Terrific Bad News for Lean Six Sigma

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The lynchpin characteristic of Lean Six Sigma is that the stages of its DMAIC backbone eliminate waste, mistakes and variance through heavily quantitative methodologies. In fact, the quantitative foundation is what separates Lean Six Sigma from all other business improvement methods; the raison d'etre for making the strategic commitment to Lean Six Sigma.

But there is terrific bad news. The “bad” news is that the quantitative methods of DMAIC are behind the curve. The “terrific” news is that the quantitative methods of DMAIC are behind the curve. By moving to the front of the curve, the reality of Lean Six Sigma will finally catchup with the vision of Lean Six Sigma.

How Lean Six Sigma Fell Behind the Curve

Lean Six Sigma emerged during the 1990s as a cutting edge strategy to improve manufacturing processes. The dominate quantitative methods were statistical process control, basic statistical practices and base-level ANOVA modeling. Minitab and Excel became the software of choice and ubiquitous in Lean Six Sigma literature. Contrast that with the article’s header graphic.

The methods and software worked well enough for manufacturing processes. However, they are not nearly strong enough to deal with non-manufacturing processes; the vast majority of enterprise processes.

There is a reason this is so. Although Lean Six Sigma took hold in the 1990s, the ability for firms to bring advanced analytics to their quantitative frontline has only really emerged in the last ten years. Unnoticed, the barriers holding Lean Six Sigma behind the curve melted away.

Data from every event, decision and action accumulate in operating and enterprise resource planning (ERP) systems surrounded by an internet of things (IoT). Friendly tools to get at the captured troves of data are plentiful. Access to the knowledge and skills of advanced analytics has become hands-on accessible to belts that wish to learn them. The strongest of statistical software (R) is a free open system, with an immense support community, that anyone, team or organization can download to their notebook computers. Short of the extreme, standard office-grade notebook computers easily handle massive data and advanced analytics.

Getting to the Front of the Curve

How can your firm move its Lean Six Sigma projects to the front of the curve? Obviously, the firm must first recruit the seed skills to guide projects to engage front-of-the-curve analytics. It follows that each project would be approached as a means to disperse the seed's skills to the firm's belts.

The most direct approach is to recruit operations excellence professionals who are Lean Six Sigma Black Belts and fully competent in data and advanced analytics. The problem is that such people are currently in short supply.

In the face of scarcity, it is rational to think of recruiting data scientists into the firm's operational excellence organization. However, there is a fatal flaw to the strategy. It requires that the firm find people willing to abdicate a hard-won future as a data scientist.

For the data scientist it entails a career choice. One is to choose to remain in a career for which they are top notch—data scientist. The other is to choose a career for which they must start over with no professional credentials—management advisor.

In the absence of a seed black belt, it makes sense to engage advisor data scientists to build and vet front-of-the-curve analytic models. However, visiting data scientists cannot twist our Rubik's cubes for us.

With this strategy, for each project we belts must be able to specify to the data scientist the models and structures which will best serve each unique issue for insight across the DMAIC stages. Thence, we belts must be able to amend and interpret the models once built by the data scientist.

Accordingly, other than to build or guide others to build models while participating in projects, a primary role of the seed black belt is to disperse the skills to specify, amend and interpret models to peer belts. In turn, a role for them is to disperse the skills to amend and interpret to their project teams.

To accelerate the dispersion of analytic strength, the firm can provide incentives for its belts to take it upon themselves to gain the competence of a seed belt rather than wait for project experiences. An incentive strategy is viable because there are paths to gain the knowledge by self-motivated independent study.

At the most intense extreme is to complete formal graduate-level classwork to gain a certificate in applied statistics offered by a top-tier department of statistics (e.g., Certificate of Applied

Statistics, Texas A&M). At the other extreme, for the self-directed, is to work through the approximately 2,000 pages of text that explain data analytics, demonstrated in R (e.g., see footnote, Sequential Reading List). In the middle is to gain certification from a massive open online course (MOOC) through organizations such as Coursera and presented by top-tier departments of statistics (e.g., Data Science Specialization, John Hopkins). My personal strategy was the first two trails.

It is readily evident that "behind-the-curve" is the current competitive norm to operational excellence programs built upon Lean Six Sigma. Remaining at that position is contrary to the Lean Six Sigma philosophy of continual improvement until reaching excellence—that is if we believe it takes quantitative excellence to achieve operational excellence.

Sources for self-directed learning: *Discovering Statistics Using R*, Field and Miles, 2012 **|** *Multilevel Modeling Using R*, Holmes, 2014 **|** *Machine Learning with R,* Lantz, 2015 **|** *ggplot2, Elegant Graphics for Data Analysis*, Wickham, 2016 **|** *Introductory Time Series with R*, Cowpertwait and Metcalfe, 2009 **|** *Event History Analytics with R*, Bostrom, 2012 **|** Package "tsoutliers," Javier López-de-Lacalle, 2017

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