by territory in a different way. BI may provide some input to strategic decision making, but macro factors are likely to be much more important - economic conditions, competitor activity, market growth, and so on. Production level decisions are barely served by BI in any significant way - it would just be too time consuming to perform an analysis for every transaction a business was involved in. So the natural role for BI is to aid tactical decision making.

- Machine learning and predictive analytics. Machine learning algorithms are used to create predictive models, which in turn facilitate predictive analysis. Predictive models are generated by trawling through historical data and finding patterns that might be useful in future activities. Classic examples include identifying which customers might churn, and transactions that might be fraudulent. Clearly this is most useful in business operations at the transaction level. Predictive analysis would not have much to say about tactical or strategic decision making, simply because we tend to not have significant amounts of data for activity at these levels. If we did, the applicability could be extended. So, as things stand, predictive analytics is most useful for transaction level operational decisions.

- Prescriptive analytics differs from other form of analysis in that it concerns itself with 'how' rather than 'what'. In BI and predictive analytics, we are concerned with what has happened and what might happen respectively. Prescriptive analytics deals with how resources should be used to achieve a certain aim in the most efficient manner. Optimization technologies are particularly relevant, where resources, constraints and objectives are specified, and the most efficient deployment of those resources is found. So, unlike predictive analytics, prescriptive analysis is largely concerned with tactical decisions, although it is sometimes also used in real-time for finer granularity decision making.

Having outlined these three modes of analysis, the next step is to determine how they can be used to enhance revenue and/or profitability. Knowing whether an activity is profitable or not depends on measurement. If we can't or won't measure then we will never know the effect of our our analytical activities. So even though I am not an accountant, I do know that the formula for profitability looks something like this:

Profit = Benefits - Costs

We'll start with the easiest to measure - predictive analytics. It's the easiest because the decisions are atomic and discrete. If we implement predictive models which identify customers who might churn, then it should be relatively straightforward to measure the before and after. But even here there are difficulties. It has been pointed out to me many times that most businesses are not sufficiently coordinated within to ensure that only one thing changes at a time. So in the case of customer churn, it might be that the sales team has just been on a training course. If this happens around the same time as a predictive model for churn has been deployed, then how much of a performance improvement is due to the model and how much to the training? There is probably no way of knowing. So how do we measure the benefits associated with the new churn model? Simple answer - we cannot, and as such the profitability and revenue enhancements will never be known. The costs associated with the model are easy to determine - simple cost accounting. People time, software, maybe hardware or cloud service costs. And again, how often will people resources be allocated to a particular analytical task? Some businesses are better at this than others, but most will not record the IT, data science and management time spent developing a model, and as such the real costs will never be known. What all of this says is simple. It is possible to know the revenue and profitability enhancements a predictive model may generate, but it has little to do with the model. It requires disciplines that are usually not found in most businesses - some level of change scheduling, and people cost recording.

When we turn our attention to BI the situation becomes much more confused. BI is often a fire fighting tool, used to address tactical issues. Any attempt to measure the benefits that might be associated with analysis are going to be lost in the fog of tactical chaos. It’s the same with the cost side of the equation. Someone may spend weeks or they might just send a few hours trying to analyze some pressing issue. Typically, there is no record kept of time taken to perform analysis, and as such, the cost of labor. It would be quite fair to say that the returns from a BI investment will never be known. Some suppliers have been foolish enough to claim that customers have seen a 40% lift in customer loyalty, or some other such figure, since a BI platform was installed - but the costs are largely invisible, and other changes will be hard to isolate and exclude. And so using a BI platform is largely an act of faith - a belief that access to data and the tools of analysis will deliver positive results, even though no one is really counting the labor cost, or isolating changes derived from analysis.

Prescriptive analytics suffers pretty much the same fate as the other forms of analysis. The benefits of rescheduling production, because a model indicates greater throughput and efficiency, will be hard to identify if at the same time new machinery is introduced or working practices changed.

When we look back to when system of records type applications was pretty much the only goal of IT, it was very common to estimate some form of return on investment as a justification for investment. The calculations were easy simply because they focused on labor displacement. If twenty people could do the work of fifty, then the costs savings were simple to calculate. The same disciplines are not being applied to analytics, and so the job of establishing contribution to profit and revenue is almost impossible. It will require much greater attention to the implementation of change and the recording of labor costs if the effects of analytics are to become apparent. There will be resistance to such moves, not least because the measurement of labor time now involves white collar workers. Clerical staff and blue collar workers had little say on the topic of time recording, but white collar workers might not be so amenable.

Obviously, it is a precarious situation when a business does not know the returns it is getting from analytics activities. Sooner or later things will have to change, and the catalyst will be AI. Companies like Hitachi are already using AI managers, and these will have no problem recording things to the minutest detail. Better get ready for change, and to possibly be surprised at the benefits and costs associated with business analytics.