A managerial perspective of analytics

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This article presents a managerial perspective of analytics, & technology in general. While there are several points of alignment, business professionals tend to view technology primarily from a strategy lens, which causes them to develop certain considerations that may not be completely in sync with that of analytics professionals.

I've attempted to expand on three simple, but common managerial considerations, or biases depending on one's point of view. These are:

1. A general belief in the primacy of data over algorithms;
2. A preference toward good enough solutions; &
3. A constant lookout for commodification.

They have been elaborated below.

Data > Algorithms

Though a good knowledge of ML/DL (Machine Learning/Deep Learning) techniques contribute to creating a well-rounded data science professional, businesses are aware that data trumps algorithms when solving complex problems. Hence most firms expend significant efforts on corpus development, rather than algorithm development, which is also reflected in the dominance of data preparation tasks within an analytics professional's work.

Businesses believe, in agreement with analytics professionals, that a solid domain knowledge is a prerequisite to creating a large, high quality corpus. Tasks such as selection of data, feature engineering, imputation of missing values etc., are significantly informed by the business domain. Such knowledge enables a data scientist to make good assumptions, & exploit domain specific features to improve model performance. Besides, without making assumptions about the data prior to model selection, there's no reason to prefer one model over another.

Good enough > Perfect

> "The perfect is the enemy of the good."
>
> -- Voltaire, Dictionnaire philosophique

Richard Gabriel's essay, "Worse is better" from nearly three decades ago put the spotlight on the curious phenomenon of merely "good enough" software solutions, that achieve greater acceptance than their better engineered alternatives.

One way to understand this is to notice that information goods are special as their marginal cost of production is close to zero. This creates a market dominated by strong network effects, & TTM (Time to Market) becoming a key driver of monopoly status.

Simply put, given that the cost of copying software is close to zero, a careful rival who invests time to engineer a great product will nevertheless find it difficult to unseat a first-mover who has already saturated the market with a merely "good enough" solution.

Thus, from a business perspective, companies have an incentive to prefer speedy solutions, such as repurposing existing models via transfer learning etc., & develop a "good enough" product, rather than investing in creating state-of-the-art, record beating model, that possess a longer development horizon. This is especially the case in SaaS based startups where network effects dominate, due to their markets usually being two-sided.

The constant danger of commodification

Nearly two decades earlier, Nicholas Carr observed that contrary to the prevailing hype, increasing commodification had led Information Technology (IT) to no more be a key driver of strategic business advantage. This familiar theme has played itself out many times in history, & not just with IT. This consideration prompts businesses to engage in periodic reevaluations of a technology's perceived strategic advantage, with the result that spending is directly correlated with its advantage.

It's indeed the case that a company's data can provide a strategic business advantage. However, the same cannot be said about the associated algorithms & techniques. With the increasing commodification of ML/DL techniques, firms are starting to take a second look at investing in home-grown modeling efforts.

Paralleling the rise of Auto ML, startups have sprung up, offering cheap end-to-end automated services that claim to cover the entire analytics pipeline from the raw dataset to a creating a tuned & deployable ML/DL model. And although it's still early days, especially given that data preparation, feature engineering, & many other tasks that are informed by domain knowledge are not yet amenable to automation, on the few occasions when they do work, the performance of such automated services is comparable to, or sometimes exceeds that of hand-designed ML/DL models.

I believe analytics still has a few years to go before it gets commoditized. Nevertheless, as automated ML services grow more competent, companies will increasingly begin deciding between outsourcing or developing in-house analytics capabilities, prompted by the former's potentially attractive cost savings.

Conclusion

The purpose of this article is to provide a business perspective of analytics, & illustrate the top-of-mind managerial considerations regarding not just analytics, but technology in general.

Nevertheless, it's important to mention the following caveats:

1. There is plenty of heterogeneity in managerial thought on this topic. Therefore, this article should be read as "a" manager's perspective & not "the" managerial perspective.
2. Here, we assume the context of a business that utilizes analytics to augment their existing client offerings. And though there are a large number of firms like this, our reasoning is not applicable for the subset of firms that operate in a purely analytics domain, where benchmarking & going beyond "good enough" solutions is an important point of differentiation.
3. There is another important aspect of technology strategy involving whether a given technology constitutes disruptive innovation, that impacts a company's technology investment decision. We

haven't covered these & other considerations here, as each have their own subtleties, & would constitute too large a diversion.

To conclude, I know that topics like these tend to attract a diverse opinions & responses. I look forward to hearing them. I hope you've found this an interesting read. Thank you for your attention.